# A comprehensive analysis of calendar anomalies in mature and emerging markets

Essays on the major calendar anomalies in the US and Saudi markets



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#### **Abstract:**

The research begins with a comprehensive study on 4 major calendar anomalies at industry level in the US market for 90 years which include a break point period in 1952. Daily returns are examined for the weekday, turn-of-the-month, January and Halloween effects and the results confirm that the effects of these anomalies exist and persist uniformly across almost all industries in both periods before and after the break point. Hence, calendar effects are driven by economic events affecting all industries rather than by industry-specific factors. The thesis starts with the US market given the maturity of the market and the extended data available which will provide an overall understanding of the topic of calendar anomalies. To delve deeper into the topic of calendar anomalies the research attempt to investigate the famous weekday effect in an emerging market. Saudi Arabia. This will give a deeper understanding of the topic since investors attributed to this market have many behavioural aspects that could affect the anomaly like cultural and religious beliefs. The research studies the existence of the anomaly in 15 industries in the Saudi stock market by applying a break point in June 2013 where there was a change in the weekend days. The findings confirm the existence of the anomaly pre-June 2013 only, providing evidence that the break point event of changing the weekend days directly affected the anomaly. From this standpoint, the research continue to explore the pre-holiday effect in Saudi Arabia to further investigate the effect of culture and religion on calendar anomalies. The study examines the anomaly in both market and industry level to confirm whether the effect is limited to certain sectors or is a wide-market phenomenon affecting all industries similarly. The data covers daily returns for both the general market and 15 industries over a period of almost 11 years, from 2009 to 2020. The findings confirm the existence of the pre-holiday effect at the general market and industry level for religious holidays, however, there is no evidence found on the existence of the anomaly on non-religious holidays.

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## Chapter 1

#### 1.1 Introduction

The mid eighteenth century was deemed the beginning of traditional finance theories (Pompian, M, 2011). The most highlighted concept amongst these theories was the expected utility theory, where utility is a measure of individual satisfaction by consuming goods or services (Bernoulli, D, 1738). (Von neumann, J & Morgenstern, O, 1944) describe the expected utility theory by stating that market participants make decisions under risk by comparing the expected utility values of the available options. This theory along with other significant theories like the subjective expected utility theory proposed by (Savage, L, 1964) were the most recognisable theories for decades in financial literature regarding decision making under risk. In 1952, Markowitz introduced the portfolio selection model which formed the basis of the Capital Asset Pricing Model (CAPM), one of the most significant asset pricing models in financial literature. CAPM was developed by Sharpe (1964), Litner (1965), and Mossin (1966) and it describes the risk associated with an asset regarding its expected return. However, financial scholars favoured Fama and French's (1992) three factor model over the CAPM when they found that the CAPM produces anomalies inconsistent with market efficiency (Statman, 1999). A numerous number of asset pricing theories are based on Fama's assumption of market efficiency, where he defines efficient markets as markets where security prices always entirely reflect all available information.

The Efficient Market Hypothesis (EMH) is considered as the foundation of modern financial theory and has been the dominant investing theory for more than 30 years (from the 60s through to the mid 90s). It stands to reason, a generation ago, it was the most widely accepted approach by academic financial economists.

The topic of EMH continues to be an area of increased interest and debate amongst academics and finance professionals (Lim and Brooks, 2011). Fama (1965) was the first to introduce and define the concept of EMH. Fama defined an efficient market as:

"... a market where there are large numbers of rational, profit maximizers actively competing, with each trying to predict future market values of individual securities, and where important current information is almost freely available to all participants. In an efficient market, competition among the many intelligent participants leads to a situation where, at any point in time, actual prices of individual securities already reflect the effects of information based both on events that have already occurred and on events which, as of now, the market expects to take place in the future. In other words, in an efficient market at any point in time the actual price of a security will be a good estimate of its intrinsic value" (Fama, 1965, p. 56).

EMH assumes that all stocks are traded at their fair value. There are three tenets to the EMH: weak, semi-strong and strong. The weak implies that all available information is reflected in current stock prices. The semi-strong assumes that stock prices reflect all information that is publicly available. In the strong, all available information, both public and private, is already reflected in stock prices.

Malkiel (2003) stated that security markets are extremely efficient as they reflect all available information about either individual stocks or the stock market as a whole. He argues that as soon as information arises it spreads very quickly and security prices adjust to the new

information without delay, resulting in eliminating all arbitrage opportunities that would allow investors to make above average returns without taking above average risks. According to Fama and Macbeth, (1973), the EMH is based on the principle that stock prices fully reflect all available information at any point in time. Thus, neither technical analyses which is based on studying past stock prices in an attempt to predict future stock prices, nor fundamental analysis which is analyzing financial information such as company earnings, asset values and financial statements to help investors identify undervalued stocks, would allow investors to outperform a randomly selected portfolio of individual stocks (Malkiel, 2003).

Fama (1965) linked the EMH to the concept of random walk by stating that, amidst uncertainty in the global economy and the financial markets, the value of a security can never be precisely determined. This can potentially lead to disagreement between the various participants in the financial markets (i.e. asset managers, insurance and pension funds, hedge funds and retail investors etc.) regarding the precise intrinsic value of the stock. When the markets are efficient, the purchase and sale of securities by the various market participants would result in a movement in the actual price of the stock around its intrinsic value. If the price changes are not random and systematic, active investors should be able to better forecast the future stock price changes and consequently outperform the stock market consistently. However, when there are various financial market participants attempting to benefit from their knowledge, the systematic behaviour within the price series is neutralised. The result is that actual prices of securities tend to follow a "random walk" (Fama, 1965, p. 56).

In recent years, the intellectual dominance of the EMH has become much less universal. Economists have begun to recognise that stock prices are partially predictable. By shedding light onto the psychological and behavioural aspects of stock price determination, they came to the conclusion that future stock prices can be predicted on the basis of past stock price trends and patterns. Many economists have argued that these foreseen patterns could lead investors to earn excess risk-adjusted rates of return; hence, the concept of behavioural finance was introduced.

Behavioural finance is a relatively modern field of finance that deals with the influence of psychology on the behaviour of financial practitioners and its subsequent impact on stock markets (Sewell, 2010). The psychologists Daniel Kahneman and Amos Tversky made significant contributions to the literature of finance and psychology that served as a foundation and highlighted this new field.

Joo and Durri, (2015) define behavioural finance as the field that considers how various psychological traits affect the ways that individuals or groups act as investors, analysts, and portfolio managers. Goldberg and Von Nitzsch (1999) argue that it is a financial theory oriented towards behaviour which is applied to facts that people behave rationally only within specific limits. Moreover, Bodie et al. (2007) discuss behavioural finance as a set of financial market models that emphasizes potential psychological factors intervention into investor's behaviour. Fuller (2000), Formlet (2001) and Jordan and Miller (2008) explained behavioural finance by individuals' attitude and emotions in investment decision making process and market prices. Hence, behavioural finance discusses theories regarding the consequent results of investors taking decisions based on their emotions. It is theories that aim to explain market inefficiency and market anomalies by the use of psychological biases (Levy and Post, 2005).

Market clearing activities imperfections and investors' bounded rational behaviour are blamed for the occurrence of these anomalies. Fama and French highlight patterns in average stock returns that cannot be explained by the Capital Asset Pricing Model (CAPM) nor the Fama and French three factor model. These patterns constitute a range of market anomalies that include among others, the abnormally high average returns from stocks with low market capitalisations (Banz, 1981) and stocks with high book-to-market value ratios (Rosenberg et al., 1985; Chan et al., 1991); the higher average stock returns from firms that are more profitable (Haugen & Baker, 1996; Cohen et al., 2002); the lower stock returns from firms with higher levels of accruals (Sloan, 1996) or higher levels of investment (Fairfield et al., 2003; Titman et al., 2003); the negative relation between net stock issues and average returns (Ikenberry et al., 1995; Loughran & Ritter, 1995; Daniel & Titman, 2006; Pontiff & Woodgate, 2008); the well-documented momentum effect (Jegadeesh & Titman, 1993) and a range of calendar effects (Thaler, 1987).

Calendar effects are economic consequence or market anomaly related to the calendar (Nasir et al., 2017). The calendar anomalies hypothesis states that markets behave differently at many levels like hours of the day, different days of the week, various times of the month and year (Rossi, 2015). Calendar effects have been significantly researched across many different markets around the globe and is found to be an interesting topic particularly because it has been proven in the literature that its existence violates classical finance theories like the EMH. The existence of calendar anomalies in stock markets violates the weak form of market efficiency since stock values do not stay random and their future prices can be determined according to deduced past patterns. Daily investors can develop trading strategies based on observed past patterns to make abnormal profits. For example, if past patterns indicate the existence of weekend effect, traders could carry out a trading strategy of buying/selling on Fridays and buying/selling on Mondays (depending on Friday and Monday values) to make abnormal profit. Hence, the existence of calendar anomalies provides evidence that violates the EMH and produces an opportunity to earn excess returns via existing information.

The most prevalent of these calendar effects include the famous weekend effect, where equity displays abnormally lower returns over the weekend period between Friday's close and Monday's close; turn-of-the-month, where mean returns on stocks at the beginning of each month exceed those at the end of the same month; January effect, where stock returns are significantly higher during January than other months of the year; the Halloween effect, where Stock market returns tend to be significantly higher during the winter months (November to April) than during the summer months (May to October); the pre-holiday effect, where returns are abnormally high on trading days prior to holidays (Ariel, 1990).

Over the years much attention has been attracted towards testing calendar anomalies within different settings and markets. However, an interesting area that has attracted less attention is the understanding of how the structural changes in the way we compose our week from being a six day working week to becoming five days a week. For example a change in trading days from six days to five days occurred in the US in 1952. Another area of focus that was not explored enough is the effect of certain religious and non-religious holidays on the market returns within both developed and emerging markets.

#### 1.2 Research objectives and Research questions

The objective of this research is to contribute to the extant behavioural finance literature by expanding the empirical research on the relationship between calendar anomalies and stock returns at both industry and market levels. Along these lines, this research aims to contribute by filling the gap in three underexplored topics within the field of calendar anomalies. The first topic covers four major calendar anomalies at industry level in the US market over an extended period of time and will profoundly investigate the effect of switching from a six- to a five-day work week on the stock market returns.

The second topic covers the day-of-the-week effect in Saudi Arabia, a part of the world where research is sparse. The research will focus on the effect of the 2013 structural change on the anomaly, when official weekends shifted from Thursday and Friday to Friday and Saturday.

The third study discusses the pre-holiday effect in Saudi Arabia, analysing the underexplored cultural and religious aspects that affect the behaviour of investors. This enriches extant understandings of the topic as it not only investigates the anomaly, but also addresses religious and non-religious holidays.

This study explores calendar anomalies in their entirety, from weekday to religious holiday effects. The thesis aims to contribute to the existing literature on calendar anomalies by providing a comprehensive view of how a given anomaly can be manifested in different nations over time. Therefore, the following research questions have been established to develop the discussion of calendar anomalies:

1. Are industry level returns affected by different calendar anomalies within the US market?

The study will focus on three main objectives. The first and second objectives are to investigate the existence of calendar anomalies at industry level and, if they exist, to assess whether or not they manifest themselves widely across all industries. Do they concentrate in a small cluster of industries? The third objective is to examine the effect of the change in weekly trading days on the behaviour of calendar anomalies. Before September 1952, Saturday was an official trading day, meaning that there were six weekly trading days as opposed to the current five. The study will only focus on the US industries, as these provide the longest continuous daily data set starting from the 1920s. Testing for calendar anomalies across countries has been conducted in the extant literature; however, there is a substantial loss of data in some years, since stock returns are typically only available from the 1990s onwards.

2. Weekend change and its effect on the Saudi Arabian Stock Market: Does faith play a role in the weekend anomaly?

This research focuses on three main objectives. The first objective is to investigate the day-of-the-week effect at industry level in the Tadawul All-Share Index (TASI) and whether it manifests itself across all industries or is an industry-specific phenomenon. The second objective is to assess the potential effect of the change in the weekend days after 26 June 2013 on the day-of-the-week anomaly. Prior to 26 June 2013, Saudi Arabia's official weekend took place on Thursday and Friday. However, on 23 June 2013, King Abdullah of Saudi Arabia issued a royal decree shifting the country's weekend for public workers from Thursday and

Friday to Friday and Saturday. The third objective is to examine the effect of faith orientation on the day-of-the-week anomaly since the study is based on a country ruled by Islamic law.

3. Does investors' behaviour alter between religious and non-religious holidays?

This study focuses on three key objectives. The first objective is to examine the existence and persistence of the pre-holiday effect in the Saudi stock market. The second objective is to assess the magnitude of the anomaly in each industry and whether the anomaly manifests itself across all sectors similarly. The third objective is to investigate the effect of religious holidays on the pre-holiday anomaly.

#### 1.3 Research Motivation

Calendar anomalies have been extensively researched in US, UK and Europe. Although a rich empirical effort has been sustained over several decades, there is to my knowledge no extant study that combines investigations into all calendar anomalies. This is a gap in the research because it is likely that explaining any one calendar anomaly will depend on others. For example, it is plausible that January effects manifest within other calendar anomalies like the Halloween effect. Moreover, structural changes to the calendar, like changing the number of trading days per week or changing the days of the weekend, have not been studied sufficiently in developed and emerging markets. This research will not only study major markets like the US but also emerging markets like Saudi Arabia, where religion and culture greatly influence investor decisions.

This research tends to cover different aspects within the field of calendar anomalies which could be beneficial for future research, to investors whether individuals or institutions and policy makers. To begin with, the topic of calendar anomalies has been underexplored in emerging markets specially in the GCC region and having this research include markets like Saudi Arabia adds on to the body of research in this field. This research therefore bridges an existing gap while proving that there are still opportunities for future research within the field of behavioural finance. This research may be beneficial for investors and institutions when it comes to developing or adjusting investment strategies. Finally, policymakers in Saudi Arabia may benefit from this research by studying the implications of implementing new policies, such as applying new holidays. This research covers the holiday effect that policymakers may benefit from when enacting new holidays in Saudi Arabia, especially since Saudi Arabia has relatively few holidays, three official holidays, compared to its neighboring countries like United Arab Emirates and Kuwait where there are 9 holidays.

#### 1.4 Research structure

The research is structured as follows. The rest of this chapter will cover the articles, abstracts and thesis framework. Chapter two undertakes a comprehensive analysis of the studies conducted on four calendar anomalies, namely the weekday effect, turn-of-the-month, January effect and Halloween effect. The research sheds light on the shift in weekend days that occurred in the US in 1952. The chapter begins with an overview of the efficient market hypothesis, followed by a review of the literature and findings of various researchers on the calendar anomalies in question.

Chapter three critically analyses the weekend effect in the emerging Saudi stock market. The study investigates the existence of the weekday effect in the emerging market of Saudi Arabia. The study also focuses on the behaviour of the anomaly before and after the shift in weekend days that occurred in Saudi Arabia in 2013.

Chapter four investigates the well-known pre-holiday effect in the Saudi stock market at both market and industry level. This study investigates the existence of the pre-holiday anomaly in the Saudi stock market and whether religious holidays have a greater effect on the anomaly than non-religious holidays.

Finally, chapter five provides an overall thesis conclusion as well as recommendations for further research.

#### 1.5 Article abstracts:

#### Abstract for essay 1:

We present a comprehensive analysis of four well-known calendar anomalies in the US stock returns at the industry level: the weekday, turn-of-the-month, January and Halloween effects. We examine daily returns for 39 US industries over an extended period of time (over 90 years). We study the behaviour of these four anomalies at the industry level and confirm that the effects of these anomalies exist and persist uniformly across almost all industries. We also examine the effect of reducing weekly trading days after September 1952 on the behaviour of these anomalies. Our findings show that the anomalies are present across almost all industries and that the effects are not limited to specific industries, indicating that these calendar effects are driven by economic events affecting all industries rather than by industry-specific factors. The change in weekly trading days after September 1952 only had an effect on the behaviour of the Halloween effect. Hence, we confirm the calendar anomalies' persistence for all periods considered in our study. We find no Halloween effect in the pre-1952 sub-period, while a strong and statistically significant effect appears in the post-1952 sub-period.

#### Abstract for essay 2:

This research comprehensively analyses the well-known day-of-the-week effect in the Saudi stock returns at industry level. The study investigates the existence of the day-of-the-week anomaly in 15 industries in the Saudi stock market. The anomaly is further examined by applying a break point in June 2013, when the weekend in Saudi Arabia changed, investigating whether this event affected the anomaly. This is achieved by using dummy variables within an OLS framework, covering the period from 2009 to 2017. The findings confirm the existence of the anomaly pre-June 2013 only, providing evidence that the break point event of changing the weekend directly affected the anomaly.

#### Abstract for essay 3:

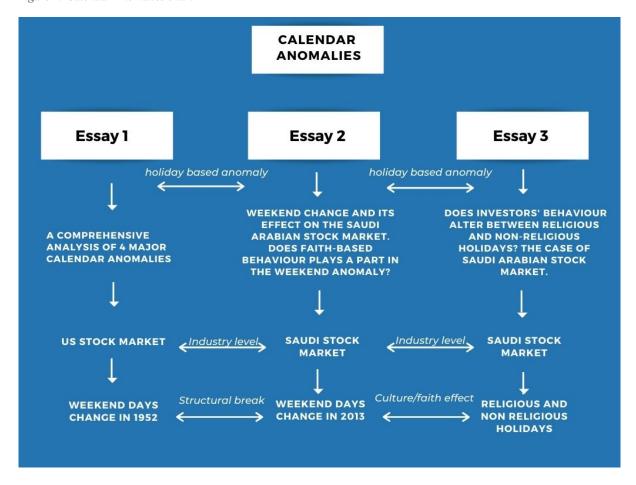
This study examines the well-known pre-holiday effect in the Saudi stock market at both market and industry level. All the official holidays in Saudi Arabia are tested in this paper, Eid al-Adha, Eid al-Fitr and the National Day holiday. The research examines daily returns for both the general market and 15 industries over a period of almost 11 years, from 2009 to 2020. The study also discusses whether investors' behaviour alters between religious and

non-religious holidays. The findings confirm the existence of the pre-holiday effect at the general market and industry level on Eid al-Adha and Eid al-Fitr. No evidence was found for the existence of the pre-holiday anomaly at both general market and industry level on the National Day holiday.

#### 1.6 Thesis framework:

The first essay of this PhD thesis expands on existing research on calendar anomalies by investigating four major calendar anomalies over an extended period of time in the US stock market at industry level. The study focuses on the change in the number of trading days per week that occurred in 1952 and analyses the effect of this event on a range of calendar anomalies. This thesis then proceeds to further analyse calendar anomalies by investigating the weekend effect in an emerging market, the Saudi stock market, at industry level by considering the shift that was applied to the weekend days in Saudi Arabia in 2013. This contributes to knowledge on the topic as it allows us to compare and examine the behaviour of the anomalies between mature and emerging markets during similar events. The third essay further investigates calendar anomalies by examining the existence of the pre-holiday effect in the Saudi stock market (TASI) and whether religious holidays have a greater effect on the anomaly than non-religious holidays. This links to the previous essays by testing holiday-based anomalies at industry level. Furthermore, it is based on the underexplored Saudi stock market, which is considered the largest market in its region in terms of market capitalisation and its advanced place in the ranking of emerging markets (Capital Market Authority, 2020). The following chart describes the relationship between the three essays of this PhD thesis.

Figure 1: Calendar Anomalies chart



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## Chapter 2: A Comprehensive Analysis of Four Major Calendar Anomalies in US Stock Returns at the Industry Level

#### **Abstract:**

We present a comprehensive analysis of four well-known calendar anomalies in US stock returns at the industry level. The four major calendar anomalies we study are the weekday, turn-of-the-month, January and Halloween effects. We examine daily returns for 39 US industries over an extended period of time (over 90 years). We study the behaviour of these four anomalies at the industry level and confirm that the effects of these anomalies exist and persist uniformly across almost all industries. We also examine the effect of reducing weekly trading days after September 1952 on the behaviour of these anomalies. Our findings show that the anomalies are present across almost all industries and that the effects are not limited to specific industries, indicating that these calendar effects are driven by economic events affecting all industries rather than by industry-specific factors. The change in weekly trading days after September 1952 only had an effect on the behaviour of the Halloween effect. Hence, we confirm the calendar anomalies' persistence for all periods considered in our study. We find no Halloween effect in the pre-1952 sub-period, while a strong and statistically significant effect appears in the post-1952 sub-period.

#### 2.1 Introduction

#### 2.1.1 Research Background

Behavioural finance primarily studies a range of bounded rational investor responses to market dynamics. The core arguments underlying this subject area stem from Herbert Simon's 1978 contention that market agents are best described as bounded rational. The subject area also infers that bounded rational behaviour typically causes what Thaler (1987) describes as economic anomalies, i.e. empirical results that are difficult to rationalise or need implausible assumptions to rationalise.

On another level, it has been suggested that these anomalies are the product of a complex of recognized faults in the market clearing operations of economies and investors' constrained rational behavior. By highlighting patterns in average stock returns that neither their own three-factor model nor the Capital Asset Pricing Model (CAPM) can account for, Fama & French (2008) extend this logic to the capital markets. These patterns make up a variety of anomalies that have been thoroughly researched in empirical literature, such as the well-known calendar effects.

Calendar effects have been studied extensively across many different market and country settings. They are particularly interesting because mainstream financial scholarship (Kling et al., 2005) avers that their existence violates different forms of the Efficient Markets Hypothesis (EMH). For example, in weakly efficient stock markets, the EMH posits that technical price and volume information is fully absorbed and instantaneously reflected in security prices. In other words, if some investors realise that particular price and volume trends are repeated at certain calendar times during the year, they will arbitrage these in order to make abnormal profits. Learning from their actions, other investors will do likewise and, over time, the seasonal pattern in security prices should disappear and no investors should be able to make abnormal profits based on these.

Different time horizons of such effects include the well-known January effect; the day-of-the-week effect; the turn-of-the-month effect and the Halloween effect; (Fields, 1931; Cross, 1973; French, 1980; Ariel, 1987; Harris, 1986a; Wong et al., 2006). It can be hard to explain potentially anomalous connections between the day, month, season or time of a given trade and its potential profitability. It can further be argued that it must be the institutional, market and regulatory rigidities that, on the one hand, interact with the bounded rational behaviour of investors and, on the other, create these calendar-based anomalous effects. Therefore, extant scholarship has tried to craft explanations based on the flow of funds in and out of markets (Ritter, 1987), window-dressed managerial practices and the systematic arrival of good and bad news (Harris & Gurel, 1986). This is beside the standard behavioural oddities of investors, such as their known preference for compound gambles over simple gambles or their mood (Coursey & Dyl, 1986).

#### 2.1.2 Rationale

Markets display a range of anomalous behaviours that are difficult to explain. Investors and their human biases and tendencies lie at the root of these anomalies. Existing theoretical and empirical literature has explored and partially explained many of these anomalies; however, recurrent patterns of trading and abnormal returns around set calendar dates have been repeatedly documented by scholars. This study aims to comprehensively and critically analyse and explain four major calendar-based anomalies across US industries. It is anticipated that this will significantly enrich understanding of the phenomenon at a level where empirical research is not sufficiently explored.

#### 2.1.3 Research Question

To further understand the effect of the anomalies, this study seeks to address the following research question:

"Are industry level returns affected by different calendar anomalies within the US market?"

We comprehensively analyse the entire range of calendar effects including the day-of-the-week, turn-of-the-month, January and Halloween effects for 39 US industries across a fairly long time period of daily returns, ranging from 1926 to 2018. Not only does this study aim to be the first to include all potential calendar effects within its ambit, it also uniquely proposes to rigorously test all effects at industry level.

#### 2.1.4 Research Objectives

The study will focus on three main objectives. The first and second objectives are to investigate the existence of calendar anomalies at industry level and, if they exist, to assess whether or not they manifest themselves widely across all industries. Do they concentrate in a small cluster of industries? The third objective is to examine the effect of the change in weekly trading days after 1952 on the behaviour of calendar anomalies. Before September 1952, Saturday was an official trading day, meaning that there were six weekly trading days as opposed to the current five. The study will only focus on the US industries, as these provide the longest continuous daily data set starting from the 1920s. Testing for calendar anomalies across countries has been conducted in the extant literature; however, there is a substantial loss of data in some years, since stock returns are typically only available from the 1990s onwards.

#### 2.1.5 Structure

The rest of the research has the following structure. Chapter two undertakes a critical analysis of the studies conducted on four calendar anomalies, namely the weekday, turn-of-the-month, January and Halloween effects. The chapter begins with an overview of the efficient market hypothesis, which is followed by a review of the literature and findings of various researchers on the calendar anomalies in question.

Chapter three discusses the research methodology used to address the research aim and objectives, including the data collection and analysis. The fourth chapter comprises both an analysis of the data using econometric techniques and compares the findings to the literature. Finally, the fifth chapter provides conclusions and recommendations.

#### 2.2 Literature Review

#### 2.2.1 Overview

The literature review chapter includes a comprehensive and critical analysis of the studies conducted on four major calendar anomalies. The chapter begins with an overview of the efficient market hypothesis, which is followed by a review of the literature and findings of various researchers on the selected calendar anomalies.

The general consensus is that, even though there is solid evidence that calendar anomalies exist in broad indices, they have not been sufficiently explored at industry level. The study will shed light on the consistency and behaviour of the anomalies when tested at industry level compared to broad indices, given that each industry is distinctive in nature. Moreover, the four calendar anomalies were chosen so as to give a comprehensive and all-round view of the topic, covering different dimensions by looking at weekday, turn-of-the-month, turn-of-the-year and seasonal effects

#### 2.2.2 Efficient Market Hypothesis (EMH)

Academics and finance professionals continue to be more interested in and engaged in discussion on the subject of EMH (Lim and Brooks, 2011). The idea of EMH was initially presented and defined by Fama in 1965. He described an efficient market as one that is competitive and in which prices converge to the fundamental value, explaining the random nature of pricing.

Malkiel and Fama (1970) argue that security markets are very efficient because they accurately reflect information about the stock market as a whole. They argued that as soon as new information is released, it is immediately incorporated into the pricing of relevant assets, producing stock prices that accurately reflect the knowledge at hand. Thus, the assumption that stock prices accurately reflect all information at any one time is the basis of EMH (Fama and Macbeth, 1973).

Given the efficiency of the financial markets in incorporating the available information into security prices, the EMH argues that neither technical analysis (analysing the past stock prices in an attempt to forecast and predict the changes in the stock prices in the future) nor fundamental analysis (conducting financial statement analysis including the review of the

income statement, balance sheet and cash flow statement etc.) can help investors to select securities that could be considered undervalued in an attempt to outperform a portfolio of randomly selected stocks (Malkiel and Fama, 1970).

The EMH and the idea of a random walk were connected by Fama (1965). He claimed that it is impossible to correctly evaluate a security's worth in the face of uncertainty in the global economy and financial markets. The many players in the financial markets, such as asset managers, insurance and pension funds, hedge funds, retail investors, etc., may dispute over the exact intrinsic value of the stock as a result of this. According to Fama (1965), in an efficient market, the buying and selling of securities by different market players causes the stock's actual price to fluctuate around its underlying value. Active investors should be better able to predict future stock price changes and, as a result, consistently outperform the stock market if price fluctuations are not random and systematic. However, the regular behaviour within the price series is neutralized when numerous financial market participants try to profit from their expertise. As a result, actual security prices tend to take a "random walk" (Fama, 1965, p. 56).

Towards the end of the 20<sup>th</sup> and start of the 21<sup>st</sup> century, several financial market participants and academics began to question the relevance, dominance and applicability of the EMH in the contemporary environment (e.g. Ojah and Karemera, 1999; Jegadeesh and Titman, 2001). Researchers began to argue that returns on securities can, at least partly, be predicted (Kothari, 2001). The emphasis on the psychological and behavioural aspects of determination of the stock prices led to a belief that future stock price changes can, to an extent, be predicted based on past changes in the stock prices and using fundamental analysis (i.e. analysis of the financial statements) (Shiller, 2003). The following section will be based on the literature on four major calendar anomalies and how the research on the topic has evolved over time.

#### 2.2.3 Weekend Effect

Thaler (1987) studied the weekend effect to understand the extent to which stock prices tend to outperform on a particular day of the week. He defined the daily return (i.e. change in price and the dividend received) for a particular day of the week as the return from the close of the previous trading day to the close of trading on that given day. Using this definition, he raised the question, "how should we expect Monday returns to compare to the returns for other weekdays?" He suggested that the most reasonable hypothesis was the "calendar time hypothesis" proposed by French in 1980, which pointed out that the time duration between the financial markets closing on Friday and opening on Monday is three days instead of one day, as is the case between other days of the week. Therefore, the returns earned on Monday should be higher to reflect the greater duration of time.

However, French (1980) also presents a different explanation of this anomaly: the trading time hypothesis, which asserts that returns are generated by investors only during the trading day and, therefore, the return earned should be the same for each trading day. This argument is criticised by Thaler (1987), who argues that it is unreasonable to only focus on the trading day, as companies tend to do business every day and, even if trading in the financial markets was restricted, this would not have a detrimental impact on the overall profitability of the business.

French (1980) used the S&P 500 index to analyse the daily returns from 1953 to 1977 and concluded that the mean return for Monday was negative, not only for the entire period but also for each five-year period (-0.168%, t-statistic = -6.8). The t-statistic value indicates that

the finding was statistically significant at the 95% and 99% level. He found that the mean return was positive for the rest of the days of the week, and noted the highest average return on Wednesday and Friday. French (1980) subsequently focused on evaluating whether the negative average return earned on Monday by the securities in the S&P500 index could be attributed to a "closed market effect", implying that the expected return should be lower after the holiday period and weekends because the financial markets remained closed during these periods. However, he concluded that, after the period of holidays when the financial markets were closed, the stock return was above average on all days of the week except Tuesday. This led him to interpret the results as mainly attributed to the weekend effect, as opposed to the effect associated with the closing of the financial markets.

One important methodological point worth noting in French's 1980 analysis is that he measured the return earned by a security on Monday as the difference between the closing share price on Friday and that on Monday. This leads to the question of whether the prices already fall between Friday's close and Monday's open, or fall on Monday during trading hours. Rogalski (1984) investigated this trend to uncover whether prices fall on Monday or between Friday and Monday. In contrast to French (1980), who conducted the analysis on the S&P 500, Rogalski's 1984 analysis was conducted on both DJIA and S&P 500 indices: DJIA during the ten-year period from 1974 to 1984 and S&P 500 index between 1979 and 1984. Rogalski concluded that the negative return was earned between Friday's close and Monday's open, as prices tended to increase on Monday during the time that financial markets were open. This led to the Monday effect being known as the "weekend effect" (Thaler, 1987, p. 171).

An interesting observation was noted by Smirlock and Starks (1986), who investigated the applicability of the weekend effect for the 20-year period from 1963 to 1983 by studying the securities on DJIA. They concluded that the negative return earned by stocks on Mondays shifted back over a period of time. For instance, from 1963 to 1968, the negative returns occurred during the trading hours on Monday (in contrast to the findings of Rogalski (1984)). From 1968 to 1974, the negative returns earned on Mondays occurred during the early hours of trading, whereas the post-1974 losses occurred between Friday's close and Monday's open.

Abraham and Ikenberry (1994) studied the weekend effect to establish whether stock returns are negative on Mondays or not. A unique aspect of the study by Abraham and Ikenberry (1994) was the focus on assessing the impact on stock returns on Mondays based on the return earned by stocks in previous trading sessions. The study included the data on mean daily return on securities on the NYSE for the period from 1963 to 1991 and concluded that mean return for Monday was -0.1161, a finding that is consistent with the earlier conclusions reached by French (1980) and Rogalski (1984). Furthermore, Abraham and Ikenberry (1994) added to the existing literature at the time by concluding that the mean return for Monday for the sub-period from 1982 to 1991 was also significantly negative (-0.1162). This was a period that had not been investigated by the researchers prior to the study by Abraham and Ikenberry (1994), implying that the violation of the EMH and the existence of the anomaly regarding the weekend effect had not diminished since it was reported.

When it comes to the mean return for other days, Abraham and Ikenberry (1994) reported a positive return for all days apart from Tuesday, as Tuesday's mean return was found to be only +0.01% (or 1 basis point), which was also concluded to be not statistically significant from zero. Abraham and Ikenberry (1994) also added to the analysis by conditioning the return earned based on the return earned on the previous day, for the entire period from 1963 to 1991. They concluded that when Friday's return is positive, mean return on Monday is not negative;

instead, it is positive (+0.1136%) which was also found to be statistically significant. Similarly, Abraham and Ikenberry (1994) reported that when Friday's return was negative, this resulted, eight out of ten times, in the subsequent Monday's return also being negative. On the other hand, a positive return on Friday led to over half of the returns on Monday being positive. The authors explained this finding by stating that selling activity is higher on a Monday. This is because investors satisfy their liquidity and cash flow needs by selling the securities on Monday after the release of bad news on Friday or over the weekend. Most of the selling takes place before 11am on Mondays, especially when the previous Friday saw a decline in the security prices (Abraham and Ikenberry, 1994).

Most of the studies investigating the weekend effect have focused on the US market. However, Agrawal and Tandon (1994) studied 18 non-US countries in order to evaluate the extent to which the calendar anomalies confirmed in the US also exist in other countries. When it comes to the weekend effect, Agrawal and Tandon (1994) found mixed evidence, as they concluded that returns on Monday are negative and lowest in half the sample (i.e. nine out of the 18 countries studied), which is in line with the earlier evidence on the weekend effect conducted in the US market (e.g. French, 1980; Rogalski, 1984; Abraham and Ikenberry, 1994). In contrast, the findings from eight other countries indicated that the weakest return occurred not on Monday but on Tuesday. Fridays were found to have a positive return in most countries, though not in Luxembourg; a finding that was also true when the time period was broken down into two sub-periods.

As with the partial evidence of the lowest returns on Mondays (consistent with the weekend effect), Agrawal and Tandon (1994) also concluded that the variance (i.e. measure of risk) was highest for the stock price returns on Mondays. This is consistent with the findings of Abraham and Ikenberry (1994): investors satisfy their liquidity and cash flow needs by selling the securities on a Monday. Increase in sales contributes to a change in prices (i.e. downward pressure), which not only reduces the price but also increases the variance and standard deviation of stock returns.

The impact of the weekend effect on volatility of returns, as uncovered by Agrawal and Tandon (1994), led Kiymaz and Berument (2003) to investigate the day-of-the-week effect and its impact on market volatility (as measured by standard deviation) and volume of trading. The study included the analysis of the major stock market indices from 1988 to 2002. Based on the conditional variance framework, Kiymaz and Berument (2003) concluded that the day-of-the-week effect is present in not only the return but also the volatility.

The highest volatility for the US and Canada was noted on Fridays, whereas the highest volatility for Japan and Germany occurred on Mondays. Furthermore, the days with the highest volatility (standard deviation) overlapped with the period of the least volume of trading activity, illustrating that riskier securities attracted less investor interest (Kiymaz and Berument, 2003). This lack of volume during the period of higher volatility is attributed to a lack of willingness on the part of liquidity traders to engage in trading activity while volatility is high, as concluded by Foster and Viswanathan (1994).

Brusa et al. (2003) used the weekend effect (i.e. returns on Monday tend to be lower and negative compared to the rest of the week) and the findings of Dubois and Louvet (1996) to argue that, even though the weekend effect continues to exist in some of the countries outside the US, it has disappeared in the US market. Thus, the findings of Dubois and Louvet (1996) suggest that the weekend effect may not necessarily coexist simultaneously across the different

countries. Brusa et al. (2003) used these findings from Dubois and Louvet (1996) to investigate the potential reverse weekend effect in the US, whereby returns on Monday can be significantly higher and positive compared to the rest of the week. The period selected by Brusa et al. (2003) ran from 1963 to 1995. They used the DJIA index and calculated the average daily return for each day of the week, including the test for whether these returns were statistically significant or not.

The reverse weekend effect was also studied by Gu (2004), who stated that the renowned historical weekend effect had been reversing across the major cities in the US from the late 1980s to the late 1990s. Gu (2004) conducted a quantitative study, using Pearson's correlation and regression analysis techniques, to investigate the persistence of the weekend effect across the DJIA and S&P 500 indices. He concluded that, as the weekend effect has become well-studied and consequently well known in the investor community, sophisticated investors have exploited the Monday effect. This means that any excess return that could be enjoyed by the investors based on the weekend effect does not occur any more.

Instead, Gu (2004) concluded that, as too many investors have deployed the investment strategy based on the weekend effect to earn an abnormal return, the weekend effect has not only been eliminated but also reversed. This elimination and declining of the weekend effect over time led Gu (2004) to favour the efficient market hypothesis and the argument that financial markets are reasonably efficient, especially within developed markets such as the US, where investors cannot consistently outperform based on using publicly available past and present information.

Short sellers have also attracted interest from academics focusing on the calendar anomalies. Chen and Singal (2003) studied the role of short sellers in influencing prices as well as the resultant impact they had on the weekend effect. They used the weekend effect as a base from which to investigate the hypothesis that short sellers engaged in speculative activity have a systematic and statistically significant influence on security prices. This is based on the argument that short sellers tend to hold short-term rather than long-term positions (given their short time horizon), which explains why many short sellers can purchase securities to cover their positions on Fridays (before the weekend), then sell the position on the market on Monday at a lower price, thus capturing the profit whilst also contributing to a reduction in price on Monday. This action taken by short sellers is seen as further reinforcing the weekend effect, since Friday's returns are higher (due to the purchase activity by the short sellers) while the returns on Monday are lower (due to the sale activity by the short sellers).

Chen and Singal (2003) found evidence consistent with this finding, concluding that securities with higher short interest (i.e. proportion of securities borrowed by short sellers) exhibited a significantly higher and stronger weekend effect, in contrast to comparative stocks with a lower short interest. Thus, the findings of Chen and Singal (2003) signify the role of short sellers in exacerbating the weekend effect, in terms of a lower return noted on Mondays.

Brusa et al. (2003) concluded that the reverse weekend effect was a unique feature occurring in the 1990s in the US, which was in contrast to all the foreign markets studied by the authors in which the weekend effect either existed or did not. Consistent with the findings of Abraham and Ikenberry (1994), Brusa et al. (2003) found that returns on Monday in the US market tend to follow the positive returns on the previous Friday, but not necessarily the negative returns of the previous Friday – i.e. if Friday's returns were noted as positive, this meant that the

subsequent Monday's returns in the US were also more likely to be positive, whereas if the returns on Friday were negative, this did not translate into negative returns on Monday.

A slightly different version of the weekend effect was investigated by Doyle and Chen (2009), who studied the wandering weekday effect, which asserts that the pattern relating to day seasonality within the stock market returns is not fixed, as has historically been assumed for the weekend effect whereby underperformance takes place on Mondays (e.g. as concluded by French, 1980; Thaler, 1987; Abraham and Ikenberry, 1994). Instead, through the analysis of eleven major stock markets between 1993 and 2007, Doyle and Chen (2009) could not conclude on the presence of the Monday or weekend effect.

This finding further supports the earlier conclusion of Brusa et al. (2003) and Dubois and Louvet (1996), who denied the existence of the weekend effect in the US market in the 1990s. Instead, Doyle and Chen (2009) concluded that a statistically significant general weekday effect did exist. This confirmed the lack of applicability of the efficient market hypothesis, as they found the wandering weekday effect, which was in contrast to the earlier finding that the weekday effect is fixed and mainly applies to Monday. Furthermore, Doyle and Chen (2009) concluded that the average return of the previous week (positive or negative) had an impact on the wandering weekday effect for the subsequent week in all the markets they analysed.

The findings of Doyle and Chen (2009) differ from the earlier research (e.g. Kohers et al., 2004) in that the weekend effect has not disappeared, despite technological advancements and the resultant improvements and efficiency in the global financial markets. Thus, the conclusion reached by Doyle and Chen (2009) on the persistence of the weekend effect, albeit in the form of the wandering weekday effect, contradicts the conclusion reached by Kohers et al. (2004, p. 170) that, "with improvements in market efficiency over time, the day-of-the-week effect may have disappeared in more recent years." This contradiction is surprising, given the overlap between the two studies in terms of the countries analysed as well as the time period during which the study was conducted.

The disappearance of the weekend effect in the US stock market was also studied by Olson et al. (2015) in a recent publication. They used the cointegration and breakpoint analysis as econometric techniques to test for the disappearance of the weekend effect in the US stock market. Olson et al. (2015) concluded that since the formal discovery of the weekend effect in the US in 1973, it had declined in magnitude as more and more sophisticated investors structured their portfolio so as to benefit from the existence of the weekend effect. The result was that the weekend effect went through a period of decline and re-emergence, and in some cases even reversal, as concluded by Brusa et al. (2003) and Gu (2004). In contrast to the wandering effect found by Doyle and Chen (2009), the findings of Olson et al. (2015) support the existence of mean reversion towards the same return as earned by the other days of the week.

The Monday effect dynamic was researched at the international level by Keef et al. (2009), who investigated the existence of the Monday effect (i.e. underperformance of the security prices on Mondays) across 50 countries. They studied the data from 1994 to 2006 and used panel regression methodology, including panel corrected standard errors. A unique aspect of the data collected by Keef et al. (2009) was that it included a comparison of the data between developed and developing countries within a comprehensive selection of 50 countries. Keef et al. (2009) concluded that the existence of the Monday effect was much stronger and statistically

significant in developing countries (i.e. those with lower gross domestic product per capita) compared to developed countries.

The findings of Keef et al. (2009) are consistent with those of Moshirian et al. (2009), who found that developing economies lack market efficiency to the extent possessed by their developed counterparts. Moshirian et al. (2009) concluded that investor reactions to analyst recommendations tend to be much stronger in less developed economies, further reinforcing the idea that, when it comes to informational efficiency, developing economies are less efficient.

Alt et al. (2011) revisited the Monday effect by questioning the traditional approaches used when testing the Monday effect on stock returns. Alt et al. (2011) criticised the traditional approaches by stating that these approaches, including empirical testing on the day-of-the-week effect, failed to appropriately consider the multiplicity effect. This is especially important as testing the day-of-the-week effect includes the testing of various null hypotheses. This means that the traditional way of conducting an empirical test of each null hypothesis by considering the significance level may increase the existence of the type 1 error, which contributes to the existence of spurious significance pertaining to the findings of the result. The type 1 error occurs when a null hypothesis is rejected (and consequently an alternative hypothesis accepted) when the null hypothesis should not have been rejected in the first place (Keppel and Wickens, 2004).

To overcome the issue of spurious significance associated with the type 1 error, Alt et al. (2011) proposed the use of an alternative approach to test the day-of-the-week effect. The methodology included testing for null hypotheses, such that multiple level alpha were controlled. Using the closure test principle technique, as devised by Marcus et al. (1976), and a Monte Carlo study to test for the presence of the Monday effect across the three markets, namely US, UK and Germany from 1971 to 2008, Alt et al. (2011) concluded that the Monday effect was present across all three markets during the 1970s and 1980s.

The Monday effect was particularly strong in the S&P 500 index during the 1970s and 1980s, in the FTSE in the 1980s and in the UK and DAX in the 1970s. The findings confirmed earlier conclusions (e.g. Abraham and Ikenberry, 1994; Agrawal and Tandon, 1994) that the Monday effect existed in the stock markets. One difference is the superior methodology used – instead of the previously used methodologies, the authors used the closed F-test to control for the type 1 error and spurious significance. Furthermore, Alt et al. (2011) noted no evidence of the Monday effect in the 1990s and 2000s in any of these markets, namely US, UK and Germany.

#### 2.2.4 Turn-of-the-month (TOM)

It is by now well established that cumulative returns on stocks at the beginning of each month exceed those at the end of the same month systematically over long periods of time. This is termed the turn-of-the-month effect. Ariel (1987) and Lakonishok & Smidt (1988) tested for the turn-of-the-month effect and found that the four days at the start of the month, including one day prior to the start of the month (day 30, 1, 2 and 3 for a 30-day month), yielded higher returns than the last four days of the month (day 26, 27, 28 and 29 for a 30-day month). This systematic excess return at the beginning of the month persists in data over long periods of time in US, Canada, UK, Australia, Switzerland and Germany, as evidenced by Cadsby & Ratner (1992). Nevertheless, the same authors find no evidence of this turn-of-the-month effect in countries such as Japan, Hong Kong, Italy or France. Similarly, Agrawal & Tandon (1994)

establish a strong turn-of-the-month effect in at least 13 of the 18 countries that make up their sample. Jaffe & Westerfield (1989) find similar effects in Australia, the reverse effect in Japan and no effect whatsoever in Canada or the UK. Extending these results to emerging markets, Tan & Wong (1996) find a significant turn-of-the-month effect in Singapore. Interestingly, such effects have been found to be disappearing in the same country in more recent studies by Wong et al. (2006).

The turn-of-the-month effect has largely been attributed to the fact that, at least in countries like the US, interest/principal payments on debt and dividend payments on equity tend to be bunched towards the end of the month (Ogden, 1990; Cadsby & Ratner, 1992). Similar fund flow practices initiated by pension and mutual funds may require them to sell/buy at specific times during the month (Ritter, 1987; Thaler, 1987). The "window dressing" practices of fund managers that require them to present "clean" fund balance sheets at specific periods during the month and year could also account for this effect (Ziemba, 1991). Beyond institutional factors, a range of psychological explanations have also been proposed within the classical scholarship, including the preference for compound gambles over simple ones and variations in the mood of the market (Coursey & Dyl, 1986).

#### 2.2.5 January Effect

Small stocks have unusually high returns from the beginning of the last trading day of December through to January of the new year, with the effect progressively wearing off. This is termed the end-of-the-year or January effect and has been extensively documented and analysed by scholars including Banz (1981), Gultekin & Gultekin (1983), Keim (1983; 1989), Roll (1983), Blume & Stambaugh (1983) and Ritter (1987). An 8.17% extra return at the turn of the year has been consistently documented on small stocks with amazing regularity across several decades. The earliest documentation of the January effect can be found in Rozeff & Kinney (1976), whose findings are crucially dependent upon whether a value-weighted or equally weighted index is used. It is in the latter that a January seasonal phenomenon is flagged because low capitalisation stock returns are the main source of the effect. Banz (1981) extends these results for US markets to the period between 1926 and 1981, confirming that the effect only relates to the January month and not the other months of the year. Other efforts by Keim and Blume & Stambaugh made it clear that the January effect and small firm effect are just two manifestations of the basic phenomenon of high returns on small firms in January each year.

One of the most important explanations offered for the January effect is tax considerations, proposed by Wachtel (1942) and Dyl (1977). They argue that investors who wish to set off losses in their portfolios against gains in order to pay the lowest amount of tax on their overall income do so at the year-end. Small cap stocks are sold off to realise a loss that can be shown in the income statement submitted to the tax authorities. This induces a downward price pressure on these stocks at year-end which disappears as prices rebound to equilibrium level in the new year. Empirical evidence from the US is clearly mixed. The work of Rozeff (1986), Reinganum (1983), Roll (1983) and Schultz (1985) supports the "tax-selling hypothesis", while that of Givoley & Ovadia (1983) and Lakonishok & Smitdt (1984) contradicts it. The situation in other developed markets with different tax year-ends is no better. For the UK and Australia, Reinganum & Shapiro (1987) and Tong (1992) document both an April and June effect, respectively, since these are the year-ends of the countries, but also uncover evidence of a January effect. Similarly, in the Netherlands, where there is no capital gains tax, or even in Japan and Canada (Van den Berge & Wessels, 1985), this effect has been noticed, raising the question of whether tax-selling is a valid and complete explanation. It is in this context that

scholars like Ikenberry & Lakonishok (1989) and Tong (1992) aver that the tax-loss selling at year-end may be a US phenomenon that spills over into other developed markets due to the fact that US mutual and pension funds are large investors globally.

Four other major explanations are offered for the January effect. These include the window dressing efforts of institutional investors (Gompers & Metrick, 2001), the well-documented disposition effect (Shefrin & Statman, 1985; Odean, 1998), the Liquidity Constraint Hypothesis (Kato & Schallheim, 1985) and the time-variant risk premium hypothesis (Rozef & Kinney 1976; Tinic & West 1984; Rogalski & Tinic 1986; Ritter & Chopra 1988; Tong 1992). Institutional investors, such as mutual and pension funds, try to avoid reporting too many losers, especially small cap stocks in their portfolios at year-end – instead, they sell them. They subsequently buy said stocks back in January after the reporting date, in order to regain their original portfolio balance. This is institutional window dressing and is said to cause the year-end effect. Similarly, the tendency of average investors to hold losers for too long and sell winners early i.e. the disposition effect (Shefrin & Statman, 1985), could also produce the yearend turnover. At another level, the year-end in different markets is often the period when large bonus payments are scheduled. This means that investors are typically flush with funds at the turn-of-the-year. They could park these proceeds into small cap stock investments in January, causing this anomaly. Finally, it is a fact that betas of small firms experience a large increase in January (between 30-60% higher) compared to their average for the other months in the year. Rogalski & Tinic (1986) suggest that this higher systematic risk, borne by investors, is compensated by the abnormal returns in January causing the year-end effect.

#### 2.2.6 Halloween Effect

Stock market returns tend to be significantly higher during the winter months (November to April) than during the summer months (May to October), causing a persistent and distinct anomaly called the Halloween effect. Bouman and Jacobsen (2002) have extensively studied this anomaly. They investigated the "sell in May and go away" saying, which implies that stock returns during the winter months should be higher than average stock returns during the summer months. They tested 37 different stock markets from 1970 to 1998 and found a significant "sell in May and go away" effect present for the whole period. Moreover, they showed that there were negative average returns during the summer months in almost one third of the countries included in their sample. The authors proposed that a trading strategy based on this anomaly could be highly profitable, since they found that the effect is robust over time, economically significant and not related to either risk or caused by data mining. Bouman and Jacobsen (2002) also reported that the effect is present in European markets and explained this by referring to vacations, which could result in changes in risk aversion behaviour or change in liquidity. They noted that the strength of the anomaly in different countries varied depending on the timing and length of summer vacations. Countries with a resilient summer vacation tradition displayed the effect most significantly.

Similarly, Kamstra, Kramer and Levi (2003) reported a significant Halloween effect and explained it as a seasonal affective disorder (SAD), where the decreased period of daylight during fall season results in depression in investors. According to them, psychological research reported that depression increases the risk aversion behaviour in investors. They argue that this is the reason behind the relatively lower returns during fall and the gradual pickup during winter when daylight periods start to lengthen.

Cao and Wei (2005) correspondingly used several psychological studies to support their research, which was based on the relationship between temperature change and stock returns. They discussed previous psychological studies that contain evidence of the impact of extreme temperatures on human behaviour. The authors theorised that higher stock returns are recorded when temperatures are lower due to aggressive risk taking, while higher temperatures can result in either higher or lower stock returns depending on the mood, aggression (taking risk) or apathy (avoiding risk). Cao and Wei (2005) examined the relationship between temperature change and stock market returns by analysing stock returns for eight countries and checking their results' robustness in 21 international markets. They found a seasonal summer-winter effect in stock markets, as stock returns recorded a significant negative relationship to temperature.

Hong and Yu (2009) also found a significant relationship between the behaviour of stock markets during summer and vacations. They adopted a similar approach to Bouman and Jacobsen (2002) in considering the link between stock returns and vacations. However, they only considered the period from July to September. They found similar results to Bouman and Jacobsen (2002), which can be justified by previously discussed explanations from the literature. Changes in investor behaviour leading to the Halloween effect can be explained by changes in risk aversion or changes in liquidity due to SAD or vacation behaviour of investors and mood changes due to temperature change. Jacobsen and Marquering (2008) found evidence that the anomaly is prolonged and that there could be alternative explanations for the witnessed seasonality. Moreover, they note that many behaviours show a correlation with the seasons. It is therefore difficult to differentiate between the causes when relating stock returns to these potential explanations. They found that explanations including SAD, temperature, airline travel and ice cream consumption could justify the same seasonal behaviour in stock returns.

Jacobsen et al. (2005) examined the Halloween anomaly for the US market in portfolios based on size, book-to-market ratio, earnings-price ratio, cash flow to price ratio and dividend yields. They found the anomaly to be significant in all portfolios and to have no relation to the anomalous behaviour of portfolios formed on these criteria. Furthermore, they found evidence that the Halloween effect is unrelated to any calendar anomaly, including the January effect, which they reported to be concentrated in portfolios with smaller firms and high book-to-market ratios.

#### 2.3 Methodology

#### 2.3.1 Introduction

This study examines four major calendar anomalies that have been extensively researched in the past at market level, but not sufficiently at industry level. The main research question is:

"Do industries have different calendar anomalies effects within the US market?

The first objective of this research is to investigate whether calendar anomalies are present and consistent across all US industries. The second objective is to examine if there is any change in the magnitude of the calendar anomalies before and after US trading was reduced to five trading days from the previous six. The final research objective is to observe if the different calendar anomalies are consistent over the time period in question.

In order to delve deeper into explaining the effect of the anomalies, this research seeks to compare and contrast between industries rather than simply observe the overall effect on the industry level data. This will help to identify if the anomalies are consistent within and between industries or if each industry has its own structural effect dictating the anomalies.

#### 2.3.2 Data collection

The focus of this study is on industry level data rather than indices. This is to make place for an understanding of the commonality or lack thereof between industries, which indices do not provide. Therefore, the industry level focus allows this study to seek new conclusions on the subject area of calendar anomalies, in order to identify if all industries show a similar effect to that exhibited in previous literature on indices. The industry level emphasis allows this study to achieve greater depth and the ability to explain new phenomena that were not addressed by previous literature.

In order to possess a significant dataset that allows for the testing of four anomalies, as well as to test a wide range of industries, the study focused on testing the effect on US-based industry level data. The reason for this is that the US market possesses one of the most established industry classification systems that is consistent over a long period of time, starting in the 1920s. Furthermore, due to the US economic activity, the number of industries and the composition of each industry exceeds other developed and developing nations.

To study the presence of calendar anomalies at industry level, average equal weighted and average value weighted daily returns of 39 different industries representing various economic segments such as agriculture, construction, transportation, fun and medical equipment will be examined. Since the results for both data sets tend to be similar, only the average value weighted will be reported in this paper. The original data consisted of 49 industries; however this was reduced to 39 due to discontinuity and gaps in the data for 10 of these industries. The data was collected from Kenneth French data library for the period from July 1926 to the end of January 2018. Kenneth French assigns each NYSE, AMEX, and NASDAQ stock to an industry portfolio at the end of June of year t based on its four-digit SIC code, which allows returns to be computed from July t to June t+1 (French, 2018). The industries are composed of different companies that fall under a specified category of firms, such as the agricultural industry consisting of agricultural services, livestock, crops and commercial fishing. Specifying the composition of each industry will provide insight into the industries' contributing effect towards the presence of the anomaly. The reason for choosing this dataset is that it allows the data to test for four different anomalies (weekday, turn-of-the-month, January and Halloween effect), without the need to collect further data.

The combination of these anomalies allows us to observe data in four different ways since we are examining days, months, years and season effects and therefore conducting a comprehensive survey on calendar anomalies.

#### 2.3.3 Break point

Prior to September 1952, the US stock markets were able to trade on Saturday; however, this system lacked continuity as many weeks during the year did not see trades commence on Saturday. This break point will show if such a characteristic change will affect the presence, magnitude and direction of the anomaly present at industry level. There are numerous break points that can be attributed to that period, such as the Great Depression, the Second World

War and the dot-com crash. However, looking at the significance and the attributes of the events, one stands out in particular: the change in the number of trading days from six to five days a week. The calendar anomalies discussed in this paper occur around holidays and the only event that was based on changes to the structure of the holiday was changing the weekend to two days and discontinuing trading on Saturday in 1952.

#### 2.3.4 Model

The modelling techniques applied in order to fully utilise the dataset will be based on incorporating dummy variables within an OLS framework. The dummy variables will consist of categorising the anomaly effect within the regression model. Therefore, this study will devise four different regression models that represent the four different calendar anomalies. The dummy variables proxy for weekdays, Monday through to Friday (with Saturday before 1952), will consist of a dummy variable for each day with the exception of Monday, in order to remove the dummy variable trap effect as illustrated in regression model 1. The second model relates to testing the turn-of-the-month effect, with dummy variables that represent four days starting from the last trading day of the previous month. This will capture the overall effect of the turn-of-the-month as suggested by Ariel (1987) and Lakonishok & Smidt (1988). The third model outlines the January effect by incorporating a dummy variable that represents the trading days in January over the entire dataset. Lastly, the fourth regression model represents the Halloween effect by considering a dummy variable that presents the data from November to April of each year throughout the dataset. This is based on the research of Bouman and Jacobsen (2002); they discovered that the months of November through April (winter months) provide higher returns than the remaining months of the year.

$$R_{t} = \beta_{0} + \beta_{1}d_{2t} + \beta_{2}d_{3t} + \beta_{3}d_{4t} + \beta_{4}d_{5t} + \beta_{5}d_{6t} + \varepsilon_{t}$$
(1)  

$$R_{t} = \beta_{0} + \beta_{1}TOM + \varepsilon_{t}$$
(2)  

$$R_{t} = \beta_{0} + \beta_{1}d_{Jan} + \varepsilon_{t}$$
(3)  

$$R_{t} = \beta_{0} + \beta_{1}d_{Hal} + \varepsilon_{t}$$
(4)

$$R_t = \beta_0 + \beta_1 TOM + \varepsilon_t \tag{2}$$

$$R_t = \beta_0 + \beta_1 d_{Ian} + \varepsilon_t \tag{3}$$

$$R_t = \beta_0 + \beta_1 d_{Hal} + \varepsilon_t \tag{4}$$

Equation 1 will examine the weekday effect, where  $R_t$  is the return of the industry on day t;  $d_{it}$  is a dummy variable to denote the day on which the return is detected;  $\beta_0$  measures the mean return for Monday; the coefficients  $\beta_1$  through to  $\beta_5$  measure the difference between the expected return for each day of the week and the expected return for Monday.

Equation 2 will examine the TOM, where  $R_t$  is the return on Day t;  $\beta_1$  is the coefficient on the dummy variable TOM that equals one on the last trading day and on the first 3 trading days of each month, and 0 otherwise; the coefficient  $\beta_1$  measures the difference between the expected return for TOM period and the expected return for the rest of the month (ROM); and the coefficient  $\beta_0$  measures the mean return for the other days of the month.

Equation 3 will examine the January effect, where  $R_t$  is the return of the industry on month t; the dummy variable  $d_{Jan}$  represents the month of January showing 1 when in January and 0 otherwise; the coefficient  $\beta_0$  measures the mean return for the other months of the year; and the coefficient  $\beta_1$  measures the difference between the expected return for January and the expected return for the other months of the year.

Equation 4 will examine the Halloween effect, where  $R_t$  is the return of the industry from November to April; the dummy variable  $d_{Hal}$  represents the Halloween effect months showing 1 during the period November through to April and 0 otherwise; the coefficient  $\beta_0$  measures the mean return from May to October; and the coefficient  $\beta_1$  measures the difference between the expected returns in both periods, November to April and May to October.

Moreover, Connolly's 1989 test, which has also been implemented by Chang et Al. (1993) and Brusa et al. (2003), will further assess the weekday effect by comparing Monday returns to the average returns of the rest of the week.

$$R_t = \beta_0 + \beta_1 MON + \varepsilon_t \tag{5}$$

 $R_t$  is the daily return on day t;  $\beta_0$  is the constant;  $\beta_1$  is the coefficient on a dummy variable MON that equals 1 on Mondays and 0 otherwise; and the error term is  $\varepsilon_t$ .

#### 2.4 Analysis

#### 2.4.1 Weekday Effect

The weekday effect was separated into two distinctive testing approaches: firstly, observing the Monday return against individual returns on other days of the week; and secondly, comparing Monday returns to the average return of the rest of the week to further assess the effect.

The sample covers a period exceeding 91 years, from 1926 to 2018. As shown in the table, there are two sub-periods, pre- and post-1952. 1952 is in addition the breakpoint for the whole time period.

Table 1 outlines the results for each industry, with the intercept  $\beta_0$  representing the Monday effect while the coefficients  $\beta_1$  through  $\beta_4$  illustrate other day-of-the-week effects. The results for the whole time period show that the intercept  $\beta_0$ , which measures the return on Monday, is significantly negative at the 10 percent level for almost all industries except hardware and smoke. The results in Table 1 also illustrate a prominent Monday return for construction (Cnstr), as seen in the highly (1% significance) statistically significant coefficient of -0.2232265, representing the lowest effect when compared to other industries. Positive effects for all industries are common from Tuesday to Friday, with the exception of smoke as certain days were not significant. This indicates that the weekday effect is present and strongly significant in virtually all the industries, except hardware and smoke, when testing the whole sample period from 1926 to 2018. While reporting a negative Monday return throughout the sample, the highest positive return compared to other days of the week was recorded on Saturday for 32 of the industries, Wednesday for six, and Friday for only one.

To examine if there is any change in the magnitude of the weekday effect before and after US trading was reduced to five trading days from the previous six, equation 1 is estimated again after applying the break point when testing the sub-periods July 1926 to Sep 1952 (six trading days) and Oct 1952 to January 2018 (five trading days). Results are presented in Table 1 Both sub-periods, pre- and post-1952, report a negative and significant Monday effect at the 5 percent level in almost all industries. For the sub-period pre-1952, Telecom and Bussv were the only insignificant industries. The sub-period post-1952 reports five insignificant industries: smoke, house hold (hsld), autos, utilities and hardware. Pre-1952 recorded a prominent and highly significant negative Monday effect in construction (Cnstr) with a

coefficient of -0.4071127. Moreover, Saturday displayed the highest returns compared to other days in 26 industries, Wednesdays reported the highest returns in five industries leaving eight industries to display highest returns on Thursdays. The post-1952 period also shows a striking and highly significant negative Monday return effect in Rlest with a coefficient of -0.1568199, which is exceptionally low when compared to the other industries included in the study. The highest weekday returns in this sub-period were reported on Wednesday and Friday for 16 and 23 industries, respectively. The least significant Monday average return effect reported in both sub-periods pre- and post-1952 were in clothes (Clths) and food with coefficients of -0.0746009 and -0.0317343, respectively.

*Table 1: Multilinear regression for the whole, pre and post 1952 periods (Weekday effect)* 

	Weekda	ay effect					
$R_t = \beta_0$	$R_t = \beta_0 + \beta_1 d_{2t} + \beta_2 d_{3t} + \beta_3 d_{4t} + \beta_4 d_{5t} + \beta_5 d_{6t} + \varepsilon_t$						
	Whole sample	Pre 1952	Post 1952				
Industries	$eta_0$	$eta_0$	$eta_0$				
Agric	-0.0975045***	-0.1505712***	-0.0760019***				
Food	-0.0594314***	-0.1277856***	-0.0317343**				
Beer	-0.1060311***	-0.2381925***	-0.0524794***				
Smoke	0.016338	-0.0961737***	-0.0619277**				
Toys	-0.1328023***	-0.205493**	-0.1033481**				
Fun	-0.1699504***	-0.3443662***	-0.0992771**				
Books	-0.1185311***	-0.243615***	-0.0678472***				
Hshld	-0.0419788**	-0.1401956***	-0.0021814				
Clths	-0.0626647***	-0.0746009**	-0.0578282***				
Medeq	-0.0811981***	-0.1238576***	-0.0639125***				
Drugs	-0.0633664***	-0.1075665***	-0.0454566**				
Chems	-0.0967419***	-0.1735368***	-0.0656246***				
Txtls	-0.1205551***	-0.2042175***	-0.086655***				
Bldmt	-0.1070939***	-0.2015336***	-0.0688269***				
Cnstr	-0.2232265***	-0.4071127***	-0.1487159***				
Steel	-0.1773082***	-0.2888185***	-0.1321243***				
Mach	-0.1074797***	-0.1953678***	-0.0718675***				
Elceq	-0.1307333***	-0.3136463***	-0.056617**				
Autos	-0.0916922***	-0.2432238***	-0.0302917				
Aero	-0.1326534***	-0.2007981***	-0.1050412***				
Ships	-0.1307401***	-0.2823161***	-0.0693215***				
Mines	-0.1107378***	-0.1213772***	-0.1064268***				
Coal	-0.161444***	-0.2651095***	-0.1194388***				
Oil	-0.1122089***	-0.1881377***	-0.0814426***				
Util	-0.0594292***	-0.2218623***	-0.0063887				
Telcm	-0.0362477**	-0.0379108	-0.0355739*				
Bussv	-0.1002098***	-0.1068232	-0.0975301***				
Hardw	-0.0308145	-0.1419953***	0.142359				
Chips	-0.0938538***	-0.1865102***	-0.0563094				
Labeq	-0.0674368***	-0.1027778**	-0.0531167**				
Boxes	-0.0918005***	-0.1688811***	-0.0605675***				
Trans	-0.1701692***	-0.2915962***	-0.120967***				
Whlsl	-0.1330731***	-0.2455243***	-0.0875079***				

Retail	-0.842893***	-0.1549296***	-0.0556658***
Meals	-0.0862793***	-0.1360485***	-0.0661129***
Banks	-0.0913222***	-0.1665649***	-0.0608339**
Insur	-0.0894224***	-0.1644523***	-0.0590203**
Rlest	-0.1980212***	-0.2997027***	-0.1568199***
Fin	-0.1668141***	-0.311698***	-0.1081072***

To further assess the Monday effect, the model is transformed into a simple linear regression outlined in equation 5. The results for the industries are presented in Table 1.1 The presented results for the whole sample show that the intercept  $\beta_0$ , which measures the average return for other days of the week, tends to be positive. A negative significant Monday effect for all industries, including smoke and hardware, is reported. Construction (Cnstr) displays the Monday effect the most, as the coefficient of -0.3326061 is the lowest negative return, while smoke reports the least effect with an average Monday return coefficient of -0.0446838. Table 1.1 also shows that the coefficient  $\beta_1$ , which measures the difference between Tuesday through Friday/Saturday (before 1952) and Monday, is positive for all industries. To further assess the effect of reducing trading days on the weekday anomaly, equation 5 is estimated for the sub-periods pre- and post-1952.

Pre-1952 shows a highly significant negative Monday effect for all industries at the 1 percent level, except for telecommunication (Telcm) and business services (Bussv) at the 5 percent level, reporting p-values of 0.012 and 0.016, respectively. The Monday effect was mostly realised in construction (Cnstr) with a coefficient of -0.548959, while the least effect was in Telcom with a coefficient of -0.0798133.

Similarly, the post-1952 sub-period reports a highly significant negative Monday effect for all industries except for smoke and hardware. Hardware was significant at the 10 percent level and smoke was the only insignificant industry. The highest effect for the Monday anomaly was in construction (Cnstr) with a coefficient of -0.2424414, while the least effect was in utilities with a coefficient of -0.0439313.

Table 1.1: Simple linear regression for the whole, pre and post 1952 periods (Weekend effect)

			Weekday eff	ect		
			$R_t = \beta_0 + \beta_1 M 0$	$ON + \varepsilon_t$		
	Whole	sample	Pre	1952	Post	1952
Industries						
Agric	-0.1721033***	0.0745988***	-0.2298997***	0.0793285***	-0.1483203***	0.0723184***
Food	-0.1264176***	0.0669862***	-0.1870284***	0.0592428***	-0.102454***	0.0707197***
Beer	-0.1965791***	0.0905479***	-0.3569507***	0.1187582***	-0.1294255***	0.0769461***
Smoke	-0.0446838**	0.0610218***	-0.1447932***	0.0486195***	-0.005074	0.0670017***
Toys	-0.2203516***	0.0875493***	-0.3092402***	0.0486195***	-0.1830874	0.797393***
Fun	-0.2742167***	0.1042663***	-0.4531867***	0.1088205***	-0.2013476***	0.1020705***
Books	-0.1989919***	0.0804607***	-0.3299114***	0.0862964***	-0.1454942***	0.0776471***
Hshld	-0.1014131***	0.0594343***	-0.1997266***	0.059531***	-0.0615691***	0.0593877***
Clths	-0.1254494***	0.0627847***	-0.1211871***	0.0465862***	-0.1284232***	0.070595***
Medeq	-0.1658729***	0.0846748***	-0.2076407***	0.0837831***	-0.1490173***	0.0851048***
Drugs	-0.137874***	0.0745076***	-0.1706142***	0.0630477***	-0.1254896***	0.0800331***
Chems	-0.177123***	0.0803812***	-0.2698456***	0.0963088***	-0.1383261***	0.0727015***
Txtls	-0.1983492***	0.0777941***	-0.2831175***	0.0789***	-0.163916***	0.0772609***
Bldmt	-0.1837242***	0.0766303***	-0.2792479***	0.0777142***	-0.1449346***	0.0761077***
Cnstr	-0.3326061***	0.1093796***	-0.548959***	0.1418464***	-0.2424414***	0.0937255***

Fin	-0.2627754***	0.0959613***	-0.416927***	0.105229***	-0.1995999***	0.0914927***
Rlest	-0.2887749***	0.0907537***	-0.4143318***	0.1146292***	-0.2360619***	0.079242***
Insur	-0.164779***	0.0753566***	-0.2463064***	0.0818542***	-0.131244***	0.0722237***
Banks	-0.17577***	0.0844478***	-0.2704104***	0.1038454***	-0.1359389***	0.075095***
Meals	-0.1640238***	0.0777444***	-0.1998675***	0.0638189***	-0.1505716***	0.0844587***
Rtail	-0.1592003***	0.074911***	-0.2260997***	0.0711701***	-0.1323806***	0.0767147***
Whlsl	-0.2112692***	0.0781961***	-0.3263392***	0.0808149**	-0.1644413***	0.0769334***
Trans	-0.2578827***	0.0877135***	-0.3832572***	0.091661***	-0.2067773***	0.0858102***
Boxes	-0.1713611***	0.0795605***	-0.2555249***	0.0866438***	-0.1367128***	0.0761453***
Labeq	-0.1451402***	0.0777034***	-0.1709392***	0.0681614***	-0.1354208***	0.0823041***
Chips	-0.1779863***	0.0841325***	-0.2832693***	0.0967591***	-0.1343539***	0.0780445***
Hardw	-0.105018***	0.0742035***	-0.2290224***	0.0870271***	-0.0537845*	0.0680204***
Bussv	-0.1850692	0.0848593***	-0.2012248**	0.0944017**	-0.1777886***	0.0802584***
Telcm	-0.0925258***	0.0562781***	-0.0798133**	0.0419025***	-0.0987833***	0.0632094***
Util	-0.1198352***	0.060406***	-0.3031867***	0.0813244	-0.0439313***	0.05032***
Oil	-0.1939039***	0.081695***	-0.2711371***	0.0829994***	-0.1625086***	0.081066***
Coal	-0.2536474***	0.0922034***	-0.3512376***	0.0861281***	-0.2145714***	0.0951326***
Mines	-0.1909157***	0.0801779***	-0.1948985***	0.0735213***	-0.1898142***	0.0833874***
Ships	-0.2134214***	0.0826813***	-0.3763719***	0.0940558***	-0.1465186***	0.0771971***
Aero	-0.2387886***	0.1061351***	-0.324053***	0.1232549***	-0.2029219***	0.0978807***
Autos	-0.1708022***	0.0791099***	-0.3590325***	0.1158087***	-0.0917071***	0.0614154***
Elceq	-0.2244902***	0.0937569***	-0.4302294***	0.116583***	-0.1393681	0.0827511***
Mach	-0.1882983***	0.0808186***	-0.2854161***	0.0900483***	-0.1482359***	0.0763684***
Steel	-0.2668713***	0.0895631***	-0.4005277***	0.1117093***	-0.2110094***	0.0788851***

<sup>\*</sup> p<0.05 \*\* p<0.01 \*\*\*p<0.001

The above results outline that the change in trading days after 1952 did not affect the anomaly's presence, magnitude or direction; the anomaly sustained its significant existence during all periods in question. Furthermore, the findings also verify that the Monday anomaly manifests itself across all industries and is not limited to certain sectors. Brusa et al. (2003) studied the weekday effect in broad indices and at industry level and came up with a similar conclusion: the weekday anomaly is caused by economic events that affect all industries rather than industry-specific factors impacting only a few industries.

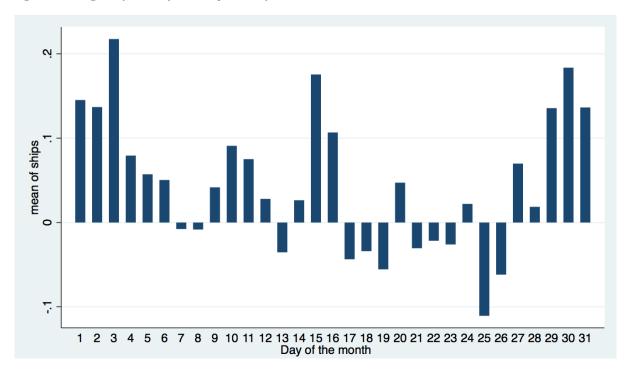
The findings on the existence and persistence of the negative Monday effect across all tested periods is consistent with several existing studies (French, 1980; Rogalski, 1984; Abraham and Ikenberry, 1994; Chen and Singal, 2003). All tested periods record a very strong and significant negative Monday effect for almost all industries, questioning the reliability of several attempted explanations of the Monday effect. Rogalski (1984) proposed that the Monday effect occurs during the weekend period between Friday's closing and Monday's opening. However, if the anomaly occurs during the weekend like Rogalski (1984) and many other scholars after him proposed, then the pre-1952 sub-period should display a decreased weekend effect. This is because this period consisted of six trading days, leaving only one non-trading day at the weekend. The results from the pre-1952 sub-period exhibit a very strong and significant negative Monday effect in the majority of the industries included in the study, challenging the explanation brought forward by Rogalski. Furthermore, the "settlement periods" phenomenon suggested by Gibbons and Hess (1981) could shed light on the findings as it explains the effect of stocks being purchased on a certain day but not paid until several days later, which adds to the weekday effect. This phenomenon has not been eradicated as the settlement period is still present, making it a feasible explanation for the presence of the Monday effect. However, according to Lakonishok and Levi (1982), only 17 percent of the weekday anomaly can be explained by settlement periods, indicating that the evidence behind such an anomaly is mixed.

Although the Monday effect has been studied extensively and solid evidence for its presence has been proved, very few trading strategies have been based on this anomaly. Boumen and Jacobsen (2002) argue that the potential benefits of such a strategy do not outweigh the cost of trading and this is the main reason that very few, if any, strategies have proved successful regarding the weekday effect.

#### 2.4.2 Turn-of-the-month Effect (TOM)

Equation 2 estimates the effect of the turn-of-the-month anomaly on the whole sample period and the results will be presented in Table 2. With Equation 2 intercepts illustrating the remaining period of the month (ROM) after the turn of the month, 30 out of 39 industries show statistically significant positive returns. Moreover, the TOM dummy variable coefficient displays positive and statistically significant returns for all industries. The findings confirm that, even though both ROM and TOM periods display positive returns, the average mean returns for the TOM are significantly greater. For example, ships display a TOM dummy variable coefficient of 0.1420076, while the intercept  $\beta_0$  displays a coefficient of 0.0176944. Both coefficients are significant at the 1 and 10 percent levels, respectively. The results constitute strong evidence for the existence of the turn-of-the-month anomaly. since the returns for the TOM exceed those for the ROM and are positive and statistically significant at the 5 percent level across all industries and throughout the sample period. Figure 1 shows average daily returns for Ships for the whole sample period; the returns during the turn-of-the-month days (days 31, 1, 2, and 3) are high when compared to the other days of the month. Moreover, the further the returns are from the turn-of-the-month period, the more diminished they are. Figure 1 shows that the turn-of-the-month could be considered as starting from day 30; however, to be consistent with previous studies, the turn-of-themonth period is determined to be from day 31 through to day 3 (in a 31-day month).

Figure 1: Average daily returns for the ships industry



The effect of the two sub-periods on the anomaly is investigated. Equation 2 is estimated again and results are presented in Table 2. The intercepts in pre-1952 outline that all ROM returns are statistically insignificant, contrary to the whole sample period. The coefficients on the TOM dummy variable show that 37 industries have positive average mean returns, while two industries (Books and Bussv) display insignificant p-values of 0.271 and 0.197, respectively. The highest TOM return industry is Real Estate (Rlest) while the lowest TOM return was in Agriculture (Agric), with coefficients of 0.366172 and 0.10553 respectively.

Moreover, the coefficients on the TOM dummy variables for the post-1952 sub-period show that all the industries have a positive average mean return that is statistically significant at the 10 percent level. The highest TOM return is reported in coal, with a coefficient of 0.165843, against the lowest TOM return in books, with a coefficient of 0.0412795. The striking difference between pre- and post-1952 is the positive significant ROM returns for all industries, with the exception of four (Steel, Autos, Coal and Rlest).

Table 2: Simple linear regression for the whole, pre and post 1952 periods (TOM effect)

		,	Turn-of-the-n	onth		
		$R_t$	$= \beta_0 + \beta_1 T$	$OM + \varepsilon_t$		
	Whol	e sample	Pre 1952		Pre 1952	
Industries						
Agric	0.093312***	0.0260511**	0.10553**	0.0239286	0.0882479***	0.0270769**
Food	0.0963137***	0.0262727***	0.1537365***	0.0030947	0.0714139***	0.0374747***
Beer	0.123843***	0.0319555***	0.2148958***	0.0244115	0.0867934***	0.0356015***
Smoke tob	0.1284091***	0.0294617***	0.1330173***	0.0028665	0.1243504***	0.0423152***
Toys	0.117787***	0.025698*	0.1617023*	0.0260047	0.1002465***	0.0255497**
Fun ent	0.1474792***	0.0271318**	0.234176***	-0.0046537	0.1101527***	0.0424938***
Books	0.0532091**	0.0342773***	0.0718274	0.0197888	0.0445548*	0.0412795***

Hshld	0.1021323***	0.0222489***	0.1432766***	0.0029814	0.0840696***	0.031561***
Clths	0.112222***	0.0193544**	0.1119238***	0.0081957	0.1114118***	0.0247475**
Medeq	0.0979368***	0.0364285***	0.1727147***	0.0211149	0.06675***	0.0438296***
Drugs	0.1039369***	0.0303056***	0.1351902***	0.0126522	0.089965***	0.0388375***
Chems	0.1281681***	0.0245707***	0.1665891***	0.0243106	0.1127781***	0.0246964**
Txtls	0.1259934***	0.0184857**	0.1556033***	0.0064907	0.1131502***	0.0242829**
Bldmt	0.13333797***	0.0186608**	0.1742349***	0.0029068	0.1157253***	0.0262747***
Cnstr	0.1498335***	0.021106	0.2665303***	0.0071879	0.1019954***	0.0278326**
Steel	0.1877978***	0.0064402	0.2629943***	0.0022764	0.1573723***	0.0084525
Mach	0.1417294***	0.0204908**	0.2162845***	0.007354	0.1108131***	0.0268398***
Elceq	0.1314846***	0.0286542**	0.2055105***	0.0115994	0.1004535***	0.0368968***
Autos	0.1848761***	0.0141412	0.2479959***	0.0157143	0.1597593***	0.0133809
Aero	0.1537264***	0.0343628***	0.2591677***	0.027146	0.1109487***	0.0378507***
Ships	0.1420076***	0.0176944*	0.1958257***	-0.0004037	0.1189727***	0.0264413**
Mines	0.1265013***	0.0221407**	0.1767119***	0.0123168	0.1055987***	0.0268886**
Coal	0.1672453***	0.0152456	0.1676672***	0.0004379	0.165843***	0.0224023
Oil	0.1312287***	0.222494**	0.2169365***	0.0025699	0.0953063***	0.0317606***
Util	0.0962911***	0.0209041***	0.1547477***	0.005722	0.0716437***	0.0282417***
Telcm	0.1078046***	0.0196909***	0.1080926***	0.0110078	0.1069661***	0.0238874***
Bussv	0.096051***	0.0334349**	0.1097614	0.043073	0.0913698***	0.0287767***
Hardw	0.0958512***	0.0374996***	0.1320924***	0.0274379	0.0805165***	0.0423625***
Chips	0.1751085***	0.0196231	0.2264494***	0.0127624	0.1540007***	0.0229388*
Labeq	0.1160694***	0.029961***	0.1478968***	0.0156382	0.1021454***	0.0368833***
Boxes	0.1267447***	0.025066***	0.1833275***	0.0142919	0.1032141***	0.0302732***
Trans	0.1551526***	0.0121791	0.1799877***	-0.0013571	0.1440909***	0.0187212*
Whlsl	0.1439574***	0.0132492	0.2296359***	-0.010854	0.1076781***	0.0248983***
Rtail	0.1247962***	0.0230018***	0.1746765***	0.0051165	0.1033542***	0.0316458***
Meals	0.1112412***	0.0274166***	0.1863146***	0.000222	0.0789465***	0.0405598***
Banks	0.1319561***	0.0281963***	0.178113***	0.0298727	0.113633	0.0273861**
Insur	0.1250437***	0.022379**	0.1557857***	0.015528	0.1121762***	0.0256901**
Rlest	0.1750394***	0.0059342	0.366172***	-0.0139348	0.0969312***	0.015537
Fin	0.159718***	0.0186987*	0.2313104***	-0.0017562	0.1293772***	0.0285846**

<sup>\*</sup> p<0.05 \*\* p<0.01 \*\*\*p<0.001

The results from the sample and sub-periods indicate that the effect of the anomaly is consistent in all periods and the magnitude of the anomaly has not changed after reducing the number of trading days to five. Moreover, the anomaly is present in almost all industries, suggesting that the turn-of-the-month anomaly is a widespread phenomenon that occurs across all industries and is not sector- or industry-specific; this is backed up by Brusa et al (2003). This contradicts Sharma and Narayan (2011), who found that TOM returns affect firm returns differently depending on the sector they belong to. Sharma and Narayan (2011) go on to explain that firms are heterogeneous and, since an industry is a composition of firms, so are industries. They should therefore experience TOM effects differently. For example, TOM should have a different impact on the financial industry than on the agricultural industry. The findings in this study provide evidence that the TOM exists almost equally in most industries and that its effect has been consistent across the sub-period samples. This

confirms that the magnitude of the effect has been consistent and persistent across most industries, suggesting that the TOM is a widespread phenomenon and not industry-specific.

#### 2.4.3 Turn-of-the-year/January Effect

The January effect relates to the hypothesis that firms encounter abnormal returns in January compared to other months in the year. According to existing literature, this phenomenon is most dominant in small firms (Easterday et al, 2009; Bouman and Jacobsen, 2002). To examine this theory, average equal weighted returns at industry level will be tested. Average equal weight returns gives the same importance to each firm in the market and therefore, stocks of smaller firms are given equal statistical significance and weight to stocks of larger firms. To put more emphasis on the presence of the January effect in small firms, average equal weighted returns at industry level will be tested instead of average value weighted returns and reported in Table 3. This is consistent with Rozeff & Kinney (1976), whose results were crucially dependent on whether a value-weighted or equally weighted index was used. This will not only investigate the anomaly at industry level but also confirm the relationship of the anomaly with small firms, since average equal weighted returns tend to give small firms greater weight than their actual market value. Finding a positive January effect would provide evidence of the relationship between the anomaly and small firms. When testing the January effect using average value weighted returns, the results did not display any presence of the anomaly.

The results from testing the whole sample show that all industries are significant at the 1% level except for coal and insurance, which were significant at the 5% level. The findings report the highest January return in construction (Cnstr) with a coefficient of 0.3351658, while the least January return is in insurance (Insur) with a coefficient of 0.0668081. The intercept representing the months other than January is positive across all industries; however, the January returns exceed the returns for the other months, providing strong evidence of the existence of the January effect.

To assess the effect of reducing trading days, pre- and post-1952 sub-periods are estimated by equation 3 and results are presented in Table 3. The pre-1952 sub-period comprises 31 significant industries, 28 of which are significant at the 5% level, displaying the magnitude of the effect. This leaves only eight insignificant industries. The findings report the highest January return in Construction (Cnstr) with a coefficient of 0.4954862, while the least January return is reported in Chemicals (Chems) with a coefficient of 0.0954406. The post-1952 sub-period displays 37 significant industries, with 35 industries significant at the 1% level and two industries, smoke and insurance, at the 10% level. The highest January return is reported in mines and the lowest January return is reported in insurance (Insur), with coefficients of 0.2737524 and 0.0452814, respectively. These results suggest that the change in trading days did not affect the anomaly since both sub-periods exhibit a strong and highly significant January effect.

Table 3: Simple linear regression for the whole, pre and post 1952 periods (Jan effect)

January Effect						
$R_t = \beta_0 + \beta_1 Jan + \varepsilon_t$						
	Whole	sample	Pre-1952		Po	st-1952
Industries						
Agric	0.1774944***	0.0744096***	0.1323023	0.1280748***	0.1980985***	0.0497959***

Food	0.139416***	0.0641499***	0.176527***	0.0751472***	0.1216935***	0.0591059***
Beer	0.0985132***	0.0666951***	0.0847156	0.0880748***	0.104731***	0.0568893***
Smoke	0.1065336***	0.070477***	0.1955216***	0.0563486***	0.0646275*	0.0769571***
Toys	0.1843641***	0.063257***	0.100129	0.0766885*	0.2240311***	0.0570966***
Fun	0.2170628***	0.0727773***	0.1813855**	0.0832902***	0.2337932***	0.0679555***
Books	0.125109***	0.0644646***	0.1522407*	0.0694185**	0.1121972***	0.0621925***
Hshld	0.1996551***	0.0570939***	0.2331193***	0.0641959***	0.1837152***	0.0538366***
Clths	0.2368804***	0.0667***	0.2927402***	0.0902915***	0.2101017***	0.0558797***
Medeq	0.2285559***	0.0595449***	0.2261199***	0.0475302*	0.2298839***	0.0650554***
Drugs	0.1454402***	0.0658631***	0.0826416	0.0470567***	0.1754328***	0.0744887***
Chems	0.130252***	0.0643555***	0.0954406**	0.0783904***	0.1465213***	0.0579184***
Txtls	0.17827***	0.0579461***	0.1739479***	0.0887217***	0.1798667***	0.0438307***
Bldmt	0.1866524***	0.0624465***	0.1587707***	0.0697512***	0.1997404***	0.0590961***
Cnstr	0.3351658***	0.0787973***	0.4954862***	0.1391895***	0.2584164***	0.0510982***
Steel	0.1870579***	0.0588626***	0.1344092**	0.0906285***	0.2115099***	0.0442931***
Mach	0.1946281***	0.064432***	0.2037252***	0.0772402***	0.1901363***	0.0585575***
Elceq	0.1966723***	0.0663267***	0.170909***	0.069272***	0.2088214***	0.0649759***
Autos	0.1911917***	0.0609594***	0.1889787***	0.0835703***	0.1919093***	0.0505889***
Aero	0.1563953***	0.0797626***	0.1437392*	0.0954614***	0.1621558***	0.0725623***
Ships	0.163768***	0.062167***	0.1587137**	0.0846197***	0.1658326***	0.051869***
Mines	0.2620335***	0.0766196***	0.2362862***	0.1085554***	0.2737524***	0.0619721***
Coal	0.1044069**	0.1017995***	0.1645198*	0.2035646***	0.0744757	0.0551246***
Oil	0.122165***	0.0755045***	0.1023395*	0.0921854***	0.131304***	0.0678538***
Util	0.0836644***	0.0547561***	0.2022103***	0.0633855***	0.0274387	0.0507982***
Telcm	0.1351446***	0.0536102***	0.0707061	0.0350405**	0.1659098***	0.0621273***
Bussv	0.21812***	0.082505***	0.2666267***	0.1136599***	0.1947108***	0.0682157***
Hardw	0.2047722***	0.0557607***	0.1057819**	0.0530869***	0.2516567***	0.0569871***
Chips	0.2207162***	0.0716918***	0.1689061**	0.0762221***	0.2451684***	0.0696139***
Labeq	0.1244746***	0.0694595***	-0.0361858	0.0422039**	0.2009019***	0.0819603***
Boxes	0.1362396***	0.0708776***	0.1456552**	0.0979497***	0.1313892***	0.0584609***
Trans	0.245917***	0.0779541***	0.3532632***	0.137853***	0.1942439***	0.0504813***
Whlsl	0.1614724***	0.0961439***	0.0674042	0.1767738***	0.2048131***	0.0591626***
Rtail	0.1377436***	0.0656963***	0.1614266***	0.0838675***	0.126271***	0.0573621***
Meals	0.2230893***	0.0592315***	0.2455767***	0.0630357***	0.212392***	0.0574866***
Banks	0.1350398***	0.0646502***	0.1670234***	0.0652239***	0.1198957***	0.064387***
Insur	0.0668081**	0.0600232***	0.1128438	0.0422693*	0.0452814*	0.0681662***
Rlest	0.2665452***	0.0780042***	0.3299631**	0.11788***	0.2359524***	0.059715***
Fin	0.1829611***	0.0786377***	0.2562549***	0.103549***	0.1479128***	0.0672121***

<sup>\*</sup> p<0.05 \*\* p<0.01 \*\*\*p<0.001

The findings for the whole, pre and post-1952 sample periods provide strong evidence of the existence and persistence of the January effect at industry level. The results confirm that the January effect is most dominant in small firms, since a strong January effect was detected in all periods when considering average equal weighted returns, unlike the results generated when average value-weighted returns were deployed (Banz, 1981; Keim, 1983; Reinganum, 1983; Easterday et al., 2009).

Many studies have discussed explanations for the January effect. Among the most important is the tax-loss-selling hypothesis, where investors set off losses in their portfolios against gains in order to pay the lowest amount of tax on their overall income by selling small cap stocks at year end. The tax-loss-selling hypothesis could be a plausible explanation, but it is responsible for only a small portion of the anomaly as several studies have proven the existence of the January effect in countries that do not have capital gains tax, like Japan and Canada before 1972 (Rozeff, 1986; Kato and Schallheim, 1985; Schultz, 1985; Berges et.al, 1984; Reinganum, 1983; Roll, 1983). In addition, Thaler (1987) outlines that the tax-loss-selling hypothesis is not a comprehensive explanation, pointing to the example of the United

Kingdom and Australia, where there was evidence for the existence of the January effect even though their tax years start on 1 April and 1 July, respectively. Another explanation that has been extensively studied is window dressing, where institutional investors such as mutual and pension funds try to avoid reporting too many losers, especially small cap stocks, in their portfolios at year-end and therefore sell them. They subsequently buy them back in January after the reporting date to regain their original portfolio balance (Gompers & Metrick, 2001). The findings confirm the feasibility of this explanation; however, there is no evidence that it fully explains the anomaly.

#### 2.4.4 Halloween effect

"Sell in May and go away" is a market saying that describes the Halloween puzzle, where returns are reported to be higher during the winter months, November through to April, when compared to the summer months, May through to October. Equation 4 examines this anomaly for the whole sample period and two sub-periods, pre- and post-1952, and the results are provided in Table 4. The whole sample period shows that the Halloween effect is present in 33 industries out of 39. All significant industries displayed positive and higher returns during the Halloween period compared to the summer months. For instance, Real Estate (Rlest) displayed strong and statistically significant returns at the 1 percent level during the Halloween effect period with a coefficient of 0.0799477, while negative returns for the summer months were reported with a coefficient of -0.001631.

When looking at the sub-periods pre- and post-1952, the results show a strong contradiction between the two sub-periods, implying that reducing trading days to five from six significantly affected the anomaly. Examining the pre-1952 sub-period, 37 industries displayed an insignificant Halloween effect, leaving only the Beer and Coal industries which exhibited negative significant dummy variable coefficients at the 5 percent and 10 percent levels, respectively. The negative coefficients indicate that the Halloween effect reported in these industries is a reversal, since the returns during the winter months are negative but positive during the summer months. This questions the existence of the anomaly in the tested period. Moreover, the reason behind such results in Beer and Coal could be due to the nature of the industry, where Beer is constantly linked to the summer festive season and Coal is consistently used to generate energy throughout the year regardless of the season. Jacobsen and Visaltanachoti (2009) tested 49 industries to find that the beer industry performs consistently better during the summer months.

The post-1952 sub-period reports a strong and significant Halloween effect in 36 industries at the 5 percent significance level with 30 industries significant at the 1 percent level. In addition, 8 industries displayed negative returns during the summer period and high positive returns during winter months, describing not only the existence of the anomaly but also its strong magnitude in the tested period. Observing both sub-periods pre- and post-1952, the contradicting results suggest that the change in the number of trading days has had a significant effect on the anomaly. This contradiction between the sub-periods may mean that longer weekends are directly associated with the anomaly. A possible explanation for the absence of the Halloween effect in the pre-1952 sub-period is the occurrence of several events that affected investor behaviour, such as the Second World War (1939 to 1945) and the Great Depression (1929 to 1939).

*Table 4: Simple linear regression for the whole, pre and post 1952 periods (Hal effect)* 

			Halloween o	effect		
		$R_t$	$= \beta_0 + \beta_1$	$Hal + \varepsilon_t$		
	Whole	e sample	Pre 1952		Po	st 1952
Industries						
Agric	0.0656846***	0.0106473	0.0286549	0.0269727	0.0830053***	0.0030567
Food	0.0106554	0.0385437***	0.0032448	0.0265792	0.0141977	0.0441067***
Beer	-0.0047655	0.0568376***	-0.0980827**	0.1080144***	0.0388335**	0.0330423***
Smoke	0.0016242	0.0520245***	-0.017924	0.0334439**	0.0109036	0.0606637***
Toys	0.0545397**	0.0202416	-0.219198	0.0632407	0.0902572***	0.0002487
Fun	0.0654675***	0.0216906	-0.0412687	0.0539841	0.115467***	0.0066754
Books	0.042515**	0.0229992	-0.0174003	0.0401209	0.0705868***	0.0150383
Hshld	0.0264687*	0.0277829**	0.0046494	0.0240638	0.0367412**	0.0295121**
Clths	0.0580929***	0.111339	0.0091244	0.021947	0.0810516***	0.0061062
Medeq	0.0351139*	0.0369371***	0.0105194	0.0440972	0.0466364**	0.033608**
Drugs	0.0282167*	0.0353061***	0.0166097	0.0264969	0.337153**	0.0394021***
Chems	0.048416***	0.024022**	-0.0221828	0.0624743**	0.0814021***	0.0061433
Txtls	0.0569988***	0.0133102	-0.0297067	0.0465844*	0.0975799***	-0.002161
Bldmt	0.0635755***	0.0115869	-0.0166553	0.0395833	0.1011403***	-0.0014303
Cnstr	0.0705728***	0.0135763	-0.0144468	0.0578344	0.1103069***	-0.0070019
Steel	0.0660936***	0.0080261	-0.0433842	0.0666641*	0.1172501***	-0.0192382
Mach	0.0709819***	0.0112849	0.000562	0.042374	0.1039206***	-0.0031703
Elceq	0.0578206***	0.0240727*	-0.000348	0.0453112	0.0850509***	0.0141976
Autos	0.0453181**	0.0254376*	-0.025477	0.0687937**	0.0783719***	0.0052786
Aero	0.0768158***	0.0244637	0.0661572	0.0367078	0.0817637***	0.0187706
Ships	0.0528938***	0.0174563	-0.0196657	0.041286	0.0868742***	0.0063765
Mines	0.071477***	0.00992	-0.0068686	0.044555	0.1081227***	-0.0061839
Coal	0.0494418*	0.0213012	-0.0814163*	0.0680864*	0.110705***	-0.000452
Oil	0.0290895*	0.0317853***	-0.0046242	0.0402623*	0.044891**	0.0278438**
Util	0.0042528	0.0363273***	-0.0183704	0.0400669	0.0148659	0.0345886***
Telcm	0.0239495*	0.0274988***	-0.0232687	0.040162**	0.0460764***	0.0216109*
Bussv	0.035012	0.0336506*	-0.0225105	0.0721245	0.0618527***	0.0157618
Hardw	0.0434467**	0.0335208**	-0.0065834	0.0522531**	0.0668649***	0.024811
Chips	0.0634604***	0.0201984	0.0160302	0.0417876	0.0856425***	0.0101602
Labeq	0.0634259***	0.0198114	-0.014224	0.0468133*	0.0997827***	0.0072566
Boxes	0.0464646***	0.0252204**	-0.0111429	0.0497248**	0.0734149***	0.0138268
Trans	0.0438552**	0.0187886	-0.0180681	0.0369573	0.0728654***	0.0103408
Whlsl	0.0417864**	0.0188416	-0.0432999	0.0480478	0.0816269***	0.00526619
Rtail	0.0290248**	0.0313992***	-0.029182	0.0480633**	0.0562959***	0.00320019
Meals	0.0630997***	0.0313992	0.0263569	0.0480033	0.0803618***	0.0160667
Banks	0.0362695*	0.0343249**	0.0203309	0.0516872*	0.0463383**	0.0262521*
Insur	0.0302093	0.0347184***	-0.0416089	0.0615406**	0.0504655***	0.0202321*
Rlest	0.0799477***	-0.001631	0.0148135	0.0384954	0.0304033***	-0.0202882
Fin	0.047346**	0.024418*	0.0148133	0.0384934	0.0624854***	0.0225066

<sup>\*</sup> p<0.05 \*\* p<0.01 \*\*\*p<0.001

Upon closely observing which industries exhibit a strong Halloween or strong winter effect, a pattern becomes visible. It appears that industries with a weak or no Halloween effect tend to be consumer-focused and related to products with short lifecycles, such as Food and Utilities. Both industries are insignificant and show no Halloween effect. Industries with a strong Halloween effect tend to be related to raw materials and manufacturing sectors, such as Construction and Steel. This observation begs the question: is the Halloween puzzle industry-specific or a market wide phenomenon affecting all industries equally? Bouman and Jacobsen (2002) attempted to answer this question in their study by proposing

the hypothesis that seasonal industries like agriculture may be linked to the Halloween effect. They tested 19 countries and found no link between the Halloween effect and countries with

large agricultural sectors, thus providing evidence that the Halloween effect is not industry-specific and manifests itself equally across all industries. Their findings are backed up by this study, where the whole and post-1952 sample periods provide evidence that the Halloween effect exists and persists in all industries, and is therefore a widespread phenomenon and not industry-specific.

On the other hand, Carrazedo et al. (2016) argue in favour of the agricultural hypothesis and raise the question of whether this link is random in nature or due to sound fundamentals. However, they outline that this argument lacks strong evidence and that, over time, science will discover the reason.

The findings for the whole and post-1952 sample periods provide strong evidence of the existence and persistence of the Halloween effect, which is supported by Shen (2017) as well as Carrazedo et al. (2016). This could be based on investors altering their trading strategies to the anomaly in order to benefit from positive returns (Bouman and Jacobsen, 2002; Carrazedo et al., 2016; Shen, 2017). Bouman and Jacobsen (2002) found that the presence of the Halloween effect outperforms the traditional buy and hold strategy. Jacobsen and Visaltanachoti (2009) proposed an investing strategy dubbed "sector rotation strategy", where investors should invest in production-focused industries during winter months and switch their investments to consumer-focused industries during summer months. According to Jacobsen and Visaltanachoti (2009), the sector rotation strategy outperforms the market in both summer and winter months.

Other possible explanations for the anomaly include risk aversion of investors' behaviour due to vacations, Seasonal Affective Disorder (SAD) and temperature changes (Bouman and Jacobsen, 2002; Kamstra, Kramer and Levi 2003; Cao and Wei, 2005). Furthermore, Jacobsen and Visaltanachoti (2009) argue that all of these justifications are based on a broad and market-wide behavioural explanation for the anomaly, since the anomaly has been proven to be a market-wide phenomenon. Jacobsen and Marquering (2009) outline that SAD is the least likely explanation for the Halloween puzzle.

Bouman and Jacobsen (2002) highlight more likely explanations, such as data mining and risk. The results in this study are robust with respect to the industries and consistent over an extremely long period of time and, for this reason, the data mining justification could be excluded. Furthermore, Bouman and Jacobsen (2002) provide evidence that the standard deviations for the summer period in relation to the winter period seem to be the same, therefore rejecting the risk explanation for the Halloween anomaly.

#### 2.4.5 Including all anomalies in one regression equation

Calendar effects are a compilation of findings that illustrate above or below average price changes in markets that investors could benefit from during the year. However, investigating four major calendar anomalies in one study begs the question of whether some effects are driven by the high positive returns of other effects. For example, the January effect falls within the Halloween effect time period and one might argue that the Halloween effect is simply the January effect in disguise (Bouman and Jacobsen, 2002). Therefore, to test this possibility and to see which anomaly has the greatest effect, an extra regression is considered. The regression model will compose of all the four anomalies, the weekday, the turn of the month, the January and the Halloween effects. However, due to the overlap between the anomalies, for example the January effect falls within the Halloween effect period, there is a

chance that multicollinearity will be present. In order to identify if there is any existence of multicollinearity the correlation matrix and variance inflation factor (VIF) will be tested. (Gujarati et.al 2012). Only one table is reported for the VIF and the correlation matrix for each sample since results for all industries displayed similar results.

$$R_t = \beta_0 + \beta_1 d_{Mon} + \beta_2 d_{TOM} + \beta_3 d_{Ian} + \beta_4 d_{Hal} + \varepsilon_t \tag{6}$$

Where  $R_t$  is the daily industry return,  $d_{Mon}$  is a dummy variable representing the returns on Monday,  $d_{TOM}$  is a dummy variable representing the days around the turn of the month (the last day of the previous month and the first three days of the current month).  $d_{Jan}$  is a dummy variable representing the month of January,  $d_{Hal}$  is a dummy variable representing the winter months from November through to April.  $\beta_0$  measures the mean return on the days that are not Monday, do not fall on the last day or the first three days of the month, not in January and not in the winter months (November-April). To test for this model, average equal weighted returns were used since all anomalies gave similar results using these returns when tested individually.

The adopted approach is consistent with the previously used data methodology. We examined the whole time period and the two sub-periods, pre- and post-1952. The results are displayed in Table 5, Table 5.1 and Table 5.2. The results for the whole time period confirm that all anomalies are independent of each other and no anomaly is driven by another since the correlation matrix and the variance inflation factor report no signs of collinearity between the anomalies (reference table). The correlation matrix display values close to zero for all combination of anomalies. The correlation between the January and the Halloween effects displayed the greatest figure 0.3, however this figure still shows a very low correlation between the effects. Examining the (VIF) for all the anomalies illustrates the VIF value ranging between 1.00 and 1.11. According to Gujarati et al (2012) in order for independent variables to be highly correlated the VIF needs to be in excess of 10 which is not the case when testing the anomalies. Examining the regression showed that the Monday and TOM effects display the same results when tested individually and when tested using the regression in eq. (6). Both regression models (individual anomaly models and the model including all anomalies at the same time) display a very strong negative Monday effect and positive TOM effect, with all industries significant at the 1 percent level. Moreover, the results for the January and Halloween effects demonstrate that the majority of the industries are still significant after integrating all anomalies into one equation. The January effect was present in 37 industries when tested using regression 6, compared to 39 industries when tested individually using regression model 3. The Halloween effect was present in 33 industries when tested individually using equation 4, compared to 22 industries when testing all anomalies together (Regression model in eq. (6)). As such, the regression model including all anomalies at the same time does not show any differential effects when compared to the model testing the anomalies individually (see regressions 2-5).

## Correlation matrix (Whole sample):

	TOM	D1	Jan	Hal
TOM	1.0000			
D1	-0.0029	1.0000		
Jan	-0.0014	-0.0057	1.0000	
Hal	0.0062	0.0058	0.3082	1.0000

# Variance Inflation Factor (Whole sample):

Variable	VIF	1/VIF
Hal	1.11	0.904902
Jan	1.11	0.904936
D1	1.00	0.999896
TOM	1.00	0.999941
Mean VIF	1.05	

Table 5: Multilinear regression for the whole sample period (Merged anomalies)

$R_t = \beta_0 + \beta_1 d_{Mon} + \beta_2 d_{TOM} + \beta_3 d_{Jan} + \beta_4 d_{Hal} + \varepsilon_t$					
Industry	d1	TOM	Jan	Hal	
agric	-0.283***	0.126**	0.149**	0.0401	
food	-0.184***	0.119***	0.123***	0.0206	
beer	-0.215***	0.139***	0.0925**	0.00262	
Smoke	-0.117***	0.103***	0.0940**	0.0108	
toys	-0.256***	0.149***	0.153**	0.0503	
Fun	-0.312***	0.187***	0.184***	0.0475*	
books	-0.252***	0.0889***	0.101**	0.0322	
hshld	-0.218***	0.143***	0.168***	0.0461**	
Clths	-0.199***	0.143***	0.209***	0.0463**	
medeq	-0.231***	0.135***	0.208***	0.0231	
drugs	-0.255***	0.142***	0.110***	0.0453**	
chems	-0.227***	0.154***	0.0918***	0.0525**	
txtls	-0.227***	0.155***	0.148***	0.0433*	
bldmat	-0.222***	0.136***	0.148***	0.0577***	
cnstr	-0.309***	0.206***	0.296***	0.0552	
steel	-0.272***	0.208***	0.148***	0.0587**	
mach	-0.226***	0.168***	0.154***	0.0582***	
elceq	-0.288***	0.172***	0.160***	0.0495**	
autos	-0.251***	0.208***	0.156***	0.0441*	
aero	-0.264***	0.165***	0.114**	0.0616**	
ships	-0.292***	0.167***	0.126**	0.0589*	
mines	-0.277***	0.183***	0.225***	0.0512*	
coal	-0.290***	0.200***	0.0828	0.0221	
oil	-0.333***	0.168***	0.0815*	0.0524**	
util	-0.141***	0.116***	0.0881***	-0.0118	

telcm	-0.219***	0.133***	0.104***	0.0437**
bussv	-0.233***	0.142***	0.191***	0.0382
Hardw	-0.269***	0.177***	0.169***	0.0532**
Chips	-0.278***	0.201***	0.181***	0.0590**
Labeq	-0.208***	0.134***	0.0810**	0.0649***
Boxes	-0.204***	0.146***	0.102**	0.0485**
trans	-0.318***	0.190***	0.220***	0.0346
whlsl	-0.278***	0.176***	0.132***	0.0404
rtail	-0.195***	0.140***	0.108***	0.0421**
meals	-0.223***	0.122***	0.187***	0.0590***
banks	-0.184***	0.127***	0.116***	0.0261
insur	-0.171***	0.115***	0.0487	0.0259
Rlest	-0.309***	0.199***	0.239***	0.0393
fin	-0.283***	0.146***	0.160***	0.0299

The pre-1952 sub-period provides additional evidence that the anomalies are not driven by one another, as the results indicate in the correlation matrix, VIF test and the results in Table 5.1. The results for the correlation matrix and VIF test in the pre-1952 sub-period display no signs of multicollinearity between anomalies. The correlation matrix report no collinearity between variables. The highest figure was displayed between the January and Halloween effects 0.3 where all other anomalies combinations displayed figures close to zero. Moreover, the VIF test did not report any signs of collinearity as the test revealed figures between 1.00 and 1.11 where high collinearity in the VIF test is at the 10.0 mark. (rewrite into 1 sentence and avoid repetition) Running the regression shows the same Monday and TOM effect results for all industries when tested individually, as well as after testing all anomalies together using regression in eq.(6). Moreover, the January effect displayed 32 significant industries compared to 31 industries when tested individually. This could be the result of extra weight given to the January effect in this regression – for example, if there is a weak or no January effect but a strong Halloween effect, this could lead to a significant January effect. That is why there are 32 significant industries when using regression 6, as opposed to the previous 31, which corroborates the findings of Bouman and Jacobsen (2002). The Halloween effect results from using regression 6 are similar to the results displayed in previous tests, revealing the majority of the industries to be insignificant. This indicates that the Halloween effect is not the January effect in disguise or driven by the high returns of any other anomaly.

#### Correlation Matrix (Pre 1952):

	D1	TOM	Jan	Hal
D1	1.0000			
TOM	-0.0090	1.0000		
Jan	-0.0026	-0.0053	1.0000	
Hal	0.0011	0.0018	0.3102	1.0000

# Variance Inflation Factor (Pre 1952):

Variable	VIF	1/VIF
Hal	1.11	0.903707
Jan	1.11	0.903734
D1	1.00	0.999877
TOM	1.00	0.999907
Mean VIF	1.05	

Table 5.1: Multilinear regression for the pre 1952 period (Merged anomalies)

$R_t = $	$\beta_0 + \beta_1 d_{Mon}$	$+\beta_2 d_{TOM} + \beta_2$	$_{3}d_{Jan}+\beta_{4}d_{H}$	$\epsilon_{al} + \epsilon_t$
Industry	d1	TOM	Jan	Hal
agric	-0.477***	0.230	0.159	-0.0479
food	-0.245***	0.191***	0.193***	-0.0281
beer	-0.344***	0.276***	0.140	-0.0981
Smoke	-0.164***	0.157***	0.218***	-0.0397
toys	-0.337***	0.213*	0.110	-0.0174
fun	-0.441***	0.303***	0.220*	-0.0683
books	-0.400***	0.0830	0.192*	-0.0731
hshld	-0.308***	0.227***	0.257***	-0.0425
Clths	-0.261***	0.177***	0.317***	-0.0431
medeq	-0.209***	0.158**	0.248**	-0.0388
drugs	-0.213***	0.122**	0.0832	-0.000897
chems	-0.315***	0.201***	0.114*	-0.0334
txtls	-0.310***	0.175***	0.215***	-0.0743
bldmt	-0.329***	0.199***	0.176**	-0.0314
cnstr	-0.442***	0.346**	0.533**	-0.0671
steel	-0.376***	0.300***	0.162*	-0.0493
mach	-0.260***	0.260***	0.216***	-0.0198
elceq	-0.414***	0.233***	0.188**	-0.0300
autos	-0.398***	0.311***	0.209**	-0.0342
aero	-0.320***	0.230**	0.123	0.0388
ships	-0.466***	0.282***	0.174*	-0.0279
mines	-0.308***	0.271***	0.251**	-0.0259
coal	-0.349***	0.277**	0.197	-0.0575
oil	-0.346***	0.239***	0.0920	0.0195
util	-0.360***	0.225***	0.248***	-0.0820
telcm	-0.195***	0.121**	0.0920	-0.0383
bussv	-0.249***	0.195**	0.287**	-0.0358
Hardw	-0.260***	0.191***	0.125*	-0.0335
Chips	-0.312***	0.306***	0.177*	-0.0132
labeq	-0.197***	0.0999*	-0.0406	0.00796

boxes	-0.290***	0.203***	0.164**	-0.0331
trans	-0.465***	0.287***	0.380***	-0.0479
whlsl	-0.439***	0.295**	0.0946	-0.0482
rtail	-0.260***	0.193***	0.187***	-0.0451
meals	-0.256***	0.165**	0.250**	-0.00709
banks	-0.262***	0.207***	0.182**	-0.0267
insur	-0.233***	0.153**	0.146	-0.0595
Rlest	-0.489***	0.438***	0.370*	-0.0698
fin	-0.472***	0.247***	0.287***	-0.0547

The results for the post-1952 sub-period displayed in Table 5.2 show no difference in the regression including all anomalies compared to that of any other time period. The results for the correlation matrix and the VIF is not different from previous sub-period or the whole sample. The correlation matrix shows no signs of correlation between all anomalies. The highest figure was found between the Halloween and the January effects 0.307 however, this does not indicate correlation between the anomalies. The VIF test displayed results between 1.00 and 1.10 which confirm the absence of multicollinearity between variables. Examining the regression report that the results for the Monday, TOM and Halloween effects are consistent with previous results, displaying all industries significant at the 1 percent level except for two industries, which were significant at the 10 percent level and one insignificant industry, smoke, in terms of the Halloween effect. The January effect displays 33 significant industries, as opposed to 37 when tested individually. These results confirm that all anomalies are independent of each other and no one anomaly is driven by the high returns of another anomaly.

## Correlation Matrix (Post 1952):

	D1	TOM	Jan	Hal
D1	1.0000			
TOM	-0.0018	1.0000		
Jan	-0.0069	0.0005	1.0000	
Hal	0.0080	0.0083	0.3073	1.0000

# Variance Inflation Factor (Post 1952):

Variable	VIF	1/VIF
Hal	1.10	0.905427
Jan	1.10	0.905503
D1	1.00	0.999837
TOM	1.00	0.999924
Mean VIF	1.05	

Table 5.2: Multilinear regression for the post 1952 period (Merged anomalies)

$R_t = \mu$	$\beta_0 + \beta_1 d_{Mon} +$	$\beta_2 d_{TOM} + \beta_2$	$B_3d_{Ian} + \beta_4d_{II}$	$\epsilon_{tal} + \epsilon_{t}$
Industry	d1	TOM	Jan	Hal
agric	-0.198***	0.0859**	0.146***	0.0806***
food	-0.158***	0.0903***	0.0909***	0.0432***
beer	-0.159***	0.0835***	0.0713*	0.0494**
Smoke	-0.0982***	0.0794**	0.0353	0.0344
toys	-0.222***	0.122***	0.174***	0.0818***
Fun	-0.258***	0.139***	0.169***	0.101***
books	-0.190***	0.0910***	0.0580	0.0809***
hshld	-0.180***	0.109***	0.126***	0.0873***
Clths	-0.171***	0.131***	0.157***	0.0878***
medeq	-0.241***	0.124***	0.190***	0.0521**
drugs	-0.275***	0.148***	0.124***	0.0670***
chems	-0.190***	0.135***	0.0820**	0.0924***
txtls	-0.191***	0.149***	0.117***	0.0979***
bldmt	-0.178***	0.109***	0.135***	0.0990***
cnstr	-0.249***	0.153***	0.183***	0.112***
steel	-0.227***	0.172***	0.142***	0.109***
mach	-0.211***	0.131***	0.126***	0.0947***
elceq	-0.236***	0.145***	0.147***	0.0864***
autos	-0.189***	0.166***	0.132***	0.0803***

aero	-0.239***	0.138***	0.111**	0.0721***
ships	-0.218***	0.120***	0.104*	0.0990***
mines	-0.262***	0.149***	0.213***	0.0871***
coal	-0.257***	0.176***	0.0278	0.0588
oil	-0.326***	0.140***	0.0767	0.0678**
util	-0.0485***	0.0723***	0.0129	0.0204
telcm	-0.232***	0.135***	0.111**	0.0821***
bussv	-0.224***	0.123***	0.146***	0.0727***
hardw	-0.275***	0.170***	0.191***	0.0937***
chips	-0.264***	0.158***	0.183***	0.0928***
labeq	-0.216***	0.144***	0.140***	0.0916***
boxes	-0.166***	0.124***	0.0723*	0.0863***
trans	-0.252***	0.155***	0.143***	0.0725***
whlsl	-0.205***	0.131***	0.151***	0.0812***
rtail	-0.166***	0.119***	0.0706*	0.0825***
Meals	-0.209***	0.104***	0.157***	0.0897***
banks	-0.151***	0.0939***	0.0857***	0.0506***
insur	-0.146***	0.0973***	0.00309	0.0658***
Rlest	-0.230***	0.103***	0.177***	0.0899***
fin	-0.202***	0.106***	0.101***	0.0689***

#### 2.5 Conclusion

We provide a comprehensive study of four calendar anomalies in US stock returns at the industry level. We address the research question, "Do industries have different calendar anomaly effects within the US market?" To assist in addressing the research question, three objectives were devised. The first and second objectives were to investigate the existence and persistence of calendar anomalies at industry level and to assess whether these anomalies are sector- or industry-specific, or a market-wide phenomenon existing in all industries. The third objective was to examine the effect of reducing trading days after September 1952 on the behaviour of calendar anomalies.

To test the anomalies, daily returns for 39 US industries from 1926 to 2018 were utilised. The four calendar anomalies chosen explore different dimensions as they look at daily, monthly and seasonal returns. Consistent with the previous literature, the modelling techniques applied in order to fully utilise the dataset are based on incorporating dummy variables within an OLS framework. The dummy variables consisted of categorising the anomaly effect within the regression model.

The results indicate that the four calendar effects are very strong and significant at industry level. The weekday effect was tested using a multivariate and a simple linear regression. Both regressions showed results confirming the strong and significant existence of the weekday effect across most industries. The TOM and the Halloween anomalies exhibited effects in all industries during the whole sample period.

The January effect showed no evidence of the anomaly when average value weighted returns were examined. However, upon examining average equal weighted returns, a very strong and significant January effect was observed. This does not only provide evidence of the existence of the anomaly, but also sheds light on the visible relationship between the January effect and the small firms, since the average equal weighted returns tend to give smaller firms greater weight.

The existence and persistence of the anomalies across all industries suggests that the calendar anomalies investigated here are not industry-specific but instead a market-wide phenomenon. Theories like the agricultural hypothesis have suggested that seasonal anomalies like the Halloween effect may display industry-specific effects. However, the results provided in this research, along with several previous studies, provide evidence against this theory and confirm that the effect manifests itself across all industries. The reasons behind calendar anomalies are economic factors affecting all industries similarly and not industry-specific factors, such as earnings or dividend change announcements or business cycles. Even considering period break points – such as the September 1952 break point where Saturday trading ceased to exist – only the Halloween effect reported a change in the behaviour of the anomaly when comparing sub-periods pre- and post-1952. The pre-1952 sample shows no Halloween effect in 37 industries and a reversed Halloween effect in two industries. On the contrary, the post-1952 sub-period shows the Halloween effect in 36 industries.

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# Chapter 3: Weekend change and its effect on the Saudi Arabian Stock Market. Does faith-based behaviour play a part in the weekend anomaly?

#### Abstract:

This research comprehensively analyses the well-known day-of-the-week effect in the Saudi stock returns at industry level, investigating 15 industries in the Saudi stock market. The anomaly is further examined by applying a break point in June 2013 where the weekend in Saudi Arabia changed and investigating whether this event affected the anomaly. This is achieved by using dummy variables within an OLS framework, covering a period from 2009 to 2017. The findings confirm the existence of the anomaly pre-June 2013 only, providing evidence that the break point event – changing the weekend – directly affected the anomaly.

**Key words**: behavioural finance, efficient market hypothesis, weekend effect, weekday effect, Saturday effect, calendar anomalies

#### 3.1 Introduction

#### 3.1.1 Research Background

The theories in the field of economics and finance have been dominated by the Efficient Market Hypothesis (EMH) for a considerable length of time. EMH states that market prices fully reflect all available information (Fama, 1970). Moreover, Miller (1977) concluded that efficient markets do not allow investors to earn above average returns unless they accept above average risk.

The global economic downturn that followed the US house price fall in 2007-08 has led to considerable blame being placed on the Efficient Market Hypothesis (EMH). According to EMH, stock market prices are mainly driven by new information, i.e., news rather than present and past prices. Since news is unpredictable, stock market prices will follow a random walk pattern and are unlikely to be predicted with more than 50% accuracy.

A majority of the huge losses suffered by banks and financial institutions in 2007-08 originated in the proprietary trading desks of investment banks, whose strategies and existence were premised on exploiting market inefficiencies and asset mispricing. Investors who bought into the real estate and stock market in 2007-08, while the bubble was forming, seemed to do so in the expectation that prices would continue to rise and with the implication that they believed market prices were incorrect. As Chuck Prince, CEO of Citigroup famously said near the peak of the bubble in July 2007:

"When the music stops, in terms of liquidity, things will be complicated. But as long as the music is playing, you've got to get up and dance. We're still dancing." (Nakamoto and Wighton, 2007)

Prince did not realise that the music had stopped a few months prior and did not "dance" for much longer, retiring from Citigroup in November 2007.

The argument is that, if homeowners, speculators, investors and financial institutions indeed believed the prices to be correct, they would not have bid them up to the extent that they did,

and the crisis could have been subdued or even averted. Related to this is the argument that, when prices of assets are rising, investors have little to complain about. When Alan Greenspan – the then Chairman of Federal Reserve – famously used the words "irrational exuberance" in a speech in 1996 (Federal Reserve Board, 1996), the reference received extensive media coverage both at the time and almost throughout the next decade. The speech was given on 5<sup>th</sup> December 1996, the day on which the Dow Jones index closed at 6,437.

If that statement is taken to mean that prices were too high at the time, the evident inference is that today, when we all know how inefficient the market is and how irrationally exuberant we were 16 years ago, and after having had plenty of opportunities to change our behaviour as a result of this knowledge, there should have been a significant price correction. Nevertheless, at the time this thesis is being written, the Dow is at 26,957 – indicating a more than 400 per cent increase since the time Greenspan spoke. In other words, after being given 23 years to reflect on Greenspan's warning and Shiller's best-selling book, *Irrational Exuberance*, investors have not acted in response to the existence of a bubble.

Behavioural finance suggests that emotions can severely impact an individual's behaviour and decision-making. This can also be applied to societies at large, as societies can experience mood states that impact their collective decision-making. As stated earlier, according to EMH, stock market prices are largely driven by new information rather than present and past prices. Since news is unpredictable, stock market prices will follow a random walk pattern.

From an academic standpoint, one of the most important reasons for behavioural finance's increased prominence is the difficulties faced by the traditional theories, such as Capital Asset Pricing Model, Arbitrage Pricing Theory, Modigliani-Miller Theory of Capital Structure etc. when it comes to fully explaining asset price returns and investor behaviour. From the standpoint of a practitioner, behavioural finance identifies several concepts that result in irrational human behaviour, resulting in decisions that are suboptimal.

Behavioural finance is a relatively modern field of finance that aims to complement traditional finance theories by introducing behavioural aspects to the decision-making process. Two of the earliest proponents of behavioural finance were the Nobel Prize-winning economist Daniel Kahneman, who studied human judgment and decision-making under uncertainty, and the experimental economist Vernon Smith, who analysed alternative market mechanisms through experimental research (Kahneman and Smith, 2002).

Shleifer (2000) defines behavioural finance as the study of the influence of psychology on the behaviour of financial practitioners and the consequent effect of this on the markets. Thus, behavioural finance deals with experiments and theories emphasising what happens when investors undertake decisions based on their emotions. It is a field of finance which aims to provide explanations of stock market anomalies through the use of identified psychological biases, instead of dismissing such behaviour as chance events consistent with the efficient market hypothesis (Barberis and Thaler, 2003).

Behavioural finance is primarily concerned with the bounded rational responses of investors to market dynamics. Herbert Simon's (1978) contention that market agents are best described as bounded rational agents underpins the central arguments underlying this topic. The topic also implies that bounded rational behavior frequently results in what Thaler (1987) refers to as economic anomalies, or empirical results that are difficult to rationalize or require

implausible assumptions to explain. Furthermore, it is argued that known defects in economies' market clearing activities integrate with investors' bounded rational behavior to cause these anomalies.

One of the major anomalies is calendar effects, which have been comprehensively investigated across many different market and country settings. This research focuses on a single calendar anomaly, the day-of-the-week effect, which refers to the empirical fact that stock returns tend to be abnormally low on Mondays and abnormally high on Fridays. Extant scholarship has attempted explanations regarding this anomaly based on flow of funds in and out of markets (Ritter, 1987), window dressing managerial practices and the systematic arrival of good and bad news (Harris and Gurel, 1986). These are beside the standard behavioural oddities of investors, such as their known preference for compound gambles over simple gambles or their mood (Coursey and Dyl, 1986).

Research on calendar anomalies in Saudi Arabia, where this study is based, is very sparse. Tadawul All Share Index (TASI), the Saudi stock exchange market, is an emerging market that was informal throughout the 1970s, with only 14 companies listed. However, TASI currently has around 200 listed and traded companies. Tadawul is the only stock exchange in Saudi Arabia and is considered the major stock exchange, not only amongst the Gulf Cooperation Council (GCC) countries but also in the Middle East and North Africa (MENA) regions. Despite all the development that Tadawul has achieved and continues to achieve, the exchange does not yet offer derivative products, such as futures and options.

#### 3.1.2 Rationale

The purpose of this study is to investigate the existence of the day-of-the-week anomaly at industry level and to assess whether it stands after the change in the weekend days in the Saudi stock market, Tadawul All Share Index (TASI). There is no previous study that has tested the effect of the change in weekend days in Saudi Arabia on the day-of-the-week anomaly. This research aims to critically analyse and explain the well-known day-of-the-week anomaly in the sparsely researched Saudi stock Market Tadawul All-Share Index (TASI). It is anticipated that this will significantly enrich extant understanding of the phenomenon in a region of the world where empirical research is rare.

#### 3.1.3 Research Ouestion

To understand the effect of the day-of-the-week anomaly in emerging markets, this study seeks to address the following research question:

"Weekend change and its effect on the Saudi Arabian Stock Market. Does faith play a part in the weekend anomaly?"

The day-of-the-week effect will be comprehensively analysed at the industry level covering the period from 1 Jan 2009 to 5 Jan 2017. Not only does this study aim to be the first to investigate the effect of the change in the weekend days on stock markets in Saudi Arabia, but also to delve deeper into how the weekend change affects the behaviour of religious investors.

#### 3.1.4 Aim and objectives

This research focuses on three main objectives. The first objective is to investigate the day-of-the-week effect at industry level in the Tadawul All-Share Index (TASI) and whether it manifests itself across all industries or is an industry-specific phenomenon. The second

objective is to assess the effect the change in the weekend days after 26 June 2013 may have had on the day-of-the-week anomaly. The third objective is to examine the effect of faith orientation on the day-of-the-week anomaly, since the study is based in a country ruled under Islamic law.

#### 3.1.5 Structure

The rest of the research follows the following structure. The literature review chapter includes a comprehensive and critical analysis of the studies conducted on the weekday effect (i.e. the extent to which stock prices tend to outperform on a particular day of the week). The chapter begins with a review of the literature, followed by findings of various researchers on the weekend effect and a brief on the characteristics of the Saudi stock market Tadawul All-Share Index (TASI) where this study is based.

Chapter three discusses the research methodology used to address the research aim and objectives, including data collection and analysis. The fourth chapter includes the analysis of the data using econometric techniques, and also compares the findings to the literature. Finally, the fifth chapter includes conclusions and recommendations.

#### 3.2 Literature Review

#### 3.2.1 Overview

The general consensus is that a weekend effect existed in the 1970s and 1980s in the US, whereby stock prices underperformed on Monday (or between close on Friday and opening on Monday) (Thaler, 1987). However, this calendar anomaly has become less significant over time, as financial markets have become more efficient – especially in developed markets such as the US, where sophisticated investors have exploited the market inefficiency relating to the weekend effect. This paper investigates the existence of one such anomaly in the Saudi stock market.

#### 3.2.2 Weekend Effect

Thaler (1987) conducted extensive research on the weekend effect in an effort to determine the extent to which stocks outperformed on a particular day of the week. Thaler defined daily returns as the change from the previous trading day's close to the current trading day. Thaler posed the query, "How should we expect Monday returns to compare to the returns for other weekdays?" using this concept. He states that the "calendar time hypothesis" of French (1980) was the most logical theory, highlighting the fact that the time between the financial markets' close on Friday and its opening on Monday is three days rather than the ordinary one day on other weekdays. Consequently, Monday's returns ought to be higher due to the longer period of time.

The "trading time hyothesis," which contends that returns are only generated on trading days and that, as a result, the returns earned should be the same for all trading days, was another explanation for the anomaly offered by French (1980). This was criticized by Thaler (1987), who contended that it was not wise to focus just on trading days because businesses often operate on all days, including the weekends, when trading in the financial markets is either prohibited or severely curtailed. The total profitability of the company would not be harmed by this.

Jain and Joh (1988) show that liquidity in stock markets is lower on Monday compared to other days of the week; they state that the total volume of the New York Exchange (NYSE) on Monday is nearly 90% of its average trading volume for Tuesday through Friday. Lakonishok and Maberly (1990) argue that individual investors have the tendency to increase trading activity on Monday resulting for the weekend effect as it might be related to the trading pattern of individual traders. Moreover, Wang et al. (1997) used a long time series (1962 to 1993) and report that in the US market, the weekend effect appears primarily in the last two weeks of each month. These findings collectively imply that the existence of the weekend effect and the violation of the EMH had not diminished since it was first reported by Osborne (1962).

The weekend effect was comprehensively studied by Kiymaz and Berument (2003). They explore the existence of the day-of-the-week anomaly on stock markets using the S&P 500 index covering the period from January 1972 to October 1997. They report that the day-of-the-week anomaly exists in both volatility and returns. They found that the highest return was found on Wednesdays where the lowest return was on Mondays, however, the highest and lowest volatilities were reported on Wednesdays and Fridays respectively.

While many studies have focused on US markets when studying the weekend effect, Agrawal and Tandon (1994) explored the anomaly in 18 non-US countries, to assess whether the calendar anomalies confirmed in US markets exist in other countries. Agrawal and Tandon concluded that there is mixed evidence regarding the presence of the weekend effect, since the returns on Monday are low and negative in half of the sample. Moreover, the research found that the lowest return was reported on Tuesday and not Monday in the other eight countries of the sample. Chinko and Avci (2009) study the weekend effect in Istanbul stock exchange (ISE) for the period 1995 to 2008. They report negative Mondays and a positive Thursday and Friday returns. Their study conclude that regardless of market capitalisation, all portfolios display significant negative Monday and a positive Thursday and Friday returns.

#### 3.2.3 Saudi Stock Market

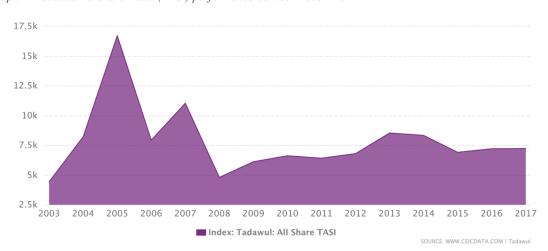
The Saudi stock market from the 1970s did not possess official backing and operated with only 14 listed companies. However, in 1984, the Saudi government initiated a ministerial committee to develop and regulate the market. Here, the Saudi Arabian Monetary Agency (SAMA) was formed, tasked with the responsibility of regulating and supervising the Saudi Exchange Market. SAMA's responsibility ended in July 2003, when the Capital Market Authority (CMA) became the only regulator and supervisor of the exchange seeking to protect investors and ensure equality and efficiency. The Saudi Exchange Market possessed its own index, which was then transferred to a new stock exchange known as Tadawul in 2007 (Tadawul, 2020).

The Saudi stock market was initially opened only for Saudi nationals. This changed in December 2007, after which Gulf Community Council (GCC) investors were allowed to participate in a move to form a GCC common stock market that did not end up materialising. In August 2008, the CMA issued new regulations allowing international investors who were not residents of the Kingdom of Saudi Arabia to participate in share trading through swap arrangements with local intermediaries that are approved by the CMA.

Tadawul sector classification was established in 2008 and changed in January 2017 due to the constant developments in the Saudi economy which resulted in new industries emerging. Tadawul's previous industry classification had some limitations: when a company decided to

go public, it was allocated to a sector that does not accurately relate to its business operations. This prompted the Saudi stock exchange to reclassify its sectors according to the Global Industry Classification Standard (GICS), which is a common global classification developed jointly by Standard and Poor's and Morgan Stanley Capital International, and used widely by many market participants. The new classification system is believed to overcome prior limitations by diligently aligning companies' business activities and sources of revenues to its relevant industry classification.

The new classification of the market has helped the market to become more organised, allowing the Tadawul to reach new heights and to now be considered the largest stock exchange in the MENA (Middle East and North Africa) region, with a market capitalisation of 7.464 trillion SAR (\$2.33 trillion) (Tadawul, 2020a). The Saudi stock exchange currently lists around 200 companies divided into 20 different industries. Materials and financial industries represent the largest part of the market. Share ownership of the markets is relatively equally divided between Saudi institutions, government-related entities and individual investors, both local and foreign.



Graph 1: Tadawul All Share Index (TASI) performance between 2003 - 2017

This phenomenal growth witnessed under Tadawul was also evident between 2003 and February 2006 when the Saudi Stock Market reached its peak: the index increased by 700%, with market capitalisation of 800 billion US dollars, representing around two and a half times the nominal GDP (Ulussever et al, 2011). Moreover, On 25 February 2006, Tadawul was the tenth largest stock market by value globally, despite its only having 78 listed stocks (Ulussever et al, 2011). However, soon after, the market began to collapse, losing about 65 percent of its value by the end of 2006, plunging the market capitalisation to \$326.9 billion (Argaam, 2020). The 2006 crash effect was prolonged into the global financial crisis in 2008, as TASI was lower than 4000 points in 2008.

#### 3.2.4 Saudi Stock exchange and Islamic law (Shariah)

Saudi Arabia is perceived to be an Islamic nation as the laws governing the people stem from the Quran and holy scriptures. The majority of the nation's culture stems from religious connotations, for example the use of the Hijri calendar and the adherence to Islamic holidays. It is assumed that every action corresponds to Islamic laws and regulations and that people's lives are built upon Islamic laws and traditions.

The Saudi stock market and most related investors are surrounded by a heavily religious social environment. Unlike other countries with large Muslim populations, such as Dubai and Malaysia, Tadawul does not offer a Shariah compliant index. However, Alosaimi (2017) provides a highly regarded list of classification of traded securities approved by the authoritative religious experts. The Alosaimi list illustrates traded companies that are involved in producing products forbidden by Islam or financial services that offer interest and are not suitable for devout Muslims, as they are non-Shariah-compliant. On the other hand, Shariah-compliant companies are considered to be firms that correspond to Islamic jurisprudence, making them legitimate according to Islam. However, companies with Shariah-compliant activities but with non-Shariah-compliant sources of funds are considered mixed. This paper will treat such firms as non-Shariah, as the profits generated from such companies by investors is not deemed acceptable by Islamic law due to the mixed financing of the firm's capital structure.

#### 3.2.5 Weekend effect in Saudi stock market

Calendar anomalies in all forms have been extensively studied in many developed markets – however, this is not the case with developing markets, such as Saudi Arabia. Albarrak (2008) investigated the day-of-the-week effect in the three largest stock markets of the Gulf Cooperation Council (GCC), namely Saudi Arabia, Dubai and Kuwait, covering the period from January 2002 to December 2005. The results presented by Albarrak argue that the day-of-the-week effect was only present in the Kuwaiti stock market and absent in Saudi and Dubai. He found that the highest return happened to be on Saturday, while the lowest return was recorded on Sunday.

Ariss et al (2011) studied calendar anomalies on all the GCC region countries including the leading market of the region, Saudi Arabia. Using Ordinary Least Squares, Ariss et al. (2011) concluded that there is a positive last trading day-of-the-week effect in line with the literature for developed markets in the West. This anomaly, however, happened to be on Wednesdays for the GCC countries and not on Fridays, and was more noticeable in non-Ramadan periods. Furthermore, the authors attribute this result to investors' buying mood right before weekends as short selling and trading derivatives become unavailable.

Ulussever et al. (2011) researched the day-of-the-week effect in Saudi Arabia, covering the period from January 2001 to December 2009 using a non-linear Garch model. Their results confirm that all the differences between the mean returns of the first trading day and the rest of the other trading days of the week are significantly different from zero, which confirms the existence of the day-of-the-week effect in the Saudi market. The authors further suggest that there is room for investors to modify their portfolios by taking into consideration day-of-the-week variations in volatility in the Saudi stock market.

Abalala and Sollis (2015) investigated the Saturday effect (referring to the first trading day-of-the-week in the Saudi stock market at the time of the study) at industry level, including 15

different sectors and covering a period of almost three years from 21 April 2007 to 6 April 2010. The results revealed that there is a significant positive Saturday effect, implying that returns on Saturdays are positive and greater than on other days of the week. They argue that these results are contrary to the results generated from similar studies conducted on Western markets such as the US, where the first trading day of the week happens to be low and negative compared to other days of the week. According to the authors, a possible explanation for such results is the dynamic ties with US stock markets. However, if the Saudi market is informationally efficient, then such correlations should not persist. Moreover, they relate the high positive Saturdays to possible cross-border trading by investors in neighbouring GCC countries. However, Abalala and Sollis limited their study by testing a sample period of three years only which is very limited compared to this research which include 9 years sample. This research is different from Abalala and Sollis (2015) as it go beyond testing the existence of the weekend anomaly only and explore the effect on the anomaly after the shift in the weekend days occurred in 2013.

Yardimci and Erdem (2020) investigated the day-of-the-week effect in 19 Muslim countries including Saudi Arabia. They report that Saudi Arabia recorded the highest and lowest returns of the week on the fifth and fourth trading day of the week for the period January 2005 to January 2015. Although this study is a comprehensive research that include various Islamic markets, the chosen sample period represented lack continuity especially for Saudi Arabia, since there was a shift in the weekend days in Saudi Arabia that occurred in 2013 that may have affected the generated results.

## 3.3 Methodology

#### 3.3.1 Introduction

This study examines the weekday effect in the Saudi stock market, which has been extensively researched in the past at market level, but not sufficiently at industry level. One important aim of this study is to investigate how the change in the weekend days in Saudi Arabia affects the weekend effect anomaly. Moreover, the paper investigates whether faith orientation affects the anomaly's existence and persistence. The main research question is:

"Weekend change and its effect on the Saudi Arabian Stock Market: Does faith-based behaviour play a part in the weekend anomaly?"

The primary objective of this research is to investigate whether the weekday effect is present and consistent across all Saudi industries. Furthermore, the second objective is to examine if there is any change in the calendar effect before and after the change in the weekend. Prior to 28 June 2013, Saudi Arabia's official weekend was on Thursday and Friday. On 23 June 2013, King Abdullah of Saudi Arabia issued a royal decree shifting the country's weekend for public workers from Thursday and Friday to Friday and Saturday. This break point may demonstrate if the characteristic change affected the presence and magnitude of the anomaly at industry level. The final research objective is to investigate whether faith orientation affects investor behaviour and therefore the weekend effect.

To delve deeper into explaining the effect of the anomaly and its relation to faith, this research seeks to compare and contrast Shariah-compliant and non-Shariah-compliant companies in TASI and observe the effect of the anomaly before and after the change in weekend days.

#### 3.3.2 Data collection

The focus of this study is on industry level data rather than indices. This is to make place for an understanding of the commonality or lack thereof between industries, which indices do not provide. Therefore, the industry level focus allows this research to pursue new conclusions on the weekend effect anomaly in order to detect if all industries show a similar effect to that found in previous literature on indices. The industry level emphasis allows this study to achieve greater depth and the ability to explain new phenomena that were not addressed by previous literature. To delve deeper into the anomaly, company level data are obtained and divided into two main categories, namely Shariah-compliant companies and non-Shariah-compliant companies, to investigate how faith orientation effects the calendar anomaly in question.

The Saudi Stock exchange (Tadawul) was chosen for this study as it is the largest stock exchange in the Middle East and North Africa (MENA) region, with market capitalisation of \$2.33 trillion as of March 2020 (Tadawul.com). While calendar anomalies have been investigated previously in a number of studies on the Saudi stock exchange, there is no available research on the weekday effect after the change in the weekend, making this market very appealing for such a study.

To study the weekend effect anomaly at industry level, average daily returns for 15 different industries representing various economic sectors, including agriculture and food, Real estate and banks & financial services, will be investigated. The original data gathered consisted of 16 industries; however, one industry, namely REITs, was removed as the data available for this sector begins in 2016, making it ineligible for the study. The data was collected from the Tadawul exchange website, providing data ranging from January 2007 to January 2017. This research examines the period from 2009 to 2017 to avoid the effects on the returns of the global financial crisis in 2007-08 and the largest stock crisis in the history of Tadawul that occurred in February 2006. The data range from 2007 to 2017 to maintain the same industry categories, since the industry categories was changed after 2017. However, when testing Shariah- and non-Shariah-compliant portfolios, the data were extended to 17 November 2019, since the data are at company level and there is no specific categorising that needs to be maintained.

#### 3.3.3 Model

The modelling techniques applied in order to fully utilise the dataset are based on incorporating dummy variables within an OLS framework. The dummy variables categorise the anomaly effect within the regression model. This research devises two regression models that represent the weekday effect.

The dummy variables proxy for weekdays that represent Saturday through to Thursday will consist of a dummy variable for each day, with the exception of Saturday before the weekend change in June 2013 and Sunday after the weekend change, in order to remove the dummy variable trap effect as illustrated in regression model 1.

To further assess the weekend effect, Connolly's (1989) test, that has also been implemented by Chang et al (1993) and Brusa et al. (2003) will be implemented by comparing the first day of the week (Saturday before weekend change and Sunday after weekend change) to the average returns for the rest of the week as illustrated in regression model 2.

$$R_t = \beta_0 + \beta_1 d_{2t} + \beta_2 d_{3t} + \beta_3 d_{4t} + \beta_4 d_{5t} + \varepsilon_t \tag{1}$$

$$R_t = \beta_0 + \beta_1 SAT + \varepsilon_t$$
 (2)  

$$R_t = \beta_0 + \beta_1 SUN + \varepsilon_t$$
 (3)

$$R_t = \beta_0 + \beta_1 SUN + \varepsilon_t \tag{3}$$

Equation 1 will examine the weekday effect, where  $R_t$  is the return on day t;  $d_{it}$  is a dummy variable to denote the day on which the return is detected;  $\beta_0$  measures the mean return for the first day of the week; the coefficients  $\beta_1$  through to  $\beta_4$  measure the difference between the expected return for each day of the week and the expected return for the first day of the week.

Equation 2 and 3 will further investigate the anomaly, where  $R_t$  is the daily return on day t;  $\beta_0$ is the constant;  $\beta_1$  is the coefficient on a dummy variable SAT/SUN that equals one on Saturdays/Sundays and zero otherwise; and the error term is  $\varepsilon_t$ .

### 3.4 Analysis

Weekday effect was separated into two distinctive testing approaches, by observing the first return against individual returns on other days of the week and by comparing the first day of the week returns to the average return of the rest of the week. The sample spans nine years, from January 2009 to January 2017. As illustrated in Table 1 and Table 1.1, there are two segments of the sample, before and after the change in the weekend days on 28 June 2013.

Table 1 outlines the results for each industry, with the intercept  $\beta_0$  representing the first dayof-the-week effect, while coefficients  $\beta_1$  through  $\beta_4$  illustrate other days of the week effect. The results for the first segment, before the change in the weekend days, shows that the intercept  $\beta_0$  which measures the return on Saturday is significantly positive at the 5% level for all industries, except for the Cement sector where it was insignificant. The results displayed in Table 1 also display the noticeably positive Saturday returns in the insurance sector with a highly significant coefficient of (0.0063). Observing the returns on other days of the week from Sunday to Wednesday, negative coefficients are reported compared to the first day of the week in all industries including the insignificant Cement. Moreover, Table 1 illustrates that Telecom displays the lowest return on the first day of the week compared to all other industries, with a coefficient of 0.0023 and significant at the 5% level. These results suggest that investors showed efficient investment behaviour on the first day of

the week, reflecting the highly positive returns on that day (Saturday) compared to other days of the week in all industries included in the study, except for Cement where it was insignificant.

Table 1: Multilinear regression for segment 1 (pre 28 June 2013)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Agric	BanksFin	BuildingCns	Cement	Energy	Hotel	Retail	Telecom
sun	0.00358**	-0.00389**	-0.00411**	-0.000322	-0.00270**	-0.00363*	-0.00345**	-0.00206
	(-2.78)	(-3.13)	(-2.68)	(-0.28)	(-2.71)	(-2.22)	(-3.06)	(-1.70)

mon	0.00354**	-0.00303*	-0.00332*	-0.00144	-0.00169	-0.00401*	-0.00319**	-0.00277*
	(-2.83)	(-2.37)	(-2.26)	(-1.29)	(-1.68)	(-2.54)	(-2.94)	(-2.39)
tues	- 0.00436**	-0.00439**	-0.00551***	-0.00155	0.00537***	-0.00510**	-0.00384**	- 0.00350**
	(-3.26)	(-3.23)	(-3.46)	(-1.34)	(-4.39)	(-2.96)	(-3.11)	(-2.75)
wed	-0.00193	-0.00173	-0.00431**	-0.000395	-0.00288**	-0.00528**	-0.00307**	-0.00195
	(-1.50)	(-1.36)	(-2.99)	(-0.35)	(-2.83)	(-3.23)	(-2.75)	(-1.67)
cons	0.00332**	0.00278*	0.00329*	0.00146	0.00281***	0.00455***	0.00355***	0.00239*
	(3.04)	(2.53)	(2.57)	(1.57)	(3.46)	(3.50)	(3.74)	(2.36)

	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Transport	Insurance	Indstrlinv	Mediapblsh	Multiinv	Petroindst	Realestateinv
sun	-0.00336*	-0.00477*	-0.00482**	-0.00435*	-0.00584**	-0.00583**	-0.00237
	(-2.32)	(-2.43)	(-3.17)	(-2.40)	(-3.28)	(-3.14)	(-1.75)
mon	-0.00290*	-0.00612**	-0.00317*	-0.00259	-0.00365*	-0.00361	-0.00274*
	(-2.00)	(-3.14)	(-2.11)	(-1.39)	(-2.07)	(-1.91)	(-2.03)
tues	-0.00460**	-0.00853***	-0.00597***	-0.00433*	-0.00759***	-0.00676**	-0.00436**
	(-2.93)	(-4.06)	(-3.70)	(-2.28)	(-4.00)	(-3.29)	(-3.08)
wed	-0.00236	-0.00921***	-0.00374*	-0.00446*	-0.00540**	-0.00425*	-0.00239
	(-1.64)	(-4.66)	(-2.53)	(-2.51)	(-3.00)	(-2.33)	(-1.77)
cons	0.00309*	0.00632***	0.00415**	0.00356*	0.00498**	0.00467**	0.00270*
	(2.56)	(3.91)	(3.16)	(2.45)	(3.29)	(2.82)	(2.34)
N	1125	1125	1125	1125	1125	1125	1125

To investigate if there is any change in the behaviour of investors or the magnitude of the weekday effect after the change in the weekend days in the Saudi stock market, equation 1 is used again to test the period after 28 June 2013. The results are displayed in Table 1.1. The second segment displayed insignificant weekend effect in all industries. Furthermore, although all industries are insignificant unlike segment 1, the sign of the first day-of-theweek effect in this segment (i.e. Sunday) is not consistent, positive in some industries and negative in others. The strong contradiction between the results in the two segments implies that the change in the days of the weekend significantly affected the anomaly.

t statistics in parentheses p < 0.05, p < 0.01, p < 0.01, p < 0.01

Table 1.1: Multilinear regression for segment 2 (post 28 June 2013)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Agric	BanksFin	BuildingCnstr	Cement	Energy	Hotel	Retail	Telecom
mon	-0.00208	-0.000339	-0.000338	-0.000609	0.0000195	-0.00128	-0.00258	-0.00148
	(-1.22)	(-0.24)	(-0.18)	(-0.44)	(0.01)	(-0.52)	(-1.61)	(-0.92)
tues	-0.000855	0.0000980	0.000499	-0.000224	-0.00162	0.000192	-0.00238	-0.00225
	(-0.47)	(0.06)	(0.24)	(-0.14)	(-0.81)	(0.07)	(-1.39)	(-1.24)
wed	-0.000940	0.000313	-0.000522	0.000158	-0.000809	0.000609	-0.00300	-0.000693
	(-0.55)	(0.22)	(-0.27)	(0.11)	(-0.46)	(0.23)	(-1.87)	(-0.39)
thurs	0.00102	0.00226	0.000788	0.00180	0.000920	0.000345	-0.000213	-0.000645
	(0.59)	(1.55)	(0.42)	(1.27)	(0.49)	(0.13)	(-0.13)	(-0.38)
cons	0.000681	-0.000515	-0.000590	-0.000748	0.000957	-0.000155	0.00173	0.000559
	(0.50)	(-0.46)	(-0.38)	(-0.64)	(0.64)	(-0.07)	(1.36)	(0.42)

	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Transport	Insurance	Indstrlinv	Mediapblsh	multiinv	Petroindst	Realestateinv
mon	-0.000545	-0.00271	-0.00100	0.000145	0.00105	-0.00227	-0.00155
	(-0.27)	(-1.21)	(-0.49)	(0.05)	(0.57)	(-1.23)	(-0.78)
tues	-0.00157	-0.000830	0.00142	0.00180	0.00103	-0.00162	-0.000654
	(-0.70)	(-0.36)	(0.65)	(0.59)	(0.53)	(-0.81)	(-0.30)
wed	-0.00176	-0.00210	-0.00102	-0.000261	0.000174	0.000406	-0.00132
	(-0.85)	(-1.01)	(-0.50)	(-0.09)	(0.09)	(0.21)	(-0.67)
thurs	0.00156	-0.00287	0.00218	0.0000319	0.00309	0.00241	0.00129
	(0.71)	(-1.36)	(1.08)	(0.01)	(1.64)	(1.28)	(0.65)
cons	0.00104	0.00189	-0.000296	-0.000448	-0.00131	0.0000709	0.000958
	(0.66)	(1.11)	(-0.18)	(-0.21)	(-0.91)	(0.05)	(0.60)
N	876	876	876	876	876	876	876

To further assess the weekday effect, the model is transformed into a simple linear regression as illustrated in equation 2, where the results are displayed in Table 2. The results for segment 1 show that the intercept  $\beta_0$ , which measures the average return for other days of the week, tends to be negative, while a positive and highly significant Saturday effect for all industries included in the study is reported. Insurance displays the Saturday effect the most,

t statistics in parentheses \* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

as the coefficient of 0.00716 is the highest positive return, while Telecom reports the least effect with an average Saturday return coefficient of 0.00257. Table 2 also shows that the coefficient  $\beta_1$ , which measures the difference between Sunday through Wednesday and Saturday, is negative for all sectors.

Segment 2, which represents the period after 26 June 2013 when the weekend change took place, is also tested by using model 2 to measure the effect of the change on investors' behaviour and the first day of the week anomaly. The results displayed in Table 2.1 shows that all industries are insignificant regarding the weekday effect and, unlike segment 1. the sign of the first day-of-the-week effect is inconsistent between industries.

Table 2: : Simple linear regression for segment 1 (pre 28 June 2013)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Agric	BanksFin	BuildingCnstr	Cement	Energy	Hotel	Retail	Telecom
sat	0.00335**	0.00326**	0.00432**	0.000929	0.00316***	0.00451**	0.00339***	0.00257*
	(2.93)	(2.85)	(3.22)	(0.94)	(3.58)	(3.24)	(3.39)	(2.42)
cons	-0.0000328	-0.000485	-0.00103*	0.000535	-0.000349	0.0000426	0.000165	-0.000184
	(-0.09)	(-1.42)	(-2.55)	(1.63)	(-1.01)	(0.08)	(0.52)	(-0.56)

	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Transport	Insurance	Indstrlinv	Mediapblsh	multiinv	Petroindst	Realestateinv
sat	0.00331**	0.00716***	0.00443**	0.00393*	0.00562***	0.00511**	0.00297*
	(2.59)	(4.16)	(3.23)	(2.53)	(3.53)	(2.97)	(2.45)
cons	-0.000218	-0.000839	-0.000280	-0.000369	-0.000636	-0.000443	-0.000264
	(-0.51)	(-1.42)	(-0.71)	(-0.65)	(-1.28)	(-0.93)	(-0.72)
N	1125	1125	1125	1125	1125	1125	1125

*t* statistics in parentheses

Table 2.1: Multilinear regression for segment 2 (post 28 June 2013)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Agric	BanksFin	BuildingCnstr	Cement	Energy	Hotel	Retail	Telecom
sun	0.000714	-0.000581	-0.000105	-0.000282	0.000373	0.0000311	0.00205	0.00127
	(0.49)	(-0.48)	(-0.06)	(-0.23)	(0.23)	(0.01)	(1.50)	(0.88)
cons	-0.0000334	0.0000660	-0.000486	-0.000466	0.000584	-0.000186	-0.000322	-0.000709
	(-0.06)	(0.14)	(-0.81)	(-1.06)	(1.01)	(-0.23)	(-0.62)	(-1.28)

	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Transport	Insurance	Indstrlinv	Mediapblsh	multiinv	Petroindst	Realestateinv
sun	0.000583	0.00213	-0.000387	-0.000427	-0.00133	0.000265	0.000561

<sup>\*</sup> p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

	(0.34)	(1.16)	(-0.22)	(-0.18)	(-0.85)	(0.16)	(0.33)
cons	0.000453	-0.000233	0.0000909	-0.0000213	0.0000218	-0.000194	0.000396
	(0.63)	(-0.34)	(0.14)	(-0.02)	(0.04)	(-0.34)	(0.63)
N	876	876	876	876	876	876	876

t statistics in parentheses

Most literature on the weekend effect, especially in Western markets, documents a negative first day of the week compared to the rest of the days of the week, which contradicts the results in this study. However, the results generated in this research are supported by the calendar time hypothesis proposed by French (1980), which pinpointed that the time duration between financial markets closing on Friday and opening on Monday is three days instead of the regular one day, as is the case between other days of the week. Therefore, the returns earned on Monday (Saturday in the case of Saudi Arabia) should be higher to reflect the greater length of time. Moreover, Abalala and Sollis (2015) confirm similar results as they found that there is a significant positive Saturday effect in all sectors of the Saudi market at the time their study was conducted

The positive Saturday found in the Saudi stock market could be due to the active relationship with US markets. Several studies have revealed a positive Friday effect in major US markets (Keim and Stambaugh, 1984). Having the Saudi stock market correlated with the mean return of the previous day in the US suggests a positive Saturday in the Saudi market. However, if the Saudi market proves to be highly efficient, such correlations should not persist over time.

#### 3.4.1 Shariah effect

To further investigate the results generated by a highly significant positive Saturday anomaly, companies are divided into Shariah-compliant and non-Shariah-compliant portfolios and tested for the day-of-the-week effect for both periods, before and after the weekend change, and the results are displayed in Tables 3 and 3.1.

Table 3 displays the results for Shariah-compliant firms before the weekend change took place, representing segment 1. Shariah-compliant firms showed a highly significant positive Saturday in all industries except Food and staples, where Saturday was negative while having high positive returns on other days of the week, however it was insignificant. This outcome reinforces the hypothesis that faith plays a vital role in Saudi Arabian investment and decision-making. The results also show that the retailing industry holds the highest mean return for Saturday with a coefficient of 0.0064, while transportation holds the lowest with 0.0017. Closely observing the results generated for Shariah-compliant companies in segment 1, a relationship between the returns on Tuesday and Wednesday becomes visible. It appears that returns on Wednesdays always exceed returns on Tuesdays, except for Energy and Consumer services. This gives an indication that returns are increasing gradually and by the time the weekend ends the returns becomes positive on the first trading day of the week (Saturday). This supports French's (1980) calendar time hypothesis, that suggests that the time duration between the time financial markets closing on Friday and opening on Monday is three days instead of the regular one day, and therefore, the returns earned on Saturday (Monday in the case of the Western world) should be higher to reflect the greater length of time.

<sup>\*</sup> p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

Table 3: Shariah compliant pre 28 June 2013 (Segment 1)

	(1)	(2)	(3)	(4)	(5)	(6)
	Energy	Materials	Capital goods	Transportation	Consumer durables	Consumer services
sun	-0.00539*	-0.00229	-0.00549*	-0.00211	-0.00255	-0.00437*
	(-2.44)	(-1.73)	(-2.13)	(-1.69)	(-1.57)	(-2.54)
mon	-0.00384*	-0.00218	-0.00293	-0.00199	-0.00336*	-0.00519**
	(-2.03)	(-1.68)	(-1.14)	(-1.53)	(-2.18)	(-2.95)
tues	-0.00382	-0.00428**	-0.00783**	-0.00128	-0.00535**	-0.00594***
	(-1.83)	(-3.04)	(-3.02)	(-0.97)	(-3.12)	(-3.43)
wed	-0.00452*	-0.00264*	-0.00698**	-0.000875	-0.00506***	-0.00609***
	(-2.36)	(-2.02)	(-2.75)	(-0.51)	(-3.36)	(-3.53)
cons	0.00388*	0.00255*	0.00481*	0.00177	0.00323*	0.00535***
	(2.45)	(2.24)	(2.34)	(1.85)	(2.49)	(3.97)
N	1125	1125	1125	1125	1125	1125

	(7)	(8)	(9)	(10)	(11)	(12)
	Retailing	Food & staples	Food & beverage	Healthcare	Diversified financials	Real estate
sun	-0.00748***	0.00282	-0.00474**	-0.00319	-0.00467*	-0.00202
	(-3.82)	(1.61)	(-2.69)	(-1.72)	(-2.30)	(-1.48)
mon	-0.00549**	0.00512**	-0.00519**	-0.00312	-0.00455*	-0.00342*
	(-2.82)	(2.73)	(-3.04)	(-1.76)	(-2.34)	(-2.47)
tues	-0.00786***	0.00206	-0.00799***	-0.00280	-0.00721***	-0.00371**
	(-3.70)	(1.22)	(-4.31)	(-1.45)	(-3.37)	(-2.69)
wed	-0.00558**	0.00237	-0.00694***	-0.00162	-0.00661***	-0.00317*
	(-2.83)	(1.36)	(-4.01)	(-0.85)	(-3.37)	(-2.31)
cons	0.00641***	-0.00160	0.00568***	0.00263	0.00507**	0.00326**
	(3.96)	(-1.28)	(3.84)	(1.72)	(3.11)	(2.89)
N	1125	1125	1125	1125	1125	1125

Non-Shariah-compliant companies displayed in Table 3.1 show a highly significant positive Saturday in all industries except retailing, which showed an insignificant weekend effect when testing segment 1 (before the weekend change). The results show that the highest Saturday mean return was found in transportation and the least mean return was found in retailing, with coefficients of 0.0059 and 0.0023, respectively. Similar to the Shariahcompliant firms, the outcome of non-Shariah firms showed higher returns on Wednesday in relation to Tuesdays in all industries. Moreover, observing the returns of all the weekdays, a cycle becomes visible in some of the industries. Five industries, energy, consumer durables, retailing, food & beverage and telecommunication, display a cycle of returns going downwards from Sunday to Tuesday before starting to increase on Wednesday and peak on

t statistics in parentheses p < 0.05, p < 0.01, p < 0.01, p < 0.01

Saturday. However, retailing was insignificant and consumer durables displayed a slightly higher return on Monday than Sunday, breaking the cycle for these industries with the coefficients -0.00395 and -0.00399, respectively.

Table 3.1: Non-Shariah compliant pre 28 June 2013 (Segment 1)

	(1)	(2)	(3)	(4)	(5)
	Energy	Materials	Capitalgoods	Transportation	Consumerdurables
sun	-0.00336*	-0.00425**	-0.00417**	-0.00589**	-0.00399
	(-2.55)	(-2.81)	(-2.86)	(-2.72)	(-1.61)
	0.00.422**	0.00200*	0.00270**	0.00467*	0.00205
mon	-0.00422**	-0.00308*	-0.00378**	-0.00467*	-0.00395
	(-3.00)	(-2.04)	(-2.64)	(-2.31)	(-1.61)
tues	-0.00541***	-0.00595***	-0.00625***	-0.00784***	-0.00762**
	(-3.82)	(-3.64)	(-4.07)	(-3.48)	(-3.07)
wed	-0.00177	-0.00401**	-0.00547***	-0.00679**	-0.00703**
	(-1.23)	(-2.70)	(-3.81)	(-3.15)	(-2.92)
_cons	0.00301**	0.00381**	0.00382**	0.00595***	0.00519**
	(2.81)	(2.87)	(3.12)	(3.45)	(2.68)
N	1123	1125	1125	1125	1125

	(6)	(7)	(8)	(9)
	Retailing	Foodandbeverage	Telecommunication	Realestate
sun	-0.00225	-0.00507**	-0.00365*	-0.00288*
	(-1.57)	(-3.15)	(-2.16)	(-2.04)
mon	-0.00245	-0.00605***	-0.00374*	-0.00257
	(-1.61)	(-3.66)	(-2.27)	(-1.83)
tues	-0.00295	-0.00677***	-0.00514**	-0.00472**
	(-1.91)	(-4.06)	(-2.95)	(-3.16)
wed	-0.00244	-0.00438**	-0.00343*	-0.00320*
	(-1.72)	(-2.80)	(-2.09)	(-2.21)
cons	0.00239	0.00479***	0.00341*	0.00270*
_	(1.94)	(3.63)	(2.24)	(2.23)
N	1125	1125	1123	1125

Results for testing Shariah- and non-Shariah-compliant portfolios for segment 2 (after weekend change) are displayed in Tables 3.2 and 3.3 respectively. The results are insignificant in all sectors for both portfolios. However, this outcome does not mean that faith

t statistics in parentheses p < 0.05, p < 0.01, p < 0.01

does not directly affect stock prices. Although both categories, Shariah- and non-Shariah-compliant portfolios, showed insignificant effect after the change in weekend days, evidence can be brought forward from the results generated confirming the effect faith has on the day-of-the-week anomaly. Every religious activity reflects hardship and reward – for example, Ramadan is a month of fasting followed by the three-day "Eid al-Fitr" celebration, marking the end of this holy month. This is also evident on a weekly basis: during the whole week, people work and are pressured by daily activities, but the existence of Friday is a way of providing Muslims with a tension release mechanism to take them back to normality. Friday is a very special day for all Muslims worldwide. Muslims gather to pray in congregation, as it is believed that Friday was chosen by God as a dedicated day of worship. In Saudi Arabia, Friday is not only special because of the Friday prayer, but it is also a day where families gather and spend a joyous time away from the stress and pressure of regular working days. Furthermore, in Saudi Arabia, Friday is a day for spiritual uplift and relaxation which helps people prepare for the working week ahead.

Before the weekend was changed (prior to June 2013), Thursday, the weekend day before Friday was seen as a preparation day for Friday, the day chosen by God as a dedicated day for worship. The spiritual uplift found in Friday results in a "spillover effect" into Saturday as it demonstrates a highly significant positive Saturday effect in segment 1.

However, after the weekend change, Thursday, a day people usually use to prepare for Sabbath, became a regular weekday. The privilege of having a day prior to Friday is no longer available. Moreover, the change in the weekend, making Saturday the second day of the weekend after Friday, resulted in the dissolution of the spillover effect.

Table 3.2: Shariah compliant post 28 June 2013 (Segment 1)

	(1)	(2)	(3)	(4)	(5)	(6)
	Energy	Materials	Capitalgoods	Transportation	Consumerdurables	Consumerservices
mon	-0.001578	-0.000493	-0.0015373	-0.0006856	-0.0002084	-0.0011145 364
	(-0.62)	(-0.33)	(-0.62)	(-0.34)	(-0.10)	(-0.56)
tues	0012759	-0.000449	-0.0011123	0. 0006768	0.0016535	-0.0024674
	(-0.50)	(-0.30)	(-0.45)	(0.33)	(0.84)	(-1.23)
wed	0.0009467	0.0001667	-0.002204	-0.0009257	0.0000562	0.0001612
	(0.37)	(0.11)	(-0.90)	(-0.46)	(0.03)	(0.08)
thurs	-0.003280	0.0014176	-0.0014263	0016965	-0.0000848	-0.0010981
	(-1.28)	(0.94)	(-0.58)	(-0.84)	(-0.04)	(-0.55)
_cons	0.0032806	-0.000558	0.0005811	0.0002084	-0.0008678	-0.0002219
	(0.59)	(-0.52)	(0.33)	(0.14)	(-0.62)	(0.16)
N	876	876	876	876	876	876

	(7)	(8)	(9)	(10)	(11)	(12)
	Retailing	Foodandstaples	Foodandbeverage	Healthcare	Diversifiedfinancials	Realestate
mon	-0.002239	-0.0003138	-0.0007454	-0.0016867	0.0007926	-0.0017391
	(-0.84)	(-0.09)	(-0.39)	(-0.91)	(0.35)	(-0.88)
tues	-0.005816	0.0012173	0.0007371	-0.0012949	0.0014537	-0. 001629
	(-2.18)	(0.37)	(0.38)	(-0.70)	(0.63)	(-0.83)

wed	-0.003839	-0.0036092	-0.0004285	-0.000359	-0.000704	-0.0015531
	(-1.44)	(-1.09)	(-0.22)	(-0.19)	(-0.31)	(-0.79)
thurs	-0.00121	0.0011611	-0.0018391	0.0022119	0.001163	00002024
	(-0.45)	(0.35)	(-0.96)	(1.19)	(0.51)	(0.10)
_cons	0.0010546	0.0005844	0.0002109	0.0004139	-0.0005936	0.0011458
	(0.56)	(0.25)	(0.15)	(0.32)	(-0.37)	(-0.82)
N	876	876	876	876	876	876

Table 3.3: Non-Shariah compliant post 28 June 2013 (Segment 2)

	(1)	(2)	(3)	(4)	(5)
	Energy	Materials	Capitalgoods	Transportation	Consumerdurables
mon	0.0005019	-0.0015224	-0.0007991	-0.0012338	0.0032236
	(0.28)	(-0.90)	(-0.49)	(-0.52)	(1.22)
tues	0.0002913	0.0003083	-0.0001049	0.0000984	00010374
	(0.16)	(-0.18)	(-0.06)	(0.04)	(0.39)
wed	0.0002822	0.0000627	-0.0009415	0.0018903	-0.0013885
	(0.16)	(0.04)	(-0.58	(0.80)	(-0.53)
thurs	0.0010535	0.0012056	0.002436	0.0021738	0.0002654
	(0.59)	(0.71)	(-0.15)	(0.92)	(0.10)
cons	-0.000396	-0.0003207	-0.0003017	-0.000579	-0.0010059
_	(0.31)	(-0.27)	(-0.26)	(-0.34)	(-0.54)
N	876	876	876	876	876

	(6)	(7)	(8)	(9)
	Retailing	Foodandbeverage	Telecommunication	Realestate
mon	-0.0009295	-0.0012682	-0.0016764	-0.0015266
	(-0.46)	(-0.70)	(-0.91)	(-0.78)
tues	-0.0003896	-0.0009064	-0.0026073	-0.0007793
	(-0.19)	(-0.50)	(-1.42)	(-0.40)
wed	-0.0021661	-0.0010103	-0.0026073	-0.0013303
	(-1.07)	(-0.56)	(-0.858	(-0.68)
thurs	-0.0000798	0.0012359	-0.0004629	0.0011406
	(-0.04)	(0.68)	(-0.25)	(0.58)
_cons	0.0001375	-0.0001412	0.0008618	0.0006251
	(0.10)	(-0.11)	(0.66)	(0.45)
N	876	876	876	876

t statistics in parentheses p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

t statistics in parentheses p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

The change in the weekend can create resentment in people as it changes traditions that are built upon religious values, leading to disruption or a lack of demand for trading in people who want to show that they are against such a move. The change in the weekend has made Shariah-compliant investors alter their moods and behaviour so as to not show any anomaly after the weekend change, as this would be seen as contradicting Islamic traditions. This is also observed in non-Shariah-compliant firms. Saudis and Arabian people in that region have been ruled and governed by Shariah for the past 1400 years, which implies that they are also affected by the change, and the only way to see this is the change in their behaviour. This is also supported by Canepa & Ibnrubbian (2014) who tested the effects of faith on stock prices and found that religious tenets have crucial bearing on investor behaviour. This is the only clear indication for why there is an anomaly before the weekend change and not afterwards. Alkhazali et al. (2017) investigated the effect of religion on stock prices by testing returns during the month of Ramadan against the mean returns of all the other months and found that the mean return during Ramadan is not only positive and higher than other months, but also holds less risk, thus reinforcing the effect of faith on investor's behaviour.

#### 3.5 Conclusion and Recommendations

This research aims to test the weekday effect anomaly by addressing the research question:

"Weekend change and its effect on the Saudi Arabian Stock Market: Does faith play a part in the weekend anomaly?"

To contribute to addressing this question, two main objectives are considered. The first objective is to investigate the existence of the weekday anomaly at industry level and whether this is affected after the change in the weekend. The second objective is to assess the effect of faith practices on the existence of the weekday anomaly.

To investigate the weekday anomaly, daily returns for 15 different industries representing various economic sectors from 1 January 2009 to 5 January 2017 are examined. Testing the weekday anomaly in Tadawul would give further insight into the topic of calendar anomalies due to the unique change in the weekend days in the region. Consistent with previous literature, the modelling techniques used are based on incorporating dummy variables within an OLS framework.

The results provide strong evidence of the existence of the weekday anomaly at industry level in the period 1 January 2009 to 27 June 2013, shown in the significant positive mean returns recorded on Saturday. This outcome confirms that the weekday anomaly is not industry-specific but a market-wide phenomenon, as it affects most industries in a similar manner (like the US). This result is supported by the findings of Abalala and Sollis (2015) who found a positive Saturday anomaly at industry level during the period of their sample, running from 2007 to 2010. However, testing segment 2 after the weekend change to Friday and Saturday instead of Thursday and Friday, represented by the period 27 June 2013 to 5 January 2017, shows that the anomaly disappeared, providing evidence that the change in the weekend affected the anomaly. Moreover, since all industries demonstrated insignificant results regarding the weekday anomaly, this confirms that the anomaly is a market-wide phenomenon rather than industry-specific.

To further assess the anomaly, a simple linear regression is used to test the mean return of the first trading day against the mean return of all other trading days of the week. The results indicate a positive and highly significant Saturday effect in segment 1, reinforcing the results

generated by regression 1. On the other hand, when testing segment 2, which represents the period after the change in the weekend, insignificant results were found in all industries.

In a country ruled by Islamic law, it is anticipated that the whole market should be Shariah-compliant. To test this, Shariah- and non-Shariah-compliant portfolios are tested for the weekday anomaly. The results show positive significant Saturday returns before the weekend change for both portfolios and insignificant results for both portfolios after the change in the weekend. This result supports the argument that faith directly affects investor behaviour, by altering their mood and trading behaviour so as to not show the anomaly after the weekend change, as it is seen as contradicting the country's traditional Thursday-Friday weekend.

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# Chapter 4: Does investors' behaviour alter between religious and non-religious holidays? The Case of Saudi Arabian Stock Market

#### **Abstract:**

This study examines the well-known pre-holiday effect in the Saudi stock market at both market and industry level. All the official holidays in Saudi Arabia are tested in this paper: Eid al-Adha, Eid al-Fitr and the National Day holiday. The research examines daily returns for both the general market and 15 industries over a period of almost 11 years, from 2009 to 2020. The study also discusses whether investors' behaviour alters between religious and non-religious holidays. The findings confirm the existence of the pre-holiday effect at the general market and industry level for only Eid al-Adha and Eid al-Fitr. The National Day holiday did not display any evidence of the existence of the pre-holiday anomaly at general market or industry level.

**Key words:** Behavioural finance, efficient market hypothesis, calendar anomalies, preholiday effect

#### 4.1 Introduction

# 4.1.1 Research background

The theories in the area of finance have been dominated by the Efficient Market Hypothesis (EMH) for a significant time period. The EMH, also known as the random walk theory, argues that the current stock prices reflect all the available information and that investors cannot make excess profit by using this information. However, evidence against the EMH is growing and several researchers in behavioural finance have reported return predictability (Rossi, 2016).

Behavioural finance is a new discipline of finance that seeks to augment classic finance theories by introducing behavioral components into decision-making. Shleifer (2000) defines behavioral finance as the study of the influence of psychology on the conduct of financial practitioners and the impact on markets. Thus, behavioral finance is concerned with research and ideas that investigate what occurs when investors make emotional judgments. It is a discipline of finance that aims to explain stock market anomalies by exploiting established psychological biases, rather than rejecting such behavior as random events, as the market efficiency hypothesis does (Barberis and Thaler, 2003).

Behavioural finance is primarily concerned with the constrained rational reactions of investors to market dynamics. The primary ideas behind this topic are based on Herbert Simon's (1978) claim that market agents are best represented as bounded rational. The topic also implies that constrained rational behavior frequently results in what Thaler (1987) refers to as economic anomalies, or actual findings that are difficult to rationalize or need implausible assumptions to explain. The well-known calendar anomalies are among these anomalies. Calendar effects are fascinating since conventional financial study (Wong et al, 2006) claims that their presence contradicts various variants of the traditional Efficient Markets Hypothesis (EMH). Different time spans of such effects include the well-known January effect, the day-of-the-week effect, the turn-of-the-month effect, the Halloween effect and the pre-holiday effect (Fields, 1931; Cross, 1973; French, 1980; Ariel, 1987; Harris, 1986a; Wong et al, 2006; Kim and Park, 1994).

One of the major calendar anomalies mentioned above is the pre-holiday effect, which refers to the tendency of the market to do abnormally well in the period that precedes a holiday. The pre-holiday anomaly has been comprehensively investigated across several markets and country settings, including US, UK and Japan. A large number of studies have provided evidence of this anomaly: for example, Pettingill (1989) provided evidence of the pre-holiday effect in portfolios of both large and small firms. Lakonishok and Smidt (1988) and Ariel (1990) confirmed the existence of the anomaly in several stock markets. Liano et.al (1992) studied a number of over-the-counter stock markets and found evidence of the presence of the pre-holiday effect. Kim and Park (1994) reported similar patterns of the anomaly in different trading systems. However, this research will focus on investigating the pre-holiday effect in a sparsely researched market: the Saudi stock market.

Research on calendar anomalies in Saudi Arabia, where this study is based, is very sparse. Tadawul All Share Index (TASI), the Saudi stock exchange market, is an emerging market that was informal throughout the 1970s, with only 14 companies listed at that time. However, TASI currently has around 200 listed trading companies. Tadawul is the only stock exchange in Saudi Arabia and is considered the major stock exchange, not only amongst the Gulf Cooperation Council (GCC) countries, but also in the Middle East and North Africa (MENA) region.

#### 4.1.2 Rationale

The purpose of this study is to investigate the existence of the pre-holiday anomaly in the Saudi stock market and whether religious holidays have greater effect on the anomaly than non-religious holidays. No previous research has investigated the effect of the pre-holiday anomaly in the Saudi stock market. This study aims to critically analyse and explain the pre-holiday effect in the sparsely researched Saudi stock Market Tadawul All-Share Index (TASI). This will considerably enrich our knowledge understanding of the subject in a region of the world where empirical research is sparse.

# 4.1.3 Research question

To understand the effect of the pre-holiday anomaly in emerging markets, like Saudi Arabia, this study seeks to address the following question:

"Does investors' behaviour alter between religious and non-religious holidays?"

The pre-holiday effect will be extensively analysed across three official holidays from 2009 to 2019. Not only does this study aim to be the first to investigate the pre-holiday effect in the Saudi stock market, but also to shed light on how the anomaly will be affected by religious and non-religious holidays.

# 4.1.4 Aims and objectives

This study focuses on three key objectives. The first objective is to examine the existence and persistence of the pre-holiday effect in the Saudi stock market. The second objective is to assess the magnitude of the anomaly in each industry and whether the anomaly manifests itself across all sectors similarly. The third objective is to investigate the effect of religious holidays on the pre-holiday anomaly.

#### 4.1.5 Structure

This research is structured as follows. The literature review chapter includes a comprehensive and critical analysis of the studies conducted on the pre-holiday effect (i.e. the extent to which stock prices tend to outperform on the last trading day before a holiday). The chapter begins with a review of the literature, followed by the findings of various researchers on the pre-holiday effect and a brief outline of the characteristics of the Saudi stock market, Tadawul All-Share Index (TASI), upon which this study is based.

Chapter three discusses the research methodology used to address the research aim and objectives, including data collection and analysis. The fourth chapter comprises an analysis of the data using econometric techniques, as well as a comparison of the findings and the existing literature. Finally, the fifth chapter provides a conclusion and recommendations for future research.

# 4.2 Literature review

Evidence of significant abnormal returns around pre-holidays has been extensively documented in the US markets, including stock markets (Lakonishok and Smidt, 1988; Pettengill, 1989; Ariel, 1990), over-the-counter stock markets (Liano et al., 1992), future markets (Fabozzi et al., 1994) and different trading system markets (Kim and Park, 1994; Brockman and Michayluk, 1998). For example, Lakonishok and Smidt (1988) found that returns on pre-holidays were 23 times higher than on other days, and 2 to 5 times higher than on days before weekends.

Research on the pre-holiday effect was also conducted and evidenced outside the US market, in countries like Italy (Barone, 1990), Japan (Ziemba, 1991), the UK (Mills and Coutts, 1995; Arsad and Coutts, 1997), India (Arumugam, 1999), Greece (Coutts et al., 2000), Spain (Meneu and Pardo, 2001, 2004), Hong Kong (McGuiness, 2005), New Zealand (Cao et al., 2009), Australia (Marrett and Worthington, 2009) and Israel (Kaplanski and Levy, 2012).

Kim and Park (1994) studied the pre-holiday effect in several markets and brought evidence of this effect in all three major US markets, in the UK and Japan. Moreover, a number of studies confirmed that returns on days preceding religious holidays tended to be abnormally higher than returns on other days (Cao et al., 2009; Bley and Saad, 2010).

Meneu and Pardo (2004) studied the pre-holiday effect in individual stocks of the Spanish stock exchange, which are also traded in the NYSE and Frankfurt stock exchanges. Investigating the period from 1990 to 2000, they found evidence of significant abnormal high returns on the day preceding a holiday. Moreover, the authors concluded that the abnormal returns in the pre-holiday period were not related to any other calendar anomaly, indicating that the pre-holiday effect may be based on small investors' tendency to not buy in the pre-holiday period.

Marrett and Worthington (2009) investigated the pre-holiday effect in Australia, covering the period from 1996 to 2006. The research not only analysed the effect at market level but also at industry level, as well as small cap returns. The results generated provide evidence of the existence of the pre-holiday effect; however, the study indicates that the effect detected at the

market level seems to be caused by the highly significant pre-holiday effect in the retail sector. Consistent with Lakonishok and Smidt (1988), the authors conclude that, on average, the returns on pre-holidays are five times higher than returns on other days.

Dimitrius et al. (2011) investigated the existence of the pre-holiday effect in the Romanian stock exchange from 2002 to 2011. The study confirms the existence of a pre-holiday effect for the main index of the stock market. Although the sample period was affected by the global crisis, the results did not show evidence of any effect of the global crisis on holiday returns.

Some mixed results were also found. Cadsby and Ratner (1992) investigated the pre-holiday effect in 11 different markets. Their findings confirm the existence of the pre-holiday effect in the US, Canada, Japan, Hong Kong and Australia. However, all European markets in the sample were insignificant and did not show the pre-holiday effect. According to the authors, these results suggest that the pre-holiday effect is a result of country-specific institutional practices.

Chong et al. (2005) extended previous studies by investigating the existence and persistence of the pre-holiday effect in three major international markets over the last three decades of the twentieth century. Evidence was found that the pre-holiday effect has declined in the US, UK and Hong Kong markets; however, the decline of the effect was remarkable only in the US. The authors argue that the results generated can be explained by the relative sophistication of the market.

Dodd and Gakhovich (2011) studied the holiday effect in 14 emerging Central and Eastern European (CEE) markets for the period between 1991 and 2002. The research showed evidence of the pre-holiday effect in 10 out of the 14 markets included in the study. The research revealed that 80% of the studied firms had lower volumes in the day preceding a holiday. This is consistent with Meneu and Pardo (2004) and Cao et al. (2009), who found evidence that there is less trading involved before holidays. Furthermore, the study indicates that the pre-holiday effect was most pronounced in earlier years, before declining over time. The authors argue that this indicates an enhancement in market efficiency in the related Central and East European (CEE) markets, which is consistent with the findings of Chong et al. (2005) and Marquering et al. (2006), as well as Iorgova and Ong (2008), who found similar results regarding US markets and emerging European countries, respectively.

Marquering et al. (2006) investigated the existence and persistence of stock market anomalies, covering the period from 1960 to 2003. According to the authors and as proven by Sullivan et al. (2001), if an anomaly results from data snooping, it is expected that the anomaly disappears in the new data. The study revealed evidence that the holiday effect as well as other anomalies disappear after having been published. This indicates that the market becomes more efficient over time. Moreover, the evidence found of the reversed holiday effect is consistent with and supports the findings of Hudson et al. (2002). However, this result contrasts with the findings of Brockman and Michayluk (1998), who found evidence for the persistence of the holiday effect. It also contrasts with the findings of Lucey and Pardo (2005), who argue that it is possible to earn more from trading based on the pre-holiday effect than it is possible to earn by chance.

Casado et al. (2013) studied the effect of US holidays in European markets during European non-holidays over a period of 17 years, from 1991 to 2008. The study reported a significant

impact of US holidays on European stock market returns. The authors argue that this result is not explained by calendar anomalies, such as the holiday effect, nor by behavioural finance models, which predict a positive correlation between trading volumes and returns (Hong and Stein, 2007). Moreover, according to the authors, a possible explanation for this evidence is the information provided and the volume trading.

Frieder and Subrahmanyam (2004) examined the returns and volume in US equity markets around Jewish high holidays where market remain open. They found that the returns are abnormally high on Rosh Hashanah (Jewish new year) and the two days prior to it, but returns where significantly low on Yom Kippur (somber day) and the day after it. The authors report a decline in trading volume for both holidays and attribute these results to the sentiment of Jewish investors and their trades around these holidays.

A related stream of research is the literature on the effects of the holy month of Ramadan that takes place before Eid Alfitr holiday on the behaviour of stock returns. Seyyed et al. (2005) investigates the Saudi Arabian stock market during the month of Ramadan from 1985 to 2000 and found no abnormal change in mean return but a significant decline in volatility.

Both Ramadan and Rosh Hashanah are events that are capable of influencing the behaviour, moods and decision making process of the adherents. During Ramadan, Muslims seek a closer relationship with Allah and obliged to follow a set of given standards of behaviour to make them become better believers and more responsible members of society which in turn improve their feelings of self-worth.

Many attempts to explain the pre-holiday effect have been made. Some scholars claim that the pre-holiday effect is correlated with other calendar anomalies, such as the day-of-the-week effect, the turn-of-the-month effect and the January effect (Ariel, 1990; Liano et al., 1992). Other scholars argue that the abnormal returns before a holiday result from a closing effect (Keim, 1989; Pettengill, 1989). Furthermore, Ariel (1990) suggests that the holiday effect occurs due to some investors' preference for buying on pre-holidays, avoiding selling. Other research indicates that firm size has a direct impact on the holiday effect (Pettengill, 1989; Kim and Park, 1994; Brockman and Michayluk, 1998; Vergin and McGinnis, 1999). However, Dimson and Marsh (1999) state that the size effect has reversed. Moreover, Fabozzi et al. (1994) found evidence that there is a greater effect before holidays when the market was closed, suggesting that a good mood may influence returns on trading days before a holiday.

Numerous studies have brought forward evidence for good mood in investors affecting stock returns positively. Deldin et al. (1986) report that investors' mood changes by days of the week as a possible explanation for the day-of-the-week effect. Dodd and Gakhovich (2011) suggest that behavioural finance may explain the existence of the holiday effect, since the attitude of investors may become positive around public holidays, thus increasing the chances of them buying shares before holidays (Vergin and McGinnis, 1999).

#### 4.2.1 Public holidays in Saudi Arabia

Saudi Arabia is a Muslim nation with three main holidays: Eid al-Fitr, Eid al-Adha and the Saudi National Day. Eid al-Fitr and Eid al-Adha are religious holidays that mark the end of the holy month of Ramadan and the end of Hajj season, respectively. The Saudi National Day is the only non-religious holiday among the official holidays and is celebrated on the 23<sup>rd</sup> of

September each year. Eid al-Fitr marks the end of a month of fasting and culturally lasts for three days; however, the official holiday is 10 days long. Eid al-Adha is the latter of the two religious holidays in Saudi Arabia and is considered to be the holier of the two Eids. It is celebrated 2 months and 10 days after Eid al-Fitr. Eid al-Adha lasts for five days; however, the official holiday is 10 days long. The Saudi National Day was established in 2005, in honour of the renaming of the Kingdom of Najd and Hejaz to the Kingdom of Saudi Arabia by a 1932 royal decree from King Abdulaziz, the founder and first king of Saudi Arabia.

# 4.3 Methodology

# 4.3.1 Introduction

This study examines the holiday effect in the Saudi stock market (TASI) "Tadawul" which has, to my knowledge, not yet been tested at both market and industry levels. This research will also highlight and analyse investors' behaviour around religious and non-religious holidays. The main research question is:

# "Does investors' behaviour alter between religious and non-religious holidays?"

The primary objective of this research is to investigate whether the holiday effect exists in the Saudi market. The second objective is to examine whether it is correlated to certain sectors or is a market-wide phenomenon affecting all sectors similarly. The third objective is to study investors' behaviour around religious and non-religious holidays.

#### 4.3.2 Data collection

This study focuses on both index level and industry level data to fully analyse the effect of the holiday anomaly. Examining index level data will provide evidence of whether the anomaly exists in the Saudi market, while the industry level data will display which industry exhibits the effect the most and whether all industries are similarly affected by the anomaly. To delve deeper into the anomaly, holidays will be divided into religious and non-religious holidays to investigate how faith-based holidays affect investors' behaviour regarding the holiday anomaly.

The Saudi Stock exchange (Tadawul) was chosen for this study as it is the largest stock exchange in the Middle East and North Africa (MENA) region, with a market capitalisation of \$2.33 trillion as of March 2020 (Tadawul.com). While calendar anomalies have been investigated in a number of studies on the Saudi stock exchange, there is no available research on the holiday effect, making this market very appealing for study.

To study the holiday anomaly, average returns for the whole index and for 15 different industries representing various economic sectors including real estate, agriculture and Banks services will be examined. The original data gathered consists of 16 industries; however, one industry, namely REITs, was removed as the data available for this sector begins in 2016, making it ineligible for the study. The data was collected from the Tadawul exchange website, which provided data ranging from January 2007 to 2 January 2020. However, this research examines the period from 2009 to 2020 to avoid including the effects on the returns of the global financial crisis in 2007-08 as well as the largest stock crisis in the history of Tadawul that occurred in February 2006. The sector data will be limited to the period 2009 to 2017 due to a categorisation change in 2017, which expanded the market sectors to 21 instead of 16.

#### 4.3.3 Model

The modelling techniques applied in order to fully utilise the dataset are based on incorporating dummy variables within an OLS framework. The dummy variables categorise the anomaly effect within the regression model. This research devises three main regression models that represent the three official holidays in Saudi Arabia.

The dummy variable proxy for holidays that represent five days preceding a holiday will consist of one dummy variable for the five-day period prior to a holiday.

To further assess the holiday effect, a dummy variable for each of the five days prior to a holiday will be tested to determine where the effect occurs most, as illustrated in regression model 4.

$$R_t = \beta_0 + \beta_1 NAT + \varepsilon_t \tag{1}$$

$$R_t = \beta_0 + \beta_1 FITR + \varepsilon_t \tag{2}$$

$$R_{t} = \beta_{0} + \beta_{1}NAT + \varepsilon_{t}$$

$$R_{t} = \beta_{0} + \beta_{1}FITR + \varepsilon_{t}$$

$$R_{t} = \beta_{0} + \beta_{1}ADHA + \varepsilon_{t}$$

$$(1)$$

$$(2)$$

$$(3)$$

$$R_t = \beta_0 + \beta_1 d_{2t} + \beta_2 d_{3t} + \beta_3 d_{4t} + \beta_4 d_{5t} + \varepsilon_t \tag{4}$$

Equation 1 to 3 will examine the existence of the anomaly, where  $R_t$  is the daily return on day t;  $\beta_0$  is the constant;  $\beta_1$  is the coefficient on a dummy variable NAT/FITR/ADHA that equals one on the five days preceding a holiday and zero otherwise; and the error term is  $\varepsilon_t$ .

Equation 4 will further investigate the anomaly, where  $R_t$  is the return on day t;  $d_{it}$  is a dummy variable to denote the day on which the return is detected;  $\beta_0$  measures the mean return for the day preceding a holiday; the coefficients  $\beta_1$  through to  $\beta_4$  measure the difference between the expected return for each of the five days prior to a holiday and the expected return for the last day prior to a holiday.

# 4.4 Analysis

### 4.4.1 Introduction

This section will apply the methodology outlined in section 3 to address the research question "Does investors' behaviour alter between religious and non-religious holidays?". The preholiday effect was separated into two distinctive approaches: observing the average effect of the five days preceding a holiday compared to all other days of the year, and observing the individual returns of the five days preceding a holiday compared to all other days of the year. The sample covers a period of 11 years, ranging from 4 January 2009 to 2 January 2020. This section will perform a detailed analysis of the results and discuss the findings generated with consideration for previous findings.

# 4.4.2 Index Analyses

To assist in identifying the presence of an anomaly, it is vital to identify the pre- and posteffect of the holiday, as investors' behaviour can alter depending on the season or holiday. Narrowing the focus to a five-day period will help to identify the presence of an anomaly and provide greater insight into the immediate effect of the holiday on investors' behaviour. Table 1 illustrates the five-day pre- and post-holiday effect for three holidays.

*Table 1: Multilinear regression for the three official holidays (Pre and Post holidays):* 

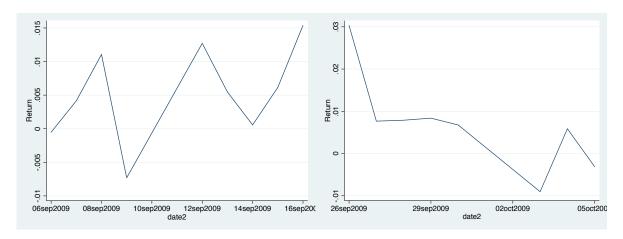
	Pre								Post					
Holiday	Significance D1 D2 D3 D4 D5				Significance	D6	D7	D8	D9	D10				
Eid al-Fitr	0.012	0.000					0.016	0.001	0.038					
Eid al-		0.001					(0.047)							
Adha														
National									0.043			0.014		
Day														

# 4.4.2.1 Eid al-Fitr Holiday

The results outlined in Table 1, relating to the average five days preceding Eid al-Fitr holiday, indicate that the  $\beta_1$  intercept, measuring the average return of the five days before Eid al-Fitr holiday is significant at the 5% level, implying a positive return when compared to the rest of the year. To delve deeper into the occurrence of the anomaly, dummy variables are employed for each of the five days preceding Eid al-Fitr. Table 1 shows that D1, which represents the last trading day before the holiday, is the only significant day at the 1% level.

To repeat the methodology for post-Eid al-Fitr, the overall average five day value shows significance at the 5% level. Applying dummy variables to each day in the post-Eid al-Fitr period indicates a prolonged holiday effect, as both days after the holiday season ends are statistically significant at the 1% and 5% levels for D6 and D7. This implies that the holiday effect lasts for three days, starting from D1 until D7, the second trading day after the holiday. The positive post-period anomaly can be attributed to the TASI attempting to catch up with global and local markets after the short trading hours maintained during Ramadan (JADWA, 2015). Moreover, the positive investor sentiment can be linked to the return to normality in economic trading and activity after the month of Ramadan.

Graph 1: Pre- & Post-Eid al-Fitr returns for the year 2009



Graph 1 displays the returns for a period of ten days before the holiday and ten days after the holiday for the initial year of the sample data. The graph shows that, in the last trading day before Eid al-Fitr, the highest positive return is found. Moreover, observing the post-holiday period, it is clear that the first day of trading after Eid al-Fitr (26th Sept 2009) is the highest day in the post-holiday period, followed by the second day after the holiday period (27th Sept 2009), before returns begin to decline. This graphical illustration coincides with the findings in Table 1. This pattern is repeated in subsequent years.

# 4.4.2.2 Eid al-Adha Holiday

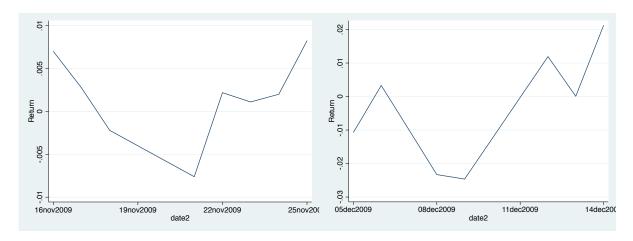
The results reported in Table 1 indicate that the  $\beta_1$  intercept, which measures the average return of the five days preceding the Eid al-Adha, shows insignificant results. To delve deeper into the occurrence of this anomaly, dummy variables are allocated for each of the five days preceding the holiday. The dummies were tested and the results are displayed in Table 1. The results indicate that D1, which represents the last trading day before the holiday, is highly significant at the 1% level. The reported overall insignificance of the model can be attributed to the equal weights given to each dummy variable from D2 to D5, which contributed to the overall insignificance of the model.

To repeat the methodology for post-Eid al-Adha, the overall average five-day value shows significance at the 5% level with a negative coefficient. Applying dummy variables for each day in the post-Eid al-Adha period displays insignificant results, implying that there is an overall negative effect throughout the five-day post-Eid al-Adha period, but this is not attributed to a specific day or days within the five days tested.

Eid al-Adha only shows the pre-holiday effect when tested using dummy variables, not when testing the overall effect. The anomaly present around Eid al-Adha is weak compared to the anomaly found in Eid al-Fitr.

The weak effect of the anomaly around Eid al-Adha holiday may be a result of Eid al-Adha falling in the fourth quarter of the year for most of the sample data. According to Jadwa's (2015) report, the decline in returns around Eid al-Adha is primarily because firms tend to clear their balance sheets before the start of the new year. In addition, other companies attempt to clear their financial reports by writing off bad debts and investments in the fourth quarter.

Graph 2: Pre- & Post-Eid al-Adha returns for the year 2009



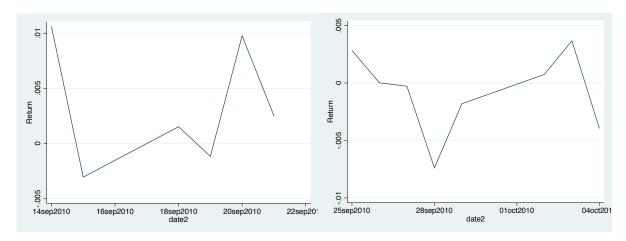
Graph 2 demonstrates the returns of the five days before and after Eid al-Adha holiday in the initial year of the sample data. The graph shows that the last trading day before the holiday, 25 Nov 2009, has abnormal returns compared to the other four days before the holiday, which show no difference from other days of the year. The graph also displays the returns of the five days after Eid al-Adha, clearly showing that the post-holiday period returns are indifferent to returns on other days of the year and lower than those in the pre-holiday period.

# 4.4.2.3 National Day Holiday

The third official holiday reported in Table 1 is the Saudi National Day, which is the only holiday that is not attached to religious grounds. The results in Table 1 report that the average returns in the five days preceding the holiday are insignificant. Applying dummy variables for each of the five days also shows insignificant results in all of the five days before the National Day holiday.

To fully analyse the National Day holiday, as in previous models, the five days after the holiday are also tested. The  $\beta_1$  intercept, which measures the average return of the five days after the holiday, shows insignificant results. Delving deeper into the occurrence of this anomaly, dummy variables are allocated for each of the five days after the National Day holiday. Table 1 displays significant results at the 5% level in D7 and D10, which represent the second and fifth trading days after the holiday. The results displayed suggest that the preholiday anomaly is not present in the National Day holiday.

Graph 3: Pre- & Post-National Day returns for the year 2010



Graph 3 displays the returns for a period of 10 days before and 10 days after the holiday in the second year of the sample period and shows that the returns for both pre- and post-periods are not different from the returns on other days of the year. The graph displays the second year of the data sample instead of the first year to avoid holiday overlap with Eid al-Adha.

The non-existence of the pre-holiday effect around the National Day holiday may be due to the short length of the holiday as well as the non-religious nature of the holiday altering investors' mood. Unlike Eid al-Adha and Eid al-Fitr, the National Day does not have the religious characteristics that could directly affect investors' behaviour, like the long hours of fasting during Ramadan before Eid al-Fitr and the performance of Hajj before Eid al-Adha. Moreover, according to Jadwa (2015), in the Kingdom of Saudi Arabia the activity slows down during summer as hot weather restrains physical activity and encourages people to take vacations. Since the National Day holiday is based on the Georgian calendar and not on the Hijri calendar, it falls at the end of the summer season every year; unlike the Eid al-Adha and Eid al-Fitr holidays that shift 11 days every year, as they are based on the Hijri lunar calendar.

#### 4.4.2.4 Combined effect

Upon viewing the results for all three official holidays in Saudi Arabia, it becomes clear that the classical pre-holiday effect does not exist during all the official holidays. Eid al-Fitr holiday displayed positive abnormal returns on the last trading day before the holiday, which is in line with the pre-holiday effect theory. However, the first and second trading days after the holiday displayed positive highly significant results. This suggests that the classical preholiday effect that has been reported in previous studies in Western markets has developed into a prolonged holiday effect that starts in the last trading day and stretches until the second trading day after the holiday. Moreover, Eid al-Fitr is the only holiday that detected highly significant abnormal returns around the holiday. This may be due to the religious background of the holiday – it takes place after the holy month of Ramadan and involves the participation of all Muslims in incessant worship. The major difference between Eid al-Fitr and Eid al-Adha is that Eid al-Fitr is all-inclusive and consists of a whole month of worship, which ends with the reward of a joyous occasion in which Muslims from all around the world partake. On the other hand, Eid al-Adha is celebrated by those who voluntarily partake in Hajj ceremonies; while those who do not tend not to experience the full magnitude of the celebration. This implies that the overall magnitude of Eid al-Fitr tends to be more widereaching than Eid al-Adha, which is why the results show greater significance in Eid al-Fitr than Eid al-Adha.

The results for Eid al-Adha indicate that the classical pre-holiday effect does exist in the Saudi market. The highly abnormal returns on the last trading day before the holiday confirm the theory of the pre-holiday effect that suggests that this day generates abnormal returns compared to other days of the year. The effect is, however, less significant than the effect detected around Eid al-Fitr. Moreover, the pre-holiday anomaly detected in Eid al-Adha is the classical pre-holiday effect, as the last trading day before the holiday reported positive abnormal returns and the post-holiday period displayed significant negative returns. The returns around the National Day holiday, both before and after, are indifferent to other days of the year, suggesting that the pre-holiday effect does not exist during this holiday. This result may also be due to the background of the holiday since it is the only holiday that does not have a religious background and is instead based on the day Saudi Arabia was renamed from the Kingdom of Najd and Hejaz to the Kingdom of Saudi Arabia in 1932. Moreover, the National Day holiday was only established post-2005, which implies that this is a new phenomenon that the Saudi people are enjoying. Another factor that may affect the anomaly in this holiday is the short duration of the holiday – two to three days – unlike Eid al-Fitr and Eid al-Adha, which both last for 10 days, giving more time for relaxation and readjustment of strategy for investors.

The Saudi market is not open to foreign investors. However, it is open to investors from the GCC countries, who are also called regional investors. Regional investors come from the same religious background as the Saudi investors and therefore follow the same pattern with exception of the National Day. This is why the anomaly is not shown during the National Day holiday.

#### 4.4.3 Sector Analysis

To fully investigate the pre-holiday effect in the Saudi market, the 15 sectors that make up the stock market are tested individually. Testing the sectors helps to investigate whether the anomaly is a market-wide phenomenon that affects all sectors in the same way or whether it affects them differently. The same approach that was used to test the index will be applied to sectors.

#### 4.4.3.1 Eid al-Fitr

Table 2: Multilinear regression for Eid al-Fitr at industry level (Pre and Post Eid Al-Fitr holiday)

	Pre							Post					
Sectors	Sig	D1	D2	D3	D4	D5	Sig	D6	D7	D8	D9	D10	
Agric & food	0.000	0.000	0.094	0.075			0.059	0.000					
Banks & Fin srvc	0.003	0.000	0.072	0.081			0.018	0.041				0.004	
Build & cnstr	0.027	0.005	0.018		0.031		0.000	0.000	0.027			0.064	
Cement	0.003	0.035	0.027		0.010		0.058	0.004					
Energy & Utl	0.040											0.010	
Hotel & Tourism							0.037	0.000	0.029				

Industrial Invs	0.031			0.057	0.040	0.046	0.000			
Insurance			0.006	0.009		0.000	0.000			
Media & Publ	0.098					0.081				
Multi-inv		0.005				0.000	0.002	0.035	0.000	0.052
Petrochem	0.055	0.000				0.061	0.002			
Real est & dvlp		0.047	(0.023)		0.094		0.003			
Retail							0.001			0.067
Telcmm	0.005	0.003	0.000			0.014	0.021			
Transport						0.018	0.002			

Table 2 displays the results for the five days before and the five days after Eid al-Fitr in relation to each sector. The table shows that the overall results for the five days preceding Eid al-Fitr display 9 significant sectors out of the total 15 included in the study. Agriculture & food, banks & financial services, cement and telecommunication & technology sectors showed the most significant results at the 1% level. The agriculture and food industry displayed the highest coefficient among all significant industries at 0.006, while building and construction displayed the lowest coefficient at 0.002. Testing the five days before the holiday individually using dummy variables revealed 8 significant sectors. However, only 6 sectors out of the 9 overall significant sectors reported positive abnormal returns on D1, which represents the last trading day before the holiday. Moreover, multi-investment and real estate and development sectors displayed significant results on D1, even though the initial test for the overall effect of the five days preceding the holiday generated insignificant results. This could be due to the equal weight distribution across the five days, which allowed the other insignificant days contribute to the overall insignificance of the model. The agriculture and food sector showed the highest coefficient on D1, 0.0123, while the Multi investment sector showed the lowest coefficient, 0.0043.

Examining the overall effect of the five days after Eid al-Fitr revealed 13 significant sectors. However, only 3 sectors, building and construction, insurance and multi-investment are highly significant at the 1% level. The insurance sector displayed the highest coefficient at 0.0072 while building and construction displayed the lowest coefficient at 0.0058. Testing the five days after the holiday individually using dummy variables displayed 13 significant sectors on D6, which is the first trading day after the holiday. All the significant sectors on D6 were also significant when initially tested for the overall effect, except for real estate & development and retail sectors, where they were insignificant in the overall effect but highly significant on D6. This could be attributed to the equal weight distribution across the five days, which allowed the other four insignificant days contribute to the overall insignificance of the model. The insurance industry displayed the highest coefficient at 0.0206 while cement displayed the lowest coefficient at 0.0065.

#### 4.4.3.2 Eid al-Adha

Table 3: Multilinear regression for Eid al-Adha at industry level (Pre and Post Eid Al-Adha holiday)

Sectors				Pre		Post						
	Sig	D1	D2	D3	D4	D5	Sig	D6	D7	D8	D9	D10
Agric & food												
Banks & Fin srvc	0.099	0.070					(0.001)	(0.010)		0.002	0.085	
Build & cnstr			0.056									
Cement		0.001		0.0304	0.092					0.070		
Energy & Utl							(0.042)	(0.070)		0.033		
Hotel & Tourism			0.050			0.053						
Industrial Invs							(0.037)					
Insurance												
Media & Publ			0.005	0.067								
Multi-inv		0.099		0.031								
Petrochem		0.059										
Real est & dvlp							(0.056)			0.009		0.085
Retail												
Telcmm		0.000										
Transport												

Table 3 (Eid al-Adha)

Table 3 above displays the results for the five days before and after Eid al-Adha holiday in relation to each sector. The results in the table show that only one sector, banks and financial services, is significant at the 10% level with a coefficient of 0.0025 when testing the overall effect of the five days preceding Eid al-Adha. To further test the anomaly, the five days preceding Eid al-Adha were tested individually using dummy variables and the results are reported in Table 3. The results show that five sectors were significant on D1, which represents the last trading day before the holiday. Out of these five significant sectors, cement and telecommunication and technology were the only highly significant sectors at the 1% level. The banks & financial services sector displayed the highest coefficient at 0.0065 while multi-investment displayed the lowest coefficient at 0.0031. Four out of the five significant sectors showed insignificant results when initially tested for the overall effect. This could be linked to the equal weight distribution across the 5 days in question, which allowed the insignificant days to contribute to the overall insignificance of the model.

Studying the five days after Eid al-Adha holiday revealed four significant sectors; however, only one sector, banks and financial services, is highly significant at the 1% level. The coefficients for the significant industries display negative figures, implying that returns on post-holidays are negative. The banks & financial services industry displayed the lowest coefficient at -0.0085 while energy & utilities displayed the highest at -0.0043. Moreover, testing the five days post-Eid al-Adha individually using dummy variables revealed two significant sectors, banks and financial services and energy and utilities, at the 1% and 10% levels respectively. However, the coefficients of these sectors are negative, indicating the negative returns documented on D6, the first trading day post-holiday. The industrial investment sector reported significant results when tested for the overall effect. However, testing the five days individually using dummies report insignificant results for all five days.

which may imply that there is an overall negative effect over the five-day post-Eid al-Adha period.

# 4.4.3.3 National Day

Table 4: Multilinear regression for the National day at industry level (Pre and Post National day holiday)

Sectors	Pre						Post						
	Sig	D1	D2	D3	D4	D5	Sig	D6	D7	D8	D9	D10	
Agric & food								-0.058	0.016		-0.046	0.006	
Banks & Fin srvc				-0.009					0.063	-0.023		0.007	
Building & cnstr									0.054	-0.084		0.000	
Cement													
Energy & Utl													
Hotel &				-0.010									
Tourism													
<b>Industrial Inv</b>				-0.056		0.005	-0.087	-0.015	0.015	-0.062		0.018	
Insurance									0.000			0.039	
Media & Publ			-0.030					-0.024					
Multi-inv													
Petrochem				0.000				-0.001	0.043			0.039	
Real est & dvlp				-0.016		0.012	-0.058	-0.089	0.005	-0.014	-0.099		
Retail								-0.097				0.001	
Telecomm											-0.090	0.034	
Transport												0.008	

Table 4 (National Day)

The results for the third official holiday in Saudi Arabia, the National Day, are reported in Table 4 above. The table reports the results for the five trading days before and after the holiday in order to fully investigate the anomaly. The results for the five days preceding the National Day show that all 15 sectors are insignificant when testing for the overall effect. Furthermore, D1, which represents the last trading day before the holiday, shows that all sectors are insignificant.

Investigating the five days after the holiday revealed two sectors that are significant at the 10% level, with negative coefficients when testing for the overall effect. Moreover, D6, which represents the first trading day after the holiday, shows that six sectors are significant with negative coefficients indicating negative returns; unlike D1, where all sectors were insignificant, implying that the pre-holiday anomaly does not exist in this holiday. D6 shows that petrochemicals are the only highly significant industry at the 1% level, while industrial investment and media and publishing are significant at the 5% level, and agriculture & food, real estate & development and retail industries are significant at the 10% level. The agriculture & food industry display the highest coefficient at -0.0045, while petrochemicals display the lowest coefficient at -0.0089.

The results for mean returns before and after the holidays as described above contribute to further explaining the anomaly. Eid al-Fitr displayed highly significant results for most industries, implying that the anomaly is a market-wide phenomenon affecting industries in the same manner. Eid al-Adha displayed significant results in few industries, which suggests that the pre-holiday anomaly does not manifest itself similarly across all industries in relation

to this holiday. Moreover, the pre-holiday effect was not detected in any of the 15 tested sectors for the National Day holiday .

The different results observed regarding sectors may be due to the unique characteristics and time periods for each holiday. Although both Eid al-Fitr and Eid al-Adha are religious holidays, they exhibited the anomaly to different extents due to the specific characteristics of each holiday and the religious activity involved before each holiday. On the other hand, the National Day holiday is not a religious holiday and is short in length compared to Eid al-Fitr and Eid al-Adha. As such, the anomaly was not present in all 15 sectors.

#### 4.5 Discussion

Research into the holiday effect in the Middle East, whether religious or non-religious, is limited.

With the lack of prior articles discussing Islamic religious holiday effect on stock market returns, the closest comparison is looking at the religious holiday effect in non-Muslim countries. For instance, Cao et.al (2009) and Dodd and Gakhovich (2011) empirically identified a significant pre-holiday effect in the religious holidays of Christmas and Easter in New Zealand and 14 Central and Eastern European (CEE) countries. These studies were not limited to religious holidays; however, Cao et.al (2009) found that the pre-holiday average return was highest during Christmas and followed by Easter, at 14.67 times and 13.09 times higher than returns on other trading days, respectively. According to the author, this indicates that, if returns are subject to investor mood and emotions during economical neutral events, these positive mood swings are highest during Christmas and Easter holidays. Dodd and Gakhovich (2011) found that the pre-holiday anomaly is mainly driven by the Christmas, Easter and New Year holidays. These findings collectively indicate that the aggregate pre-holiday effect may mainly be driven by a specific or a select group of holidays and may not be widespread across all holidays.

This is in line with the results generated in this research, as the results suggest that the preholiday effect affects the three holidays differently. The religious and longer holidays, Eid al-Adha and Eid al-Fitr, showed abnormal returns in pre-holiday trading days, unlike the National Day holiday. Although both Eid al-Fitr and Eid al-Adha showed abnormal returns on the last trading day before the holiday, Eid al-Fitr display a prolonged holiday effect that stretched abnormal returns until the second day after the holiday. Eid al-Adha, on the other hand, displayed significant results after the holiday, indicating an overall positive effect for all five days after the holiday. This confirms that the pre-holiday effect may be mainly driven by the selected group of holidays. The main difference between the results found in this research and those found by Cao et.al (2009) and Dodd and Gakhovich (2011) is that nonreligious holidays like the Saudi National Day were found insignificant, whereas the New Year holiday was significant. The reason for this disparity could be the difference in the duration of the holidays. Another reason is that regional investors (i.e. investors from GCC) who are participants in the Saudi market do not celebrate or witness the Saudi National Day holiday like local Saudi investors do. Indeed, in Western markets, all participants in the market celebrate and witness the New Year holiday and therefore the behaviour pattern of these investors becomes similar, leading to the presence of the anomaly.

Research into mood changes around holidays indicates that extended weekends may positively affect mood and emotions (Rossi and Rossi, 1977). This supports the finding that the holiday duration affects the presence of the anomaly. On the other hand, Kossof (1992) reported poor mood and emotions during the Christmas holiday, which calls into question the

findings of Cao et.al (2009) and Dodd and Gakhovich (2011). However, Marret and Worthington (2009) studied the pre-holiday effect at market and industry level in the Australian stock market across eight official holidays, including Christmas, and found highly significant results, thus contradicting the findings of Kossof (1992).

Investigating the pre-holiday effect in the Saudi stock market at industry level contributes substantially to analysing the anomaly thoroughly. The results indicate that most sectors behave in the same manner regarding the pre-holiday effect. For example, significant results were reported in the pre-holiday period for Eid al-Fitr, and most of the sectors examined showed significant results. Marret and Worthington (2009) investigated the pre-holiday effect at industry level in the Australian stock market. They found that the retail industry was the only significant industry – in fact, the retail industry was the sole reason for the significant results. This indicates that the behaviour of investors in the Saudi stock market is in contrast with the behaviour of investors in the Australian stock market, since most industries behave similarly in the Saudi stock market pre-holiday, unlike the Australian stock market where the anomaly is highly correlated with one sector only. The pre-holiday effect in the Saudi stock market is a market-wide phenomenon that affects all sectors similarly when it exists; however, in the Australian stock market, the pre-holiday effect is only related to the retail sector (Marret and Worthington, 2009). This behavioural disparity in Saudi and Australian investors could be related to the strong religious setting in Saudi culture, which results in the anomaly manifesting itself similarly across all sectors in the Saudi market.

Numerous factors, both economical and behavioural, could provide explanations for the existence of the positive pre-holiday effect. Positive returns before holidays could be a manifestation of the well-documented closing effect, in which returns tend to be positively high at market closing (Cao et.al, 2009). One behavioural explanation (Cao et.al, 2009) argues that short sellers tend to close their allegedly risky positions prior to holidays. Another proposes psychological reasons, such as investors' good mood around holidays, as this implies greater optimism about future prospects, resulting in the abnormal positive return before a holiday. Moreover, the average returns post-holiday indicate that these positions are not reinstituted post-holiday (Ariel, 1990). Ariel (1990) also argues that if the closing of short positions is responsible for the abnormal positive returns before a holiday, it cannot explain the reported positive returns from pre-holiday close to post holiday open. Results reported in this research, along with many previous studies, confirm the persistence of the holiday effect across countries. Nevertheless, the persistence of the holiday effect across countries indicates that the holiday effect is not driven by institutional factors unique to a country's stock market.

#### 4.6 Conclusion

This research aimed to investigate the holiday effect by addressing the following research question:

"Does investors' behaviour alter between religious and non-religious holidays?"

Three main objectives were considered in addressing this question. The first objective was to investigate the existence of the holiday effect in TASI (Tadawul All Share index). The second objective was to test the anomaly at industry level to examine whether the anomaly has the same effect across all industries or if it affects certain industries more than others. Finally, the third objective was to study the holiday effect's existence across religious and non-religious holidays.

As with many calendar anomalies, the holiday effect has been extensively researched in Western markets. However, research on the holiday effect in Saudi Arabia is very sparse. Meneu & Pardo (2001) and Marrett & Worthington (2009) found strong evidence of the existence of the pre-holiday effect at both market and industry level in the Spanish and Australian markets, respectively. Moreover, Cadsby and Ratner (1992) investigated the anomaly in 11 different markets and found mixed results – all European countries included in the study did not show the holiday effect for the whole sample period. Casado et.al (2013) provided further understanding to the topic by studying the effect of US holidays on European markets during European non-holidays. They found a significant impact of the US holidays on European markets but argued that this result is not related to calendar anomalies.

To investigate the holiday effect, daily returns for the main market and 15 different industries from 2009 to 2019 were examined. Examining the holiday effect in TASI gave further understanding of the topic of calendar anomalies, due to the unique cultural and religious connection shared by investors in this region. Consistent with previous research on calendar anomalies, the modelling techniques used are based on incorporating dummy variables within an OLS framework.

The results provide evidence of the existence of the pre-holiday effect in the Saudi stock market. However, the existence and magnitude of the anomaly is not the same in all tested holidays. Eid al-Fitr and Eid al-Adha displayed the effect of the anomaly but to different extents. Eid al-Fitr showed a stretched effect, starting in the last trading day before the holiday until the second trading day after the holiday at the market level. Eid al-Adha showed positive significant returns on the last trading day before the holiday, while the post-holiday period recorded significant negative returns. Moreover, Eid al-Fitr displayed the anomaly in most industries, indicating that the anomaly in Eid al-Fitr is a market-wide phenomenon affecting all industries similarly; unlike Eid al-Adha, where only five significant industries were reported in the pre-holiday period. Tests for the National Day, the third official holiday, did not present any evidence of the anomaly, neither at market nor industry level. The differences in the existence and magnitudes of the anomaly between holidays may be attributed to the religious backgrounds and duration attached to each holiday.

This research provides insight to investors as it reveals that such holidays can be exploited to make abnormal returns if observed carefully, and if an investment strategy has been developed.

One limitation faced in this study is the issue of the change in the Saudi stock market categorisation in 2017, which limited the sector testing to 8 years instead of 11 years. Moreover, this study looks at the pre-Covid-19 era, which might limit its applicability to the present and future due to underlying structural changes that investors and institutions have witnessed during the pandemic. The lack of research papers on the pre-holiday effect in the Middle East and GCC region further limited the comparison of results, which would have helped to fully understand the anomaly in this region of the world.

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# Chapter 5

# 5.1 Overall conclusion

This thesis critically analysed and explain a wide range of calendar-based anomalies in the US and sparsely researched Saudi market. This chapter will summarise the key findings of each research paper included in the thesis.

Chapter 2 covers four major calendar anomalies over an extended period of time, testing and analysing the effect of the 1952 change in the number of trading days per week from six to five. The data collected in this paper are average daily industry returns of the three largest stock markets in the world: NYSE, AMEX, and NASDAQ. The findings that the anomalies are present across almost all industries and that the effects are not limited to specific industries indicate that these calendar effects are driven by economic events affecting all industries, rather than by industry-specific factors. The change in weekly trading days after September 1952 only had an effect on the behaviour of the Halloween effect. Hence, we confirm the persistence of these three anomalies for all periods considered in our study. We find no Halloween effect in the pre-1952 sub-period, while a strong and statistically significant effect appears in the post-1952 sub-period.

Chapter 3 presents a comprehensive analysis of the well-known day-of-the-week effect in the emerging Saudi stock market (TASI) returns at industry level. The research investigated the existence of the day-of-the-week anomaly in 15 industries in the underexplored Saudi stock market. The research also explored the effect of shifting the weekend days to Friday and Saturday from Thursday and Friday in 2013 on the behaviour of the weekend effect. To the best of our knowledge, there is no previous study that has tested the effect of the change in weekend days in Saudi Arabia on the day-of-the-week anomaly. The results display strong evidence of the existence of the weekend anomaly at industry level before the changing of the weekend days (break point). Testing the period after changing the weekend days revealed that the anomaly had disappeared, providing evidence that the change in the weekend affected the anomaly. Moreover, since all industries demonstrated similar behaviour before and after the event of changing the weekend days, it can be confirmed that the anomaly is a market-wide phenomenon and not industry-specific.

Chapter 4 aims to explore the pre-holiday effect in the Saudi stock market (TASI) and whether religious holidays have a greater effect on the anomaly than non-religious holidays. All the official holidays in Saudi Arabia are tested in this paper: Eid al-Adha, Eid al-Fitr and the National Day holiday. As mentioned earlier, TASI is the largest stock market in its region, but there is no research on the pre-holiday effect on the Saudi stock market. The findings in this study confirm the existence of the pre-holiday effect at the general market and industry level for Eid al-Adha and Eid al-Fitr, which are the only religious holidays in Saudi Arabia. The National Day holiday, the only non-religious holiday, did not display any evidence of the existence of the pre-holiday anomaly, neither at general market nor industry level.

The presence of calendar anomalies was found in both US and Saudi markets, especially the day-of-the-week effect. However, testing for the change in the behaviour of the anomaly after the break point revealed that the anomaly disappeared in the Saudi market but continued in the US market. One of the explanations for this is that the study covering the US market included an extended period of time compared to the study covering the emerging Saudi market, due to the lack of data in the latter. The US data set dates back to 1926, therefore

allowing for early years, when the weekend effect was highly significant, to overturn recent years, when the weekend effect may have declined or even vanished. The data therefore showed an overall significance regarding the weekend effect after the event of changing trading days to five instead of six. Another explanation is that the type of change that happened in Saudi Arabia, making Friday, which is a religious day in Saudi Arabia, the first day of the weekend, resulted in the disappearance of the anomaly since investors' behaviour was altered – their religious routine of having a rest day to prepare for the holy Friday was changed. However, in the case of the US, the change of adding an extra day to the weekend before Sunday, which is considered a religious day, resulted in the presence and persistence of the anomaly.

Chapter 2 looked at four calendar anomalies, including two holiday-based effects, the January effect and Halloween effect. Comparing the results of these effects with the pre-holiday anomalies in the Saudi market researched in Chapter 4 revealed that the pre-holiday effect is present and persistent in both markets. However, non-religious holidays in Saudi Arabia proved to be insignificant. This could be due to the recent establishment of the holiday which was made public in 2007 and due to not all investors being adapted to celebrate the holiday.

Calendar anomalies evolve across time, as investors adjust their behaviour by becoming more aware and taking advantages of such anomalies. However, some anomalies continue to persist, like the January effect in the US and the pre-holiday effect in Saudi Arabia. There are various reasons for the occurrence of such anomalies. The settlement period suggested by Gibbons and Hess (1981) is one of the most discussed explanations for the weekend effect. It argues that stocks purchased on a certain day are not paid until several days later, resulting in the weekend effect. Lakonishok and Levi (1982) found that only 17 percent of the weekday anomaly can be explained by settlement periods, indicating that the evidence behind this anomaly is mixed. Moreover, despite the many existing explanations, the tax-loss-selling hypothesis seems to be the most accepted. This is where investors set off losses in their portfolios against gains in order to pay the lowest amount of tax on their overall income by selling small cap stocks at year end. The tax-loss-selling hypothesis could be a plausible explanation; however, it is responsible for only a small portion of the anomaly, as several studies have proven the existence of the January effect in countries that do not have capital gains tax, like Japan and Canada before 1972 (Rozeff, 1986; Kato and Schallheim, 1985; Schultz, 1985; Berges et.al, 1984; Reinganum, 1983; Roll, 1983). In addition, Thaler (1987) stated that the tax-loss-selling hypothesis cannot be the entire explanation, mentioning the example of the United Kingdom and Australia, where evidence of the January effect was found even though their tax year starts on 1 April and 1 July, respectively.

As investors become increasingly aware and benefit from calendar anomalies, they tend to gradually disappear. However, these anomalies continue to prove their persistence. One of the most used explanations for the weekend effect is the settlement period – this explanation also justifies the anomaly's persistence, since settlement periods are still present today. In markets like Saudi Arabia, where religion and culture have great influence on investors' behaviour, calendar anomalies persist as their existence is correlated with these beliefs. For example, the pre-holiday anomaly found around Eid al-Fitr could be explained by the joy investors are experiencing after the strenuous month of worship that precedes the holiday. As long as investors maintain these religious beliefs, the anomaly will continue to occur. This PhD thesis demonstrates that calendar anomalies reflect inefficiency within markets, whether mature or emerging. Some anomalies appear for a period of time and then disappear,

while others occur and continue to persist for different reasons that have been discussed in this thesis. This research could assist policymakers in several ways – for example, it is crucial to look at the kind of anomaly associated before changing or introducing holidays, as changes affect investors' behaviour and by extension the market. The main limitation for this research is the limited data regarding the Saudi stock market, since the industry classification was changed in 2017 due to constant developments in the Saudi economy, which resulted in new industries emerging.

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# 6 Appendix:

#### Sic codes for Industries:

# 1 Agric Agriculture

0100-0199 Agricultural production - crops

0200-0299 Agricultural production - livestock

0700-0799 Agricultural services

0910-0919 Commercial fishing

2048-2048 Prepared feeds for animals

#### 2 Food Food Products

2000-2009 Food and kindred products

2010-2019 Meat products

2020-2029 Dairy products

2030-2039 Canned & preserved fruits & vegetables

2040-2046 Flour and other grain mill products

2050-2059 Bakery products

2060-2063 Sugar and confectionery products

2070-2079 Fats and oils

2090-2092 Misc food preparations and kindred products

2095-2095 Roasted coffee

2098-2099 Misc food preparations

# 3 Soda Candy & Soda

2064-2068 Candy and other confectionery

2086-2086 Bottled-canned soft drinks

2087-2087 Flavoring syrup

2096-2096 Potato chips

2097-2097 Manufactured ice

# 4 Beer Beer & Liquor

2080-2080 Beverages

2082-2082 Malt beverages

2083-2083 Malt

2084-2084 Wine

2085-2085 Distilled and blended liquors

# 5 Smoke Tobacco Products

2100-2199 Tobacco products

#### 6 Toys Recreation

0920-0999 Fishing, hunting & trapping

3650-3651 Household audio visual equipment

3652-3652 Phonograph records

3732-3732 Boat building and repairing

3930-3931 Musical instruments

3940-3949 Toys

# 7 Fun Entertainment

7800-7829 Services - motion picture production and distribution

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7830-7833 Services - motion picture theaters
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7840-7841 Services - video rental

7900-7900 Services - amusement and recreation

7910-7911 Services - dance studios

7920-7929 Services - bands, entertainers

7930-7933 Services - bowling centers

7940-7949 Services - professional sports

7980-7980 Amusement and recreation services (?)

7990-7999 Services - Misc entertainment

# 8 Books Printing and Publishing

2700-2709 Printing publishing and allied

2710-2719 Newspapers: publishing-printing

2720-2729 Periodicals: publishing-printing

2730-2739 Books: publishing-printing

2740-2749 Misc publishing

2770-2771 Greeting card

2780-2789 Bookbinding

2790-2799 Service industries for the print trade

# 9 Hshld Consumer Goods

2047-2047 Dog and cat food

2391-2392 Curtains, home furnishings

2510-2519 Household furniture

2590-2599 Misc furniture and fixtures

2840-2843 Soap & other detergents

2844-2844 Perfumes, cosmetics and other toilet preparations

3160-3161 Luggage

3170-3171 Handbags and purses

3172-3172 Personal leather goods, except handbags and purses

3190-3199 Leather goods

3229-3229 Pressed and blown glass

3260-3260 Pottery and related products

3262-3263 China and earthenware table articles

3269-3269 Pottery products

3230-3231 Glass products

3630-3639 Household appliances

3750-3751 Motorcycles, bicycles and parts (Harley & Huffy)

3800-3800 Misc instruments, photo goods & watches

3860-3861 Photographic equipment (Kodak etc, but also Xerox)

3870-3873 Watches, clocks and parts

3910-3911 Jewelry, precious metals

3914-3914 Silverware

3915-3915 Jewelers' findings and materials

3960-3962 Costume jewelry and novelties

3991-3991 Brooms and brushes

3995-3995 Burial caskets

# 10 Clths Apparel

2300-2390 Apparel and other finished products

3020-3021 Rubber and plastics footwear

3100-3111 Leather tanning and finishing

3130-3131 Boot & shoe cut stock & findings

3140-3149 Footwear, except rubber

3150-3151 Leather gloves and mittens

3963-3965 Fasteners, buttons, needles, pins

#### 11 Hlth Healthcare

8000-8099 Services - health

# 12 MedEq Medical Equipment

3693-3693 X-ray, electromedical app

3840-3849 Surgical, medical, and dental instruments and supplies

3850-3851 Ophthalmic goods

#### 13 Drugs Pharmaceutical Products

2830-2830 Drugs

2831-2831 Biological products

2833-2833 Medicinal chemicals

2834-2834 Pharmaceutical preparations

2835-2835 In vitro, in vivo diagnostic substances

2836-2836 Biological products, except diagnostic substances

# 14 Chems Chemicals

2800-2809 Chemicals and allied products

2810-2819 Industrial inorganic chemicals

2820-2829 Plastic material & synthetic resin/rubber

2850-2859 Paints

2860-2869 Industrial organic chemicals

2870-2879 Agriculture chemicals

2890-2899 Misc chemical products

# 15 Rubbr Rubber and Plastic Products

3031-3031 Reclaimed rubber

3041-3041 Rubber & plastic hose & belting

3050-3053 Gaskets, hoses, etc

3060-3069 Fabricated rubber products

3070-3079 Misc rubber products (?)

3080-3089 Misc plastic products

3090-3099 Misc rubber and plastic products (?)

#### 16 Txtls Textiles

2200-2269 Textile mill products

2270-2279 Floor covering mills

2280-2284 Yarn and thread mills

2290-2295 Misc textile goods

2297-2297 Non-woven fabrics

2298-2298 Cordage and twine

2299-2299 Misc textile products

2393-2395 Textile bags, canvas products

# 2397-2399 Misc textile products

# 17 BldMt Construction Materials 0800-0899 Forestry 2400-2439 Lumber and wood products 2450-2459 Wood buildings & mobile homes 2490-2499 Misc wood products 2660-2661 Building paper and board mills 2950-2952 Paving & roofing materials 3200-3200 Stone, clay, glass, concrete, etc 3210-3211 Flat glass 3240-3241 Cement, hydraulic 3250-3259 Structural clay products 3261-3261 Vitreous china plumbing fixtures 3264-3264 Porcelain electrical supplies 3270-3275 Concrete, gypsum & plaster products 3280-3281 Cut stone and stone products 3290-3293 Abrasive and asbestos products 3295-3299 Misc nonmetallic mineral products 3420-3429 Cutlery, hand tools and general hardware 3430-3433 Heating equipment & plumbing fixtures 3440-3441 Fabricated structural metal products 3442-3442 Metal doors, frames 3446-3446 Architectural or ornamental metal work 3448-3448 Prefabricated metal buildings and components 3449-3449 Misc structural metal work 3450-3451 Screw machine products 3452-3452 Bolts, nuts, screws, rivets and washers 3490-3499 Misc fabricated metal products 3996-3996 Hard surface floor coverings

#### 18 Cnstr Construction

1500-1511 Build construction - general contractors 1520-1529 General building contractors - residential 1530-1539 Operative builders 1540-1549 General building contractors - non-residential 1600-1699 Heavy construction - not building contractors

1700-1799 Construction - special contractors

# 19 Steel Steel Works Etc

3300-3300 Primary metal industries
3310-3317 Blast furnaces & steel works
3320-3325 Iron & steel foundries
3330-3339 Primary smelting & refining of nonferrous metals
3340-3341 Secondary smelting & refining of nonferrous metals
3350-3357 Rolling, drawing & extruding of nonferrous metals
3360-3369 Nonferrous foundries and casting
3370-3379 Steel works etc
3390-3399 Misc primary metal products

#### 20 FabPr Fabricated Products

3400-3400 Fabricated metal, except machinery and trans eq

3443-3443 Fabricated plate work

3444-3444 Sheet metal work

3460-3469 Metal forgings and stampings

3470-3479 Coating, engraving and allied services

# 21 Mach Machinery

3510-3519 Engines & turbines

3520-3529 Farm and garden machinery and equipment

3530-3530 Construction, mining & material handling machinery & equipment

3531-3531 Construction machinery & equipment

3532-3532 Mining machinery & equipment, except oil field

3533-3533 Oil & gas field machinery & equipment

3534-3534 Elevators & moving stairways

3535-3535 Conveyors & conveying equipment

3536-3536 Cranes, hoists and monorail systems

3538-3538 Machinery

3540-3549 Metalworking machinery & equipment

3550-3559 Special industry machinery

3560-3569 General industrial machinery & equipment

3580-3580 Refrigeration & service industry machinery

3581-3581 Automatic vending machines

3582-3582 Commercial laundry and dry cleaning machines

3585-3585 Air conditioning, warm air heating and refrigeration equipment

3586-3586 Measuring and dispensing pumps

3589-3589 Service industry machinery

3590-3599 Misc industrial and commercial equipment and machinery

### 22 ElcEq Electrical Equipment

3600-3600 Electronic & other electrical equipment

3610-3613 Electric transmission and distribution equipment

3620-3621 Electrical industrial apparatus

3623-3629 Electrical industrial apparatus

3640-3644 Electric lighting & wiring equipment

3645-3645 Residential electric lighting fixtures

3646-3646 Commercial, industrial and institutional electric lighting fixtures

3648-3649 Misc lighting equipment

3660-3660 Communications equipment

3690-3690 Misc electrical machinery and equipment

3691-3692 Storage batteries

3699-3699 Misc electrical machinery, equipment and supplies

# 23 Autos Automobiles and Trucks

2296-2296 Tire cord and fabric

2396-2396 Automotive trimmings, apparel findings & related products

3010-3011 Tires and inner tubes

3537-3537 Industrial trucks, tractors, trailers & stackers

3647-3647 Vehicular lighting equipment

3694-3694 Electrical equipment for internal combustion engines

3700-3700 Transportation equipment

3710-3710 Motor vehicles and motor vehicle equipment

3711-3711 Motor vehicles & passenger car bodies

3713-3713 Truck & bus bodies

3714-3714 Motor vehicle parts & accessories

3715-3715 Truck trailers

3716-3716 Motor homes

3792-3792 Travel trailers and campers

3790-3791 Misc transportation equipment

3799-3799 Misc transportation equipment

# 24 Aero Aircraft

3720-3720 Aircraft & parts

3721-3721 Aircraft

3723-3724 Aircraft engines & engine parts

3725-3725 Aircraft parts

3728-3729 Misc aircraft parts & auxiliary equipment

# 25 Ships Shipbuilding, Railroad Equipment

3730-3731 Ship building and repairing

3740-3743 Railroad Equipment

### 26 Guns Defense

3760-3769 Guided missiles and space vehicles and parts

3795-3795 Tanks and tank components

3480-3489 Ordnance & accessories

#### 27 Gold Precious Metals

1040-1049 Gold & silver ores

# 28 Mines Non-Metallic and Industrial Metal Mining

1000-1009 Metal mining

1010-1019 Iron ores

1020-1029 Copper ores

1030-1039 Lead and zinc ores

1050-1059 Bauxite and other aluminum ores

1060-1069 Ferroalloy ores

1070-1079 Mining

1080-1089 Metal mining services

1090-1099 Misc metal ores

1100-1119 Anthracite mining

1400-1499 Mining and quarrying nonmetallic minerals

# 29 Coal Coal

1200-1299 Bituminous coal and lignite mining

#### 30 Oil Petroleum and Natural Gas

1300-1300 Oil and gas extraction

1310-1319 Crude petroleum & natural gas

1320-1329 Natural gas liquids

- 1330-1339 Petroleum and natural gas
- 1370-1379 Petroleum and natural gas
- 1380-1380 Oil and gas field services
- 1381-1381 Drilling oil & gas wells
- 1382-1382 Oil & gas field exploration services
- 1389-1389 Misc oil & gas field services
- 2900-2912 Petroleum refining
- 2990-2999 Misc products of petroleum & coal

#### 31 Util Utilities

- 4900-4900 Electric, gas & sanitary services
- 4910-4911 Electric services
- 4920-4922 Natural gas transmission
- 4923-4923 Natural gas transmission & distribution
- 4924-4925 Natural gas distribution
- 4930-4931 Electric and other services combined
- 4932-4932 Gas and other services combined
- 4939-4939 Misc combination utilities
- 4940-4942 Water supply

# 32 Telcm Communication

- 4800-4800 Communications
- 4810-4813 Telephone communications
- 4820-4822 Telegraph and other message communication
- 4830-4839 Radio & TV broadcasters
- 4840-4841 Cable and other pay TV services
- 4880-4889 Communications
- 4890-4890 Communication services (Comsat)
- 4891-4891 Cable TV operators
- 4892-4892 Telephone interconnect
- 4899-4899 Misc communication services

#### 33 PerSv Personal Services

- 7020-7021 Rooming and boarding houses
- 7030-7033 Camps and recreational vehicle parks
- 7200-7200 Services personal
- 7210-7212 Services laundry, cleaning & garment services
- 7214-7214 Services diaper service
- 7215-7216 Services coin-operated cleaners, dry cleaners
- 7217-7217 Services carpet & upholstery cleaning
- 7219-7219 Services Misc laundry & garment services
- 7220-7221 Services photographic studios, portrait
- 7230-7231 Services beauty shops
- 7240-7241 Services barber shops
- 7250-7251 Services shoe repair shops & shoeshine parlors
- 7260-7269 Services funeral service & crematories
- 7270-7290 Services Misc
- 7291-7291 Services tax return
- 7292-7299 Services Misc
- 7395-7395 Services photofinishing labs (School pictures)

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7500-7500 Services - auto repair, services & parking
      7520-7529 Services - automobile parking
      7530-7539 Services - automotive repair shops
      7540-7549 Services - automotive services, except repair (car washes)
      7600-7600 Services - Misc repair services
      7620-7620 Services - Electrical repair shops
      7622-7622 Services - Radio and TV repair shops
      7623-7623 Services - Refrigeration and air conditioning service & repair shops
      7629-7629 Services - Electrical & electronic repair shops
      7630-7631 Services - Watch, clock and jewelry repair
      7640-7641 Services - Reupholster & furniture repair
      7690-7699 Services - Misc repair shops & related services
      8100-8199 Services - legal
      8200-8299 Services - educational
      8300-8399 Services - social services
      8400-8499 Services - museums, art galleries, botanical and zoological gardens
      8600-8699 Services - membership organizations
      8800-8899 Services - private households
      7510-7515 Services - truck & auto rental and leasing
34 BusSv Business Services
      2750-2759 Commercial printing
      3993-3993 Signs & advertising specialties
      7218-7218 Services - industrial launderers
      7300-7300 Services - business services
      7310-7319 Services - advertising
      7320-7329 Services - consumer credit reporting agencies, collection services
      7330-7339 Services - mailing, reproduction, commercial art & photography
      7340-7342 Services - services to dwellings & other buildings
      7349-7349 Services - building cleaning & maintenance
      7350-7351 Services - Misc equipment rental and leasing
      7352-7352 Services - medical equipment rental and leasing
      7353-7353 Services - heavy construction equipment rental and leasing
      7359-7359 Services - equipment rental and leasing
      7360-7369 Services - personnel supply services
      7374-7374 Services - computer processing, data preparation and processing
      7376-7376 Services - computer facilities management service
      7377-7377 Services - computer rental and leasing
      7378-7378 Services - computer maintenance and repair
      7379-7379 Services - computer related services
      7380-7380 Services - Misc business services
      7381-7382 Services - security
      7383-7383 Services - news syndicates
      7384-7384 Services - photofinishing labs
      7385-7385 Services - telephone interconnect systems
      7389-7390 Services - Misc business services
      7391-7391 Services - R&D labs
      7392-7392 Services - management consulting & P.R.
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7393-7393 Services - detective and protective (ADT) 7394-7394 Services - equipment rental & leasing

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7396-7396 Services - trading stamp services
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7397-7397 Services - commercial testing labs

7399-7399 Services - business services

7519-7519 Services - utility trailer & recreational vehicle rental

8700-8700 Services - engineering, accounting, research, management

8710-8713 Services - engineering, accounting, surveying

8720-8721 Services - accounting, auditing, bookkeeping

8730-8734 Services - research, development, testing labs

8740-8748 Services - management, public relations, consulting

8900-8910 Services - Misc

8911-8911 Services - Misc engineering & architect

8920-8999 Services - Misc

4220-4229 Public warehousing and storage

# 35 Hardw Computers

3570-3579 Computer & office equipment

3680-3680 Computers

3681-3681 Computers - mini

3682-3682 Computers - mainframe

3683-3683 Computers - terminals

3684-3684 Computers - disk & tape drives

3685-3685 Computers - optical scanners

3686-3686 Computers - graphics

3687-3687 Computers - office automation systems

3688-3688 Computers - peripherals

3689-3689 Computers - equipment

3695-3695 Magnetic and optical recording media

# 36 Softw Computer Software

7370-7372 Services - computer programming and data processing

7375-7375 Services - information retrieval services

7373-7373 Computer integrated systems design

# 37 Chips Electronic Equipment

3622-3622 Industrial controls

3661-3661 Telephone and telegraph apparatus

3662-3662 Communications equipment

3663-3663 Radio & TV broadcasting & communications equipment

3664-3664 Search, navigation, guidance systems

3665-3665 Training equipment & simulators

3666-3666 Alarm & signaling products

3669-3669 Communication equipment

3670-3679 Electronic components & accessories

3810-3810 Search, detection, navigation, guidance, aeronautical & nautical systems, instruments & equipment

3812-3812 Search, detection, navigation, guidance, aeronautical & nautical systems & instruments

# 38 LabEq Measuring and Control Equipment

3811-3811 Engr laboratory and research equipment

3820-3820 Measuring and controlling equipment

3821-3821 Laboratory apparatus and furniture

3822-3822 Automatic controls for regulating residential & commercial environments & appliances

3823-3823 Industrial measurement instruments & related products

3824-3824 Totalizing fluid meters & counting devices

3825-3825 Instruments for measuring & testing of electricity & electrical instruments

3826-3826 Lab analytical instruments

3827-3827 Optical instruments and lenses

3829-3829 Misc measuring and controlling devices

3830-3839 Optical instruments and lenses

# 39 Paper Business Supplies

2520-2549 Office furniture and fixtures

2600-2639 Paper and allied products

2670-2699 Paper and allied products

2760-2761 Manifold business forms

3950-3955 Pens, pencils & other artists' supplies

# 40 Boxes Shipping Containers

2440-2449 Wood containers

2640-2659 Paperboard containers, boxes, drums, tubs

3220-3221 Glass containers

3410-3412 Metal cans and shipping containers

#### 41 Trans Transportation

4000-4013 Railroads, line-haul operating

4040-4049 Railway express service

4100-4100 Local & suburban transit & interurban highway passenger transportation

4110-4119 Local & suburban passenger transportation

4120-4121 Taxicabs

4130-4131 Intercity & rural bus transportation (Greyhound)

4140-4142 Bus charter service

4150-4151 School buses

4170-4173 Motor vehicle terminals & service facilities

4190-4199 Misc transit and passenger transportation

4200-4200 Trucking & warehousing

4210-4219 Trucking & courier services, except air

4230-4231 Terminal & joint terminal maintenance

4240-4249 Transportation

4400-4499 Water transport

4500-4599 Air transportation

4600-4699 Pipelines, except natural gas

4700-4700 Transportation services

4710-4712 Freight forwarding

4720-4729 Arrangement of passenger transportation

4730-4739 Arrangement of transportation of freight and cargo

4740-4749 Rental of railroad cars

4780-4780 Misc services incidental to transportation

4782-4782 Inspection and weighing services

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4783-4783 Packing and crating
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4784-4784 Misc fixed facilities for vehicles

4785-4785 Motor vehicle inspection

4789-4789 Misc transportation services

#### 42 Whlsl Wholesale

5000-5000 Wholesale - durable goods

5010-5015 Wholesale - automotive vehicles & automotive parts & supplies

5020-5023 Wholesale - furniture and home furnishings

5030-5039 Wholesale - lumber and construction materials

5040-5042 Wholesale - professional and commercial equipment and supplies

5043-5043 Wholesale - photographic equipment & supplies

5044-5044 Wholesale - office equipment

5045-5045 Wholesale - computers & peripheral equipment & software

5046-5046 Wholesale - commercial equipment

5047-5047 Wholesale - medical, dental & hospital equipment

5048-5048 Wholesale - ophthalmic goods

5049-5049 Wholesale - professional equipment and supplies

5050-5059 Wholesale - metals and minerals, except petroleum

5060-5060 Wholesale - electrical goods

5063-5063 Wholesale - electrical apparatus and equipment

5064-5064 Wholesale - electrical appliance, TV and radio sets

5065-5065 Wholesale - electronic parts & equipment

5070-5078 Wholesale - hardware, plumbing & heating equipment

5080-5080 Wholesale - machinery, equipment & supplies

5081-5081 Wholesale - machinery & equipment (?)

5082-5082 Wholesale - construction and mining machinery & equipment

5083-5083 Wholesale - farm and garden machinery & equipment

5084-5084 Wholesale - industrial machinery & equipment

5085-5085 Wholesale - industrial supplies

5086-5087 Wholesale - service establishment machinery & equipment (?)

5088-5088 Wholesale - transportation equipment, except motor vehicles

5090-5090 Wholesale - Misc durable goods

5091-5092 Wholesale - sporting goods & toys

5093-5093 Wholesale - scrap and waste materials

5094-5094 Wholesale - jewelry, watches, precious stones & metals

5099-5099 Wholesale - durable goods

5100-5100 Wholesale - nondurable goods

5110-5113 Wholesale - paper and paper products

5120-5122 Wholesale - drugs & drug proprietaries

5130-5139 Wholesale - apparel, piece goods & notions

5140-5149 Wholesale - groceries & related products

5150-5159 Wholesale - farm product raw materials

5160-5169 Wholesale - chemicals & allied products

5170-5172 Wholesale - petroleum and petroleum products

5180-5182 Wholesale - beer, wine & distilled alcoholic beverages

5190-5199 Wholesale - Misc nondurable goods

#### 43 Rtail Retail

5200-5200 Retail - retail-building materials, hardware, garden supply

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5210-5219 Retail - lumber & other building materials
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5220-5229 Retail

5230-5231 Retail - paint, glass & wallpaper stores

5250-5251 Retail - hardware stores

5260-5261 Retail - nurseries, lawn & garden supply stores

5270-5271 Retail - mobile home dealers

5300-5300 Retail - general merchandise stores

5310-5311 Retail - department stores

5320-5320 Retail - general merchandise stores (?)

5330-5331 Retail - variety stores

5334-5334 Retail - catalog showroom

5340-5349 Retail

5390-5399 Retail - Misc general merchandise stores

5400-5400 Retail - food stores

5410-5411 Retail - grocery stores

5412-5412 Retail - convenience stores

5420-5429 Retail - meat & fish markets

5430-5439 Retail - fruit and vegetable markets

5440-5449 Retail - candy, nut & confectionary stores

5450-5459 Retail - dairy products stores

5460-5469 Retail - bakeries

5490-5499 Retail - Misc food stores

5500-5500 Retail - automotive dealers and gas stations

5510-5529 Retail - automotive dealers

5530-5539 Retail - automotive and home supply stores

5540-5549 Retail - gasoline service stations

5550-5559 Retail - boat dealers

5560-5569 Retail - recreation vehicle dealers

5570-5579 Retail - motorcycle dealers

5590-5599 Retail - automotive dealers

5600-5699 Retail - apparel & accessory stores

5700-5700 Retail - home furniture and equipment stores

5710-5719 Retail - home furnishings stores

5720-5722 Retail - household appliance stores

5730-5733 Retail - radio, TV and consumer electronic stores

5734-5734 Retail - computer and computer software stores

5735-5735 Retail - record and tape stores

5736-5736 Retail - musical instrument stores

5750-5799 Retail

5900-5900 Retail - Misc

5910-5912 Retail - drug & proprietary stores

5920-5929 Retail - liquor stores

5930-5932 Retail - used merchandise stores

5940-5940 Retail - Misc

5941-5941 Retail - sporting goods stores & bike shops

5942-5942 Retail - book stores

5943-5943 Retail - stationery stores

5944-5944 Retail - jewelry stores

5945-5945 Retail - hobby, toy and game shops

5946-5946 Retail - camera and photographic supply stores

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5947-5947 Retail - gift, novelty & souvenir shops
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5948-5948 Retail - luggage & leather goods stores

5949-5949 Retail - sewing & needlework stores

5950-5959 Retail

5960-5969 Retail - non-store retailers (catalogs, etc)

5970-5979 Retail

5980-5989 Retail - fuel dealers & ice stores (Penn Central Co)

5990-5990 Retail - Misc retail stores

5992-5992 Retail - florists

5993-5993 Retail - tobacco stores and stands

5994-5994 Retail - newsdealers and news stands

5995-5995 Retail - optical goods stores

5999-5999 Misc retail stores

# 44 Meals Restaurants, Hotels, Motels

5800-5819 Retail - eating places

5820-5829 Restaurants, hotels, motels

5890-5899 Eating and drinking places

7000-7000 Hotels & other lodging places

7010-7019 Hotels & motels

7040-7049 Membership hotels and lodging houses

7213-7213 Services - linen supply

### 45 Banks Banking

6000-6000 Depository institutions

6010-6019 Federal reserve banks

6020-6020 Commercial banks

6021-6021 National commercial banks

6022-6022 State commercial banks - Fed Res System

6023-6024 State commercial banks - not Fed Res System

6025-6025 National commercial banks - Fed Res System

6026-6026 National commercial banks - not Fed Res System

6027-6027 National commercial banks, not FDIC

6028-6029 Misc commercial banks

6030-6036 Savings institutions

6040-6059 Banks (?)

6060-6062 Credit unions

6080-6082 Foreign banks

6090-6099 Functions related to depository banking

6100-6100 Non-depository credit institutions

6110-6111 Federal credit agencies

6112-6113 FNMA

6120-6129 S&Ls

6130-6139 Agricultural credit institutions

6140-6149 Personal credit institutions (Beneficial)

6150-6159 Business credit institutions

6160-6169 Mortgage bankers and brokers

6170-6179 Finance lessors

6190-6199 Financial services

#### 46 Insur Insurance

6300-6300 Insurance

6310-6319 Life insurance

6320-6329 Accident and health insurance

6330-6331 Fire, marine & casualty insurance

6350-6351 Surety insurance

6360-6361 Title insurance

6370-6379 Pension, health & welfare funds

6390-6399 Misc insurance carriers

6400-6411 Insurance agents, brokers & service

#### 47 RlEst Real Estate

6500-6500 Real estate

6510-6510 Real estate operators and lessors

6512-6512 Operators - non-resident buildings

6513-6513 Operators - apartment buildings

6514-6514 Operators - other than apartment

6515-6515 Operators - residential mobile home

6517-6519 Lessors of railroad & real property

6520-6529 Real estate

6530-6531 Real estate agents and managers

6532-6532 Real estate dealers

6540-6541 Title abstract offices

6550-6553 Land subdividers & developers

6590-6599 Real estate

6610-6611 Combined real estate, insurance, etc

# 48 Fin Trading

6200-6299 Security and commodity brokers, dealers, exchanges & services

6700-6700 Holding & other investment offices

6710-6719 Holding offices

6720-6722 Management investment offices, open-end

6723-6723 Management investment offices, closed-end

6724-6724 Unit investment trusts

6725-6725 Face-amount certificate offices

6726-6726 Unit investment trusts, closed-end

6730-6733 Trusts

6740-6779 Investment offices

6790-6791 Misc investing

6792-6792 Oil royalty traders

6793-6793 Commodity traders

6794-6794 Patent owners & lessors

6795-6795 Mineral royalty traders

6798-6798 REIT

6799-6799 Investors, NEC

# 49 Other Almost Nothing

4950-4959 Sanitary services

4960-4961 Steam & air conditioning supplies

4970-4971 Irrigation systems

# 4990-4991 Cogeneration - SM power producer <a href="#">Chapter 2:</a> <a href="#">Table 1 (Whole):</a>

Linear regress	sion			Number of F(5, 2415 Prob > F R-squared Root MSE	55)	= = = =	24,161 12.37 0.0000 0.0026 1.4916
agric	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
d2 d3 d4 d5 d6 _cons	.1151637 .2102919 .1433079 .2137972 .1960969 0975045	.0316482 .0326043 .0314951 .0310248 .0481384 .0230332	3.64 6.45 4.55 6.89 4.07 -4.23	0.000 0.000 0.000 0.000 0.000	.0531 .1463 .0815 .1529 .1017	854 756 867 426	.1771961 .2741983 .2050402 .2746077 .2904513 0523579
Linear regress	sion			Number of F(5, 2415 Prob > F R-squared Root MSE		= = = =	24,161 14.72 0.0000 0.0031 .91814
food	Coef.	Robust Std. Err.	t	P> t	[95% (	Conf.	Interval]
d2 d3 d4 d5 d6 _cons	.1031913 .1446052 .1211768 .1259133 .1692414 0594314	.0195998 .0201604 .019693 .0195723 .0258605 .0144581	5.26 7.17 6.15 6.43 6.54	0.000 0.000 0.000 0.000 0.000	.06477 .10508 .08257 .08755 .11855	396 772 504 533	.1416081 .1841209 .1597763 .1642761 .2199296
Linear regres	sion			Number of F(5, 2415 Prob > F R-squared Root MSE	55)	= = =	24,161 16.36 0.0000 0.0034 1.4526
beer	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
d2 d3 d4 d5 d6 _cons	.1364084 .2370783 .179511 .2181316 .257456 1060311	.0299641 .030733 .030708 .0302632 .0482209 .0216806	4.55 7.71 5.85 7.21 5.34 -4.89	0.000 0.000 0.000 0.000 0.000	.0776 .1768 .1193 .1588 .1629	397 213 138 401	.19514 .2973168 .2397007 .2774494 .351972 0635358

Linear regress	sion			Number	of obs =	24,161
				F(5, 24		2.13
				Prob >		0.0592
				R-squar		0.0004
				Root MS		1.1916
		Robust				
smoke	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.0262279	.0257036	1.02	0.308	0241528	. 0766087
d3	.0742997	.0264209	2.81	0.005	.0225131	.1260863
d4	.0445282	.0259349	1.72	0.086	0063058	.0953622
d5	.0268475	.0258217	1.04	0.298	0237646	.0774595
d6	.0705705	.0317128	2.23	0.026	.0084114	.1327296
_cons	.016338	.0192676	0.85	0.396	0214278	.0541037
Linear regress	sion			Number		24,161
				F(5, 24	155) =	14.00
				Prob >	F =	0.0000
				R-squar	ed =	0.0030
				Root MS	E =	2.1385
		Dahwat				
toys	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.0805001	0446020	1.80	0.072	0071007	.1681009
		.0446929				
d3	.2645383	.0448884	5.89	0.000	.1765543	.3525224
d4	.2197274	.0447548	4.91	0.000	.1320052	.3074497
d5	.2706758	.0443871	6.10	0.000	.1836744	.3576772
d6	.4074483	.0765739	5.32 -4.15	0.000	.2573587	.5575379 0700914
_cons	1328023	.0319943	-4.15	0.000	1955133	<b>-</b> . <b>0</b> / <b>0 0 9 1 2</b>
	l .					10700324
Linear regress	sion			Number	of obs =	
Linear regress	sion			Number F(5, 24		24,161
Linear regres	sion				155) =	24,161 19.69
Linear regres	sion			F(5, 24	155) = F =	24,163 19.69 0.000
Linear regress	sion			F(5, 24 Prob >	155) = F = ed =	24,161 19.69 0.0000 0.0044
Linear regress	sion	Pohust		F(5, 24 Prob > R-squar	155) = F = ed =	24,161 19.69 0.0000 0.0044
		Robust		F(5, 24 Prob > R-squar Root MS	155) = F = ed = E =	24,163 19.69 0.0006 0.0044 1.7922
Linear regress	coef.	Robust Std. Err.	t	F(5, 24 Prob > R-squar	155) = F = ed = E =	24,163 19.69 0.0006 0.0044 1.7922
			t 4.83	F(5, 24 Prob > R-squar Root MS	155) = F = ed = E =	24,161 19.69 0.0000 0.0044 1.7922
fun	Coef.	Std. Err.		F(5, 24 Prob > R-squar Root MS	155) = F = ed = E = E = E = E = E = E = E = E = E =	24,161 19.69 0.0000 0.0044 1.7922
fun d2	Coef. .1867242	.0386594	4.83	F(5, 24 Prob > R-squar Root MS P> t  0.000	155) = F = ed = E = E = E = E = E = E = E = E = E =	24,161 19.69 0.0006 0.0044 1.7922 Interval
fun d2 d3	Coef. .1867242 .33152	.0386594 .0396116	4.83	F(5, 24 Prob > R-squar Root MS P> t  0.000 0.000	155) = F = F = F = F = F = F = F = F = F =	24,161 19.69 0.0000 0.0044 1.7922 Interval] .2624991 .4091612 .3478435
fun d2 d3 d4	Coef. .1867242 .33152 .2714922	.0386594 .0396116 .0389535	4.83 8.37 6.97	F(5, 24 Prob > R-squar Root MS P> t  0.000 0.000	155) = F = F = F = F = F = F = F = F = F =	24,161 19.69 0.0000 0.0044 1.7922 

24,16	obs =	Number o			ion	Linear regress
16.2	55) =	F(5, 241				
0.000	=	Prob > F				
0.004	i =	R-square				
1.562	=	Root MSE				
Tadaa	[050 Canf	Do Late	_	Robust	Coof	haalia
Interval	[95% Conf.	P> t	t	Std. Err.	Coef.	books
.182112	.0521717	0.000	3.53	.0331471	.1171421	d2
.297974	.1621586	0.000	6.64	.0346459	.2300666	d3
.275262	.1436926	0.000	6.24	.0335626	.2094774	d4
.248848	.1221599	0.000	5.74	.0323176	.1855044	d5
.532617	.2966732	0.000	6.89	.0601879	.4146451	d6
0696	1674523	0.000	-4.75	.024959	1185311	_cons
24 161	aha -	Number of				linoon moonee
24,161		Number of			2 TOII	Linear regress
6.00		F(5, 2415				
0.0000	=	Prob > F				
0.0014	=	R-squared				
1.1581	=	Root MSE				
				Robust		
Interval]	[95% Conf.	P> t	t	Std. Err.	Coef.	hshld
.1345309	.0379583	0.000	3.50	.0246351	.0862446	d2
.1810249	.0798489	0.000	5.05	.0258094	.1304369	d3
.154861	.057754	0.000	4.29	.0247714	.1063075	d3
.1292113	.0346984	0.001	3.40	.0241097	.0819549	d5
.170311	.035201	0.003	2.98	.0344658	.102756	d6
0063669	0775906	0.021	-2.31	.0181687	0419788	_cons
24,16		Number o			sion	Linear regress
11.0	55) =	F(5, 241				
11.0 0.000	=	F(5, 241 Prob > F				
	=	F(5, 241				
0.000	=	F(5, 241 Prob > F				
0.000 0.002	= d =	F(5, 241 Prob > F R-square		Dobc+		
0.000 0.002 1.134	= = =	F(5, 241 Prob > F R-square Root MSE		Robust	- Court	-146-
0.000 0.002 1.134	= d =	F(5, 241 Prob > F R-square	t	Robust Std. Err.	Coef.	clths
0.000 0.002 1.134	= = =	F(5, 241 Prob > F R-square Root MSE	t 3.23		Coef.	clths d2
0.000 0.002 1.134	= d = = [95% Conf.	F(5, 241 Prob > F R-square Root MSE		Std. Err.		
0.000 0.002 1.134 Interval	= = = = = = = = = = = = = = = = = = =	F(5, 241 Prob > F R-square Root MSE P> t  0.001	3.23	Std. Err.	.0806604	d2
0.000 0.002 1.134 Interval .129583 .1945	[95% Conf. .031737	F(5, 241 Prob > F R-square Root MSE P> t  0.001 0.000	3.23 5.82	.0249601 .0250056	.0806604 .1455075	d2 d3
0.000 0.002 1.134 Interval .129583 .1945 .179179	[95% Conf. .031737 .0964951 .0820922	F(5, 241 Prob > F R-square Root MSE P> t  0.001 0.000 0.000	3.23 5.82 5.27	.0249601 .0250056 .0247663	.0806604 .1455075 .1306357	d2 d3 d4

d6 _cons	.2146693 0967419	.0396355	5.42 -4.70	0.000 0.000	.1369813	.2923574 0563961
d4 d5	.168078 .1861918	.0274641 .0272321	6.12 6.84	0.000 0.000	.1142467 .1328152	.2219092 .2395683
d3	.193995	.0281445	6.89	0.000	.13883	.2491601
d2	.1508576	.0274949	5.49	0.000	.0969658	.2047494
chems	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
				Root MSE	=	1.2699
				R-squared		0.0031
				Prob > F	=	0.0000
				F(5, 2415		13.42
Linear regress	sion			Number of		24,161
_cons	0633664	.0181634	-3.49	0.000	0989679	027765
d6	.1470797	.0323492	4.55	0.000	.0836733	.2104862
d5	.1328033	.0242099	5.49	0.000	.0853503	.1802563
d4	.1343539	.0243115	5.53	0.000	.0867017	.182006
d2 d3	.18336	.0250479	7.32	0.000	.1342645	.2324556
d2	.0983525	.0248366	3.96	0.000	.0496711	.1470338
drugs	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
				Root MSE	=	1.1366
				R-squared		0.0000
				Prob > F	= =	0.0000
Linear regres	sion			Number of F(5, 2415		24,161 12.17
_cons	0811981	.0209051	-3.88	0.000	1221734	0402228
d6	.2262413	.0458945	4.93	0.000	.1362852	.3161974
d5	.173466	.0375757	4.62	0.000	.0998152	.2471168
d4	.1539742	.0312105	4.93	0.000	.0927997	.2151487
d2 d3	.1069151	.0287769 .0294724	3.72 7.26	0.000 0.000	.0505105 .1561239	.1633198 .2716594
medeq	Coef.	Robust Std. Err.	t	P> t	IOE% Conf	Interval]
				Root MSE	=	1.5876
				R-squared	d =	0.0022
				Prob > F	=	0.0000
				F(5, 2415	55) =	12.97
Linear regress	sion			Number of	f obs =	24,161

Linear regres	sion			Number o		24,161
				F(5, 241	55) =	24.29
				Prob > F	=	0.0000
				R-square	d =	0.0050
				Root MSE	=	1.3033
	1					
		Robust				
txtls	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval]
d2	.1195861	.0277441	4.31	0.000	.065206	.1739663
d3	.1923209	.028387	6.77	0.000	.1366805	.2479612
d4	.2363866	.0282314	8.37	0.000	.1810513	.2917219
d5	.2074218	.0283665	7.31	0.000	.1518216	.263022
d6	.352334	.0392012	8.99	0.000	.2754973	.4291707
_cons	1205551	.020842	-5.78	0.000	1614067	0797034
	•					
Linear regres	sion			Number of	f obs =	24,161
				F(5, 241	55) =	17.61
				Prob > F	=	0.0000
				R-square	= t	0.0040
				Root MSE	=	1.2455
		Robust				
bldmt	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.1279384	.026754	4.78	0.000	.075499	.1803779
d3	.2124852	.0278504	7.63	0.000	.1578966	.2670738
d4	.1850952	.0271697	6.81	0.000	.1318408	.2383495
d5	.1883093	.0268481	7.01	0.000	.1356855	.2409332
d6	.2683201	.0384623	6.98	0.000	.1929315	.3437087
_cons	1070939	.0203485	-5.26	0.000	1469783	0672094
Linear regres	sion			Number of		24,161
				F(5, 2415	5) =	23.35
				Prob > F	=	0.0000
				R-squared	=	0.0054
				Root MSE	=	1.9941
		Robust				
cnstr	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.2494109	.041404	6.02	0.000	.1682565	.3305652
d3	.3559777	.0430341	8.27	0.000	.2716281	.4403272
d4	.3386098	.0422118	8.02	0.000	.2558721	.4213476
d5	.3183668	.0413364	7.70	0.000	.2373449	.3993886
d6	.6057309	.0776007	7.81	0.000	.4536287	.757833
_cons	2232265	.0307359	-7.26		2834709	1629822

Linear r	regress	sion			Number o		,
					F(5, 241		
					Prob > F		0.000
					R-square		
					Root MSE	=	1.663
			Robust				
s	steel	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval]
	d2	. 2217327	.0364601	6.08	0.000	.1502686	.2931967
	d3	.2816226	.0364097	7.73	0.000	.2102572	.3529879
	d4	.2191878	.0357885	6.12	0.000	.1490401	.2893355
	d5	.3031138	.0352237	8.61	0.000	.2340731	.3721545
	d6	.4352011	.0483523	9.00	0.000	.3404277	.5299746
_	cons	1773082	.0265688	-6.67	0.000	2293848	1252316
Linear r	regres	sion			Number o		= 24,16:
					F(5, 241		= 14.90
					Prob > F	:	= 0.0000
					R-square	ed :	= 0.003
					Root MSE	:	= 1.364
			Robust				
	mach	Coef.	Std. Err.	t	P> t	[95% Con	f. Interval
	d2	.1370745	.0292332	4.69	0.000	.0797758	.1943733
	d3	.2148907	.0305184	7.04	0.000	.1550728	.274708
	d4	.1825512	.0292453	6.24	0.000	.1252285	.239873
	d5	.2034636	.0293451	6.93	0.000	.1459454	.260981
	d6	.2496645	.0399436	6.25	0.000	.1713726	.327956
-	_cons	1074797	.0219441	-4.90	0.000	1504916	064467
Linear r	enress	sion			Number o	f obs =	= 24,161
Linear 1	cgicos	, 1011			F(5, 241		
					Prob > F		
					R-square		
					Root MSE	=	1.5528
			Robust				
e	lceq	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval]
	d2	.2051813	.0328299	6.25	0.000	.1408328	. 2695299
	d3	.2506565	.0339986	7.37	0.000	.1840171	.317296
	d4	.1987519	.033083	6.01	0.000	.1339073	.2635966
	d5	.2166868	.0331809	6.53	0.000	.1516502	.2817233
	d6	.3299561	.052456	6.29	0.000	.2271391	. 4327731
_	cons	1307333	.0245467	-5.33	0.000	1788463	0826203
	cons	1307333	.0245467	-5.33	0.000	1/88463	08262

Linear regress	sion			Number of	obs =	24,161
				F(5, 2415	5) =	10.93
				Prob > F	=	0.0000
				R-squared	=	0.0024
				Root MSE	=	1.5666
		Robust				
autos	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.1514522	.0337347	4.49	0.000	.0853301	.2175742
d3	.2043239	.034725	5.88	0.000	.1362608	.272387
d4	.1318763	.0335969	3.93	0.000	.0660243	.1977283
d5	.160779	.0332443	4.84	0.000	.0956182	.2259398
d6	.3080567	.0499872	6.16	0.000	.2100786	.4060347
_cons	0916922	.0250959	-3.65	0.000	1408818	0425027
Linear regress	s i o n			Number of	obs =	24,161
Linear regress	51011			F(5, 2415		13.53
				Prob > F	=	0.0000
				R-squared		0.0030
				Root MSE	=	1.7757
				ROOL MSE	-	1.7757
		Robust				
aero	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.1933094	.0379108	5.10	0.000	.1190018	.267617
d3	.2605976	.0382561	6.81	0.000	.1856132	.3355819
d4	. 2225885	.0371741	5.99	0.000	.1497248	.2954521
d5	. 2556215	.0372006	6.87	0.000	.1827059	.328537
d6	.3314444	.068026	4.87	0.000	.1981092	. 4647797
_cons	1326534	. 0277278	-4.78	0.000	1870017	0783051
linear regress	cion			Number of	obs -	24 161
Linear regres	21011			Number of F(5, 2415		24,161
						17.42
				Prob > F	=	0.0000
				R-squared		0.0037
				Root MSE	=	1.5061
		Robust				
ships	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.1544292	.0324006	4.77	0.000	.0909221	.2179364
d3	.2220261	.0329372	6.74	0.000	.1574671	.286585
d4	.2149194	.0319437	6.73	0.000	.1523078	.2775309
d5	.2272241	.0323036	7.03	0.000	.1639071	.2905411
d6	.3554378	.047645	7.46	0.000	.2620507	.4488249
_cons	1307401	.023892	-5.47	0.000	1775698	0839103

Linear regre	ession			Number	of obs	= 24,16
				F(5, 24	155)	= 13.5
				Prob >		= 0.000
				R-squar		= 0.003
				Root MS		= 1.522
		Robust				
mines	Coef.	Std. Err.	t	P> t	[95% Co	nf. Interval
d2	.1171344	.0330209	3.55	0.000	.052411	4 .181857
d3	.2189762	.0338545	6.47	0.000	.152619	3 .285333
d4	.1975763	.032962	5.99	0.000	.132968	6 .262183
d5	.2195071	.0322007	6.82	0.000	.156391	8 .282622
d6	.2344079	.0451371	5.19	0.000	.145936	3 .322879
_cons	1107378	.0244992	-4.52	0.000	158757	8062717
				Northern	-6 -1-	24.4
Linear regre	ession				of obs	= 24,10
				F(5, 2		= 14.8
				Prob >		= 0.000
				R-squa		= 0.003
				Root M	SE	= 2.110
		Robust				
coa	Coef.	Std. Err.	t	P> t	[95% Cd	onf. Interva
d	.1375769	.0452519	3.04	0.002	.048886	. 22627
d:	.2947305	.0465501	6.33	0.000	.203489	34 .38597
d4	.2385575	.0455247	5.24	0.000	.149326	33 .327788
d!	.3138163	.0446466	7.03	0.000	.226306	.40132
d	.3760986	.0634562	5.93	0.000	. 251726	.50047
_con:	161444	.0335304	-4.81	0.000	227165	57095722
Linear regre	ession			Number	of obs	= 24,16
				F(5, 24	155)	= 17.47
				Prob >	F	= 0.000
				R-squar	ed	= 0.0038
				Root MS	E	= 1.277
		Robust				
oi	Coef.	Std. Err.	t	P> t	[95% Co	nf. Interval
d	.1597631	.0279644	5.71	0.000	.10495	1 .214575
d:	.2219957	.0285372	7.78	0.000	.1660609	9 .2779304
d4	.1750175	.0278607	6.28	0.000	.1204089	9 .2296262
الم	.2034179	.0271975	7.48	0.000	.150109	.256726
d!						
d:		.0346108	7.37	0.000	. 187383	4 .323062

Linear regress	sion			Number		=	24,161
				F(5, 24	155)	=	11.62
				Prob >		=	0.0000
				R-squar		=	0.0025
				Root MS	E	=	1.0864
		Robust					
util	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
d2	.0753498	.0227298	3.32	0.001	.03	<b>0798</b>	.1199016
d3	.1245198	.0234559	5.31	0.000	.078	5448	.1704948
d4	.1216401	.0231448	5.26	0.000	.076	2749	.1670053
d5	.1349912	.023024	5.86	0.000	.089	8629	.1801196
d6	.2126848	.0375096	5.67	0.000	.139	1636	.286206
_cons	0594292	.0168768	-3.52	0.000	092	5087	0263496
incom				Number	of obo		24 161
Linear regress	510N				of obs	=	24,161
				F(5, 2		=	6.10
				Prob >		=	0.0000
				R-squa		=	0.0014
				Root M	SE	=	1.0237
		Robust					
telcm	Coef.	Std. Err.	t	P> t	[959	conf.	Interval]
d2	.0773882	.0225766	3.43	0.001	.033	31366	.1216397
d3	.0947997	.0230665	4.11	0.000	. 04	19588	.1400114
d4	.0865163	.0222067	3.90	0.000	. 042	29898	.1300427
d5	.1016098	.0217386	4.67	0.000	. 059	90007	.1442189
d6	.132189	.0302685	4.37	0.000	. 072	28609	. 1915171
_cons	0362477	.0168182	-2.16	0.031	069	2125	003283
Linear regress	sion			Number	of obs	=	24,161
				F(5, 24	155)	=	9.86
				Prob >	F	=	0.0000
				R-squar	ed	=	0.0018
				Root MS	Ε	=	1.9586
		Robust					
bussv	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
d2	.1058926	.0387773	2.73	0.006	.029	8867	.1818985
d3	.2148356	.0396225	5.42	0.000	. 137	1729	.2924982
d4	.1943372	.0377985	5.14	0.000	.120	2497	.2684247
	2000027	.0375854	5.58	0.000	.13	6214	.2835533
d5	.2098837						
d5 d6	.2479905	.0856642	2.89	0.004		0833	.4158977

linoar roaros	-ion			Number o	f obs	24 161
Linear regress	21011			F(5, 241		24,161 4.53
				Prob > F		0.0004
						0.0010
				R-square Root MSE		1.5256
				KOOL MSE	-	1.5250
		Robust				
hardw	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.0805702	.0331525	2.43	0.015	.0155891	.1455512
d3	. 1511771	.0336966	4.49	0.000	.0851296	.2172246
d4	.104773	.0328816	3.19	0.001	.040323	.1692229
d5	.078501	.0320029	2.45	0.014	.0157733	.1412287
d6	.1228871	.0394143	3.12	0.002	.0456327	.2001415
_cons	0308145	.0241013	-1.28	0.201	0780546	.0164256
					_	
Linear regress	sion			Number		24,161
				F(5, 24		10.30
				Prob >		0.000
				R-squar		0.0022
				Root MS	E =	1.7462
		Robust				
chips	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval
d2	.1170928	.036659	3.19	0.001	.0452388	.1889468
d3	. 2334827	.0377196	6.19	0.000	.1595499	.3074156
d4	. 1734445	.0372244	4.66	0.000	.1004823	.2464067
d5	.1608488	.03629	4.43	0.000	.0897181	.231979
d6	.2847519	.0558279	5.10	0.000	.1753258	.394178
_cons	0938538	.0267055	-3.51	0.000	1461982	0415094
Linear regress	sion			Number		24,16
				F(5, 24	155) =	8.34
				Prob >	F =	0.000
				R-squar		0.0019
				Root MS	E =	1.420
		Robust				
labeq	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval
	.1042557	.0307203	3.39	0.001	.0440419	.1644694
d2			5.71	0.000	.1175012	.2404264
d2 d3	.1789638	.0313575	3.71			
		.0313575 .0308488	4.17	0.000	.0682186	.1891497
d3	.1789638				.0682186 .1036965	
d3 d4	.1789638 .1286841	.0308488	4.17	0.000		.1891497 .2241365 .2472917

Linear regr	ession			Number of	obs =	24,161
Linear regio	C331011			F(5, 2415		13.21
				Prob > F	=	0.0000
				R-squared	=	0.0030
				Root MSE	=	1.2487
		Robust				
boxe	s Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d	2 .1379935	.027121	5.09	0.000	.0848345	.1911524
d:	.196309	.0274539	7.15	0.000	.1424977	.2501203
d-	4 .1681345	.0272761	6.16	0.000	.1146716	.2215973
d!	5 <b>.1820702</b>	.0269141	6.76	0.000	.1293168	.2348235
d	6 .1750993	.0363284	4.82	0.000	.1038934	.2463053
_con:	0918005	.0202541	-4.53	0.000	1314999	0521012
Linoan roam	accion.			Number of	obs -	24 161
Linear regre	2551011					24,161 27.27
				F(5, 24155 Prob > F		0.0000
					=	
				R-squared	=	0.0062
				Root MSE	=	1.3417
		Robust				
trans	Coef.	Std. Err.	t	P> t	[95% Conf.	<pre>Interval]</pre>
d2	.2015433	.0288456	6.99	0.000	.1450041	.2580825
d3	.2909093	.0295735	9.84	0.000	.2329434	.3488751
d4	.2559856	.0289087	8.85	0.000	.1993228	.3126484
d:	.2617348	.028803	9.09	0.000	.2052791	.3181904
d€	.3433817	.0427851	8.03	0.000	.2595202	.4272431
_cons	1701692	.0215926	-7.88	0.000	212492	1278464
				Northanas	-1	24.46
Linear regre	:551011			Number of		24,161
				F(5, 2415		15.13
				Prob > F	=	0.0000
				R-squared	=	0.0033
				Root MSE	=	1.6521
		Robust				
whlsl	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.1481299	.0336246	4.41	0.000	.0822236	.2140362
d3	.2336233	.0359115	6.51	0.000	.1632346	.304012
d4		.0348758	6.01	0.000	.1410917	.277809
d5		.03147	6.68	0.000	.1486851	.2720513
d6		.0646441	5.97	0.000	.2592337	.5126466
_cons		.0241165	-5.52	0.000	180343	0858032

Linear reg	ress	ion			Number of	obs =	24,161
	,				F(5, 2415		15.27
					Prob > F	= ,	0.0006
					R-squared		0.0034
					Root MSE	=	1.1287
			Robust				
rta	ail	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
	d2	.1185486	.0245017	4.84	0.000	.0705237	.1665736
	d3	.1853876	.0248238	7.47	0.000	.1367314	. 2340438
	d4	.1659112	.0245062	6.77	0.000	.1178775	.2139449
	d5	.1556722	.0241452	6.45	0.000	.1083461	.2029982
	d6	.204177	.0333906	6.11	0.000	.1387293	. 2696247
co	ons	0842893	.0181871	-4.63	0.000	119937	0486415
linoon noo		ion			Number of	aha -	24 161
Linear reg	ress	1011			Number of		24,161
					F(5, 24155		14.75
					Prob > F	=	0.0000
					R-squared Root MSE	=	0.0033
					ROOT MSE	=	1.331
			Robust				
mea	als	Coef.	Std. Err.	t	P> t	[95% Conf.	<pre>Interval]</pre>
	d2	.0870639	.0285577	3.05	0.002	.031089	.1430388
	d3	.1854966	.0296734	6.25	0.000	.127335	.2436583
	d4	.1859025	.0287387	6.47	0.000	.129573	.2422321
	d5	.1744028	.0284995	6.12	0.000	.118542	.2302637
	d6	.2586368	.044078	5.87	0.000	.1722413	.3450324
co	ons	0862793	.0216036	-3.99	0.000 -	. 1286237	0439349
Linear reg	ıress	ion			Number of	obs =	24,161
Linear reg	,,,,,,,	2011			F(5, 24155		10.22
					Prob > F	=	0.0000
					R-squared	=	0.0023
					Root MSE	=	1.4713
			Robust				
ban	ıks	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
	d2	.1455473	.0318782	4.57	0.000	.0830641	.2080305
	d3	.2027404	.0323522	6.27	0.000	.1393281	.2661527
	d4	.1750056	.0316514	5.53	0.000	.1129669	.2370443
	d5	.1671843	.0307162	5.44	0.000	.1069787	. 22739
							2257472
	d6	.2254586 0913222	.0511456	4.41	0.000 0.000	.1252101	.3257072

Linear re	egres	sion			Number of F(5, 2415		
					Prob > F	=	
					R-squared	l =	
					Root MSE	=	
		<u> </u>	Robust				
iı	nsur	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval
	d2	.1298983	.0293316	4.43	0.000	.0724064	.187390
	d3	.1639052	.0296177	5.53	0.000	.1058527	.221957
	d4	.1752539	.0299639	5.85	0.000	.1165227	. 233985
	d5	.1824904	.0288018	6.34	0.000	.1260372	. 238943
	d6	.1967194	.0464395	4.24	0.000	.1056951	. 287743
	cons	0894224	.0218877	-4.09	0.000	1323236	046521
	a n c c -				Number of	aha -	24 161
Linear re	gress	1011			Number of		24,161
					F(5, 24155		23.11
					Prob > F	=	0.0000
					R-squared	=	0.0053
					Root MSE	=	2.1249
			Robust				
rl	est	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
	d2	.1180534	.0435555	2.71	0.007	.0326819	.2034248
	d3	.3156198	.0463073	6.82	0.000	.2248546	.4063851
	d4	.2803491	.0453418	6.18	0.000	.1914762	.3692219
	d5	.3637507	.043558	8.35	0.000	.2783744	.449127
	d6	.6036602	.0904218	6.68	0.000	.4264278	.7808927
_c	ons	1980212	.0330687	-5.99	0.000 -	.2628379	1332045
.i	~ ~ ~ ~ ~	ion			Number of	aha -	24 161
_inear re	gress	1011			Number of		24,161
					F(5, 2415		20.68
					Prob > F	=	0.0000
					R-squared	=	0.0046
					Root MSE	=	1.566
			Robust				
	fin	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval]
	d2	.2050992	.0333862	6.14	0.000	.1396601	. 2705383
	d3	.2756688	.0345703	7.97	0.000	.207909	. 3434287
	d4	.2718206	.0338947	8.02	0.000	.2053848	.3382563
	d5	.2806954	.0333564	8.42	0.000	.2153147	.3460761
	46	2256742	0400467	6 04	0 000	2205207	4210007
	d6	.3356742	.0490467	6.84	0.000	.2395397	.4318087

# Table 1 Pre:

Linear regress	ion			Number of	obs =	7,696
				F(5, 7690		4.47
				Prob > F	=	0.0005
				R-squared	=	0.0029
				Root MSE	=	1.7069
						217000
		Robust				
agric	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.2407701	.067977	3.54	0.000	.1075166	.3740236
d3	.2835044	.0712064	3.98	0.000	.1439205	.4230883
d4	.2018002	.0663406	3.04	0.002	.0717545	.3318459
d5	.1755788	.0658918	2.66	0.008	.046413	.3047446
d6	.2491636	.0635313	3.92	0.000	.124625	.3737022
_cons	1505712	.0474183	-3.18	0.002	243524	0576184
Linear regres	sion			Number o		7,696
				F(5, 769		8.98
				Prob > F		0.0000
				R-square		0.0052
				Root MSE	=	1.0775
		Daharat				
<b>6</b> 1	6	Robust		D. 1+1	[050 6	T-+11
food	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval]
d2	.1209761	.0437233	2.77	0.006	.0352666	.2066857
d3	.2109664	.0464952	4.54	0.000	.1198232	.2066857 .3021096
d3 d4	.2109664 .1962436	.0464952 .0425299	4.54 4.61	0.000 0.000	.1198232 .1128734	.3021096 .2796138
d3	.2109664	.0464952	4.54	0.000	.1198232	.3021096
d3 d4	.2109664 .1962436	.0464952 .0425299	4.54 4.61	0.000 0.000	.1198232 .1128734	.3021096 .2796138
d3 d4 d5	.2109664 .1962436 .1746558	.0464952 .0425299 .0429106	4.54 4.61 4.07	0.000 0.000 0.000	.1198232 .1128734 .0905394	.3021096 .2796138 .2587723
d3 d4 d5 d6 _cons	.2109664 .1962436 .1746558 .2375956 1277856	.0464952 .0425299 .0429106 .037633	4.54 4.61 4.07 6.31	0.000 0.000 0.000 0.000 0.000	.1198232 .1128734 .0905394 .1638246 1884045	.3021096 .2796138 .2587723 .3113666 0671667
d3 d4 d5 d6 _cons	.2109664 .1962436 .1746558 .2375956 1277856	.0464952 .0425299 .0429106 .037633	4.54 4.61 4.07 6.31	0.000 0.000 0.000 0.000 0.000	.1198232 .1128734 .0905394 .1638246 1884045	.3021096 .2796138 .2587723 .3113666 0671667
d3 d4 d5 d6 _cons	.2109664 .1962436 .1746558 .2375956 1277856	.0464952 .0425299 .0429106 .037633	4.54 4.61 4.07 6.31	0.000 0.000 0.000 0.000 Number o	.1198232 .1128734 .0905394 .1638246 1884045	.3021096 .2796138 .2587723 .3113666 0671667
d3 d4 d5 d6 _cons	.2109664 .1962436 .1746558 .2375956 1277856	.0464952 .0425299 .0429106 .037633	4.54 4.61 4.07 6.31	0.000 0.000 0.000 0.000 Number o F(5, 769 Prob > F	.1198232 .1128734 .0905394 .1638246 1884045	.3021096 .2796138 .2587723 .3113666 0671667 7,696 8.22 0.0000
d3 d4 d5 d6 _cons	.2109664 .1962436 .1746558 .2375956 1277856	.0464952 .0425299 .0429106 .037633	4.54 4.61 4.07 6.31	0.000 0.000 0.000 0.000 Number o F(5, 769 Prob > F R-square	.1198232 .1128734 .0905394 .1638246 1884045	.3021096 .2796138 .2587723 .3113666 0671667 7,696 8.22 0.0000 0.0051
d3 d4 d5 d6 _cons	.2109664 .1962436 .1746558 .2375956 1277856	.0464952 .0425299 .0429106 .037633	4.54 4.61 4.07 6.31	0.000 0.000 0.000 0.000 Number o F(5, 769 Prob > F	.1198232 .1128734 .0905394 .1638246 1884045	.3021096 .2796138 .2587723 .3113666 0671667 7,696 8.22 0.0000
d3 d4 d5 d6	.2109664 .1962436 .1746558 .2375956 1277856	.0464952 .0425299 .0429106 .037633 .0309237	4.54 4.61 4.07 6.31	0.000 0.000 0.000 0.000 Number o F(5, 769 Prob > F R-square	.1198232 .1128734 .0905394 .1638246 1884045	.3021096 .2796138 .2587723 .3113666 0671667 7,696 8.22 0.0000 0.0051
d3 d4 d5 d6 _cons	.2109664 .1962436 .1746558 .2375956 1277856	.0464952 .0425299 .0429106 .037633	4.54 4.61 4.07 6.31	0.000 0.000 0.000 0.000 Number o F(5, 769 Prob > F R-square	.1198232 .1128734 .0905394 .1638246 1884045 f obs = 0) = = = = = = = = = = = = = = = = =	.3021096 .2796138 .2587723 .3113666 0671667 7,696 8.22 0.0000 0.0051
d3 d4 d5 d6 _cons	.2109664 .1962436 .1746558 .2375956 1277856	.0464952 .0425299 .0429106 .037633 .0309237	4.54 4.61 4.07 6.31 -4.13	0.000 0.000 0.000 0.000 Number o F(5, 769 Prob > F R-square Root MSE	.1198232 .1128734 .0905394 .1638246 1884045 f obs = 0) = d = = = = = = = = = = = = = = = = =	.3021096 .2796138 .2587723 .3113666 0671667 7,696 8.22 0.0000 0.0051 2.0523
d3 d4 d5 d6 _cons Linear regres	.2109664 .1962436 .1746558 .2375956 1277856	.0464952 .0425299 .0429106 .037633 .0309237 Robust Std. Err.	4.54 4.61 4.07 6.31 -4.13	0.000 0.000 0.000 0.000 Number of F(5, 769 Prob > FR-square Root MSE	.1198232 .1128734 .0905394 .1638246 1884045 If obs = 0) = 000 =	.3021096 .2796138 .2587723 .3113666 0671667 7,696 8.22 0.0000 0.0051 2.0523
d3 d4 d5 d6 _cons  Linear regress beer d2 d3	.2109664 .1962436 .1746558 .2375956 1277856 sion Coef. .2309775 .430338	.0464952 .0425299 .0429106 .037633 .0309237 Robust Std. Err. .0810282 .0833537	4.54 4.61 4.07 6.31 -4.13	0.000 0.000 0.000 0.000 Number o F(5, 769 Prob > F R-square Root MSE P> t  0.004 0.000	.1198232 .1128734 .0905394 .1638246 1884045 f obs = 0) = = d = = = = = = = = = = = = = = = =	.3021096 .2796138 .2587723 .3113666 0671667 7,696 8.22 0.0000 0.0051 2.0523 . Interval]
d3 d4 d5 d6 _cons Linear regress beer d2 d3 d4	.2109664 .1962436 .1746558 .2375956 1277856 sion Coef. .2309775 .430338 .351452	Robust Std. Err.  .0810282 .0833537 .0829209	4.54 4.61 4.07 6.31 -4.13	0.000 0.000 0.000 0.000 0.000 Number o F(5, 769 Prob > F R-square Root MSE P> t  0.004 0.000 0.000	.1198232 .1128734 .0905394 .1638246 1884045 f obs = 0) = = = = = = = = = = = = = = = = =	.3021096 .2796138 .2587723 .3113666 0671667 7,696 8.22 0.0000 0.0051 2.0523 . Interval] .3898149 .5937339 .5139997
d3 d4 d5 d6 _cons  Linear regress d2 d3 d4 d5	.2109664 .1962436 .1746558 .2375956 1277856 sion Coef. .2309775 .430338 .351452 .3845818	Robust Std. Err.  .0810282 .0833537 .0829209 .0819071	4.54 4.61 4.07 6.31 -4.13 t 2.85 5.16 4.24 4.70	0.000 0.000 0.000 0.000 0.000 Number of 5, 769 Prob > FR-square Root MSE P> t  0.004 0.000 0.000	.1198232 .1128734 .0905394 .1638246 1884045 f obs = 000 =	.3021096 .2796138 .2587723 .3113666 0671667 7,696 8.22 0.0000 0.0051 2.0523 . Interval]
d3 d4 d5 d6 _cons  Linear regress  beer d2 d3 d4	.2109664 .1962436 .1746558 .2375956 1277856 sion Coef. .2309775 .430338 .351452	Robust Std. Err.  .0810282 .0833537 .0829209	4.54 4.61 4.07 6.31 -4.13	0.000 0.000 0.000 0.000 0.000 Number o F(5, 769 Prob > F R-square Root MSE P> t  0.004 0.000 0.000	.1198232 .1128734 .0905394 .1638246 1884045 f obs = 0) = = = = = = = = = = = = = = = = =	.3021096 .2796138 .2587723 .3113666 0671667 7,696 8.22 0.0000 0.0051 2.0523 . Interval] .3898149 .5937339 .5139997

Linear regress	sion			Number		=	7,696
				F(5, 76		=	6.76
				Prob >		=	0.0000
				R-squar	ed	=	0.0044
				Root MS	E	=	. 952
		Robust					
smoke	Coef.	Std. Err.	t	P> t	[95% C	onf.	Interval]
d2	.0807414	.0376632	2.14	0.032	.00691	12	.1545716
d3	.1607273	.0394041	4.08	0.000	.08348	47	. 23797
d4	.1673874	.0375902	4.45	0.000	.09370	04	.2410745
d5	.1360439	.0373591	3.64	0.000	.062809	99	.209278
d6	.1830822	.0369974	4.95	0.000	.11055	73	.2556071
_cons	0961737	.0270925	-3.55	0.000	14928	24	043065
Linear regress	sion			Number		=	7,696
				F(5, 76		=	8.22
				Prob >		=	0.0000
				R-squar	ed	=	0.0050
				Root MS	E	=	3.0957
		Robust					
toys	Coef.	Std. Err.	t	P> t	[95% C	onf.	Interval]
d2	0885468	.1225869	-0.72	0.470	32885	06	.1517569
d3	.4031449	.1232183	3.27	0.001	.16160	35	.6446863
d4	.351554	.1212394	2.90	0.004	.11389	18	.5892162
d5	.41718	.122495	3.41	0.001	.17705	64	.6573036
d6	.4801389	.1082806	4.43	0.000	. 26787	95	.6923983
_cons	205493	.0829589	-2.48	0.013	36811	51	0428709
inear regress	sion			Number		=	7,69
_inear regress	sion			F(5, 76	90)	=	11.5
inear regress	sion			F(5, 76 Prob >	90) F		11.5 0.000
inear regress.	sion			F(5, 76	90) F	=	11.5 0.000
inear regress.	sion			F(5, 76 Prob >	90) F ed	=	11.5 0.000 0.007
inear regress	sion	Robust		F(5, 76 Prob > R-squar	90) F ed	= =	11.5 0.000 0.007
inear regress	coef.	Robust Std. Err.	t	F(5, 76 Prob > R-squar	90) F ed EE	= = =	11.5 0.000 0.007 2.250
			t 3.35	F(5, 76 Prob > R-squar Root MS	90) F ed EE	= = = = Conf.	11.5 0.000 0.007 2.250
fun	Coef.	Std. Err.		F(5, 76 Prob > R-squar Root MS	990) Feed SE [95% 0	= = = = Conf.	11.5 0.000 0.007 2.250 . Interval
fun d2	Coef. .3047947	.0909661	3.35	F(5, 76 Prob > R-squar Root MS P> t  0.001	(90) Feed SE [95% (	= = = = Conf.	11.5 0.000 0.007 2.250 . Interval .48311 .716210
fun d2 d3	Coef. .3047947 .5293474	.0909661 .0953251	3.35 5.55	F(5, 76 Prob > R-squar Root MS P> t  0.001 0.000	[95% C	= = = = Conf.	11.5 0.000 0.007 2.250 . Interval .48311 .716210 .687986
fun d2 d3 d4	Coef. .3047947 .5293474 .5076563	Std. Err0909661 .0953251 .0919924	3.35 5.55 5.52	F(5, 76 Prob > R-squar Root MS P> t  0.001 0.000 0.000	[95% ( .12647 .34248	= = = = = = = = = = = = = = = = = = =	7,69 11.5 0.000 0.007 2.250 . Interval .48311 .716210 .687986 .546434 .729913

Linear regress	ion			Number	of obs	=	7,696
				F(5, 769	90)	=	10.61
				Prob > I	F	=	0.0000
				R-square	ed	=	0.0064
				Root MS	E	=	2.1668
		Robust					
books	Coef.	Std. Err.	t	P> t	[95% Co	onf.	Interval]
d2	.142804	. 0868562	1.64	0.100	027457	78	.3130658
d3	.3742977	.0928571	4.03	0.000	. 192272	25	.5563229
d4	.3816914	.086789	4.40	0.000	.21156		.5518214
d5	.2341723	.0829115	2.82	0.005	.071643		.3967013
d6	.539729	.0833188	6.48	0.000	.37640		.7030565
_cons	243615	.0627758	-3.88	0.000	366672		1205574
Linear regress	sion			Number F(5, 76		=	7,696 5.51
				-		=	
				Prob >		=	0.0000
				R-squar		=	0.0036
				Root MS	SE	=	1.397
		Robust					
hshld	Coef.	Std. Err.	t	P> t	[95% (	onf	<pre>Interval]</pre>
	Coeri	Jtu. Liii.			[55%]	.01111	
d2	.1553831	.0534761	2.91	0.004	.05055	553	.2602108
d3	.2232039	.0611508	3.65	0.000	.10333	316	.3430761
d4	.2660506	.0561881	4.73	0.000	.15596	965	.3761946
d5	.1526536	.052955	2.88	0.004	.04884	173	.2564599
d6	.2009728	.0484942	4.14	0.000	.1059	11	.2960346
_cons	1401956	.0386451	-3.63	0.000	21595	505	0644407
Linear regress	ion				of obs	=	7,696
				F(5, 7		=	5.58
				Prob >	F	=	0.0000
				R-squa	red	=	0.0033
				Root M	SE	=	1.1291
		Robust					<u>.</u>
clths	Coef.	Std. Err.	t	P> t	[95%	Conf	. Interval]
d2	.054249	.0482619	1.12	0.261	0403	574	.1488554
d3	.1378493	.0488963	2.82	0.005	.0419	992	.2336993
d4	.1435475	.0452245	3.17	0.002	.0548	952	.2321998
d5	.0788452	.0431243	1.83	0.068	0056	901	.1633805
d6	.2001623	.0430979	4.64	0.000	.1156	786	.2846459
_cons	0746009	.0338855	-2.20	0.028	1410	258	0081761

_inear regres	sion				of obs	= 7,69
				F(5, 7		= 4.9
				Prob >		= 0.000
				R-squa		= 0.002
				Root M	SE	= 2.213
		Robust				
medeq	Coef.	Std. Err.	t	P> t	[95% Cor	nf. Interval
d2	.0800167	.0668228	1.20	0.231	0509743	.211007
d3	.2185838	.0708224	3.09	0.002	.0797526	.357414
d4	.2140561	.0780602	2.74	0.006	.0610367	.367075
d5	.2632698	.1077825	2.44	0.015	.0519867	.474552
d6	.2689008	.0619591	4.34	0.000	.147444	.390357
_cons	1238576	.04657	-2.66	0.008	2151474	
Linear regress	510N			Number		.,
				F(5, 76		
				Prob >		0.0000
				R-squar		
				Root MS	E =	1.2609
		Robust				
drugs	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval]
d2	.0505122	.0515897	0.98	0.328	0506177	.1516421
d3	.2470639	.0528174	4.68	0.000	.1435274	.3506004
d4	.2008337	.0487503	4.12	0.000	.1052698	.2963976
d5	.1641619	.0496064	3.31	0.001	.0669198	.2614041
d6	.1912798	.0441925	4.33	0.000	.1046504	.2779092
_cons	1075665	.0351574	-3.06	0.002	1764845	0386485
linear regress	-100			Number	of obs	7 606
Linear regres	2 T U II			F(5, 76		
				Prob >		
				R-square		
				Root MS	Ē =	1.5117
		Robust				
chems	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval]
d2	.227676	.0605838	3.76	0.000	.1089152	.3464369
	.2855023	.0640305	4.46	0.000	.159985	.4110196
d3			4.95	0.000	.17671	.4082261
d3 d4	.2924681	.059052				
	.2924681 .2542543	.059052	4.14	0.000	.1340098	.3744989
d4				0.000 0.000	.1340098 .1835505	.3744989 .399378

Linear regress	sion			Number of		7,696
				F(5, 7696		17.07
				Prob > F	. =	0.0000
				R-squared		0.0098
				Root MSE	=	1.4465
		Robust				
txtls	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.1367806	.05805	2.36	0.018	.0229869	.2505744
d3	. 2655529	.0604479	4.39	0.000	.1470586	.3840472
d4	.3799046	.0582143	6.53	0.000	.2657886	.4940205
d5	.2150649	.0599713	3.59	0.000	.0975048	.3326249
d6	. 4359965	.0540574	8.07	0.000	.3300293	.5419636
_cons	2042175	.0426529	-4.79	0.000	2878289	1206062
Linear regress	sion			Number o	f obs =	7,696
				F(5, 769		10.10
				Prob > F	=	0.0000
				R-square		0.0065
				Root MSE	=	1.496
				ROOT HISE	_	1.450
		Robust				
bldmt	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval]
d2	.1812353	.059785	3.03	0.002	.0640404	.2984301
d3	.3392681	.065742	5.16	0.000	.2103958	.4681404
d4	.2908619	.0598386	4.86	0.000	.1735619	.4081618
d5	.230526	.0620061	3.72	0.000	.1089772	.3520748
d6	.3627599	.0556527	6.52	0.000	.2536653	.4718544
_cons	2015336	.0450708	-4.47	0.000	2898846	1131827
Linear regress	sion			Number o	of obs =	7,696
Linear regress	sion					
Linear regress	sion			F(5, 769	(0)	11.43
Linear regress	sion			F(5, 769 Prob > F	10) = : =	11.43 0.000
Linear regress	sion			F(5, 769 Prob > F R-square	= = = = = = = = = = = = = = = = = = =	11.43 0.000 0.0068
Linear regress	sion			F(5, 769 Prob > F	= = = = = = = = = = = = = = = = = = =	11.43 0.000 0.0068
		Robust		F(5, 769 Prob > F R-square Root MSE	10) = : = d = : =	11.43 0.0006 0.0068 2.8075
Linear regress	coef.	Robust Std. Err.	t	F(5, 769 Prob > F R-square	10) = : = d = : =	11.43 0.0006 0.0068 2.8075
			t 4.02	F(5, 769 Prob > F R-square Root MSE	10) = : = d = : =	11.43 0.0006 0.0068 2.8075
cnstr	Coef.	Std. Err.		F(5, 769 Prob > F R-square Root MSE	(95% Conf	11.43 0.0000 0.0066 2.8075
cnstr d2	Coef. .4379084	.108851	4.02	F(5, 769 Prob > F R-square Root MSE P> t  0.000	[95% Conf	11.43 0.0006 0.0066 2.8075 . Interval
cnstr d2 d3	Coef. .4379084 .5528066	.108851 .116133	4.02 4.76	F(5, 769 Prob > F R-square Root MSE P> t  0.000 0.000	[95% Conf	11.43 0.0006 0.0068 2.8075 . Interval
cnstr d2 d3 d4	Coef. .4379084 .5528066 .5423035	.108851 .116133 .1126664	4.02 4.76 4.81	F(5, 769 Prob > F R-square Root MSE P> t  0.000 0.000	[95% Conf	11.43 0.000 0.006

Linear regres	sion			Number		= 7,696
				F(5, 76		= 12.91
				Prob >		= 0.0000
				R-squar		= 0.0067
				Root MS	·Ε	= 1.9924
		Robust				
steel	Coef.	Std. Err.	t	P> t	[95% Cor	nf. Interval]
d2	.3540212	.0822719	4.30	0.000	.1927459	.5152965
d3	.4184284	.080732	5.18	0.000	.2601716	.5766852
d4	.340223	.0784272	4.34	0.000	.1864844	.4939617
d5	.3597956	.0797777	4.51	0.000	.2034096	.5161816
d6	.5467114	.0686313	7.97	0.000	.4121753	.6812474
_cons	2888185	.0554739	-5.21	0.000	3975624	
Linear regress				Number	of obs	= 7,696
Linear regress	2 T U II			F(5, 76		= 7,696 = 7.60
				-		
				Prob >		= 0.0000
				R-square		= 0.0047
				Root MS	E	= 1.6835
		Robust				
mach	Coef.	Std. Err.	t	P> t	[95% Con	f. Interval]
d2	.1966761	.0672899	2.92	0.003	.0647696	.3285826
d2 d3	.1966761 .3159829	.0672899 .0728753	2.92 4.34	0.003 0.000	.0647696 .1731275	
						.4588384
d3	.3159829	.0728753	4.34	0.000	.1731275	.4588384 .4322214
d3 d4	.3159829 .3041159	.0728753 .0653509	4.34 4.65	0.000 0.000	.1731275 .1760103	.4588384 .4322214 .414163
d3 d4 d5	.3159829 .3041159 .2780624	.0728753 .0653509 .0694294	4.34 4.65 4.00	0.000 0.000 0.000	.1731275 .1760103 .1419618	.4588384 .4322214 .414163 .4530513
d3 d4 d5 d6 _cons	.3159829 .3041159 .2780624 .3375526 1953678	.0728753 .0653509 .0694294 .0589198	4.34 4.65 4.00 5.73	0.000 0.000 0.000 0.000 0.000	.1731275 .1760103 .1419618 .2220538 2905369	.4588384 .4322214 .414163 .4530513 1001986
d3 d4 d5 d6 _cons	.3159829 .3041159 .2780624 .3375526 1953678	.0728753 .0653509 .0694294 .0589198	4.34 4.65 4.00 5.73	0.000 0.000 0.000 0.000 0.000	.1731275 .1760103 .1419618 .2220538 2905369	.4588384 .4322214 .414163 .4530513 1001986
d3 d4 d5 d6 _cons	.3159829 .3041159 .2780624 .3375526 1953678	.0728753 .0653509 .0694294 .0589198	4.34 4.65 4.00 5.73	0.000 0.000 0.000 0.000 0.000 Number F(5, 76	.1731275 .1760103 .1419618 .2220538 2905369 of obs	.4588384 .4322214 .414163 .4530513 1001986 = 7,690 = 10.75
d3 d4 d5 d6 _cons	.3159829 .3041159 .2780624 .3375526 1953678	.0728753 .0653509 .0694294 .0589198	4.34 4.65 4.00 5.73	0.000 0.000 0.000 0.000 Number F(5, 76 Prob >	.1731275 .1760103 .1419618 .2220538 2905369 of obs 90)	.4588384 .4322214 .414163 .4530513 1001986 = 7,690 = 10.79
d3 d4 d5 d6 _cons	.3159829 .3041159 .2780624 .3375526 1953678	.0728753 .0653509 .0694294 .0589198	4.34 4.65 4.00 5.73	0.000 0.000 0.000 0.000 Number F(5, 76 Prob > R-squar	.1731275 .1760103 .1419618 .2220538 2905369 of obs 90) F	.4588384 .4322214 .414163 .4530513 1001986 = 7,699 = 10.79 = 0.0000 = 0.0070
d3 d4 d5 d6 _cons	.3159829 .3041159 .2780624 .3375526 1953678	.0728753 .0653509 .0694294 .0589198	4.34 4.65 4.00 5.73	0.000 0.000 0.000 0.000 Number F(5, 76 Prob >	.1731275 .1760103 .1419618 .2220538 2905369 of obs 90) F	. 4588384 . 4322214 . 414163 . 4530513 1001986 = 7,690 = 10.75 = 0.0000 = 0.0070
d3 d4 d5 d6 _cons	.3159829 .3041159 .2780624 .3375526 1953678	.0728753 .0653509 .0694294 .0589198 .0485489	4.34 4.65 4.00 5.73	0.000 0.000 0.000 0.000 Number F(5, 76 Prob > R-squar Root MS	.1731275 .1760103 .1419618 .2220538 2905369 of obs 90) F	. 4588384 . 4322214 . 414163 . 4530513 1001986 = 7,690 = 10.79 = 0.0000 = 0.0070 = 1.9899
d3 d4 d5 d6 _cons	.3159829 .3041159 .2780624 .3375526 1953678	.0728753 .0653509 .0694294 .0589198 .0485489	4.34 4.65 4.00 5.73	0.000 0.000 0.000 0.000 Number F(5, 76 Prob > R-squar	.1731275 .1760103 .1419618 .2220538 2905369 of obs 90) F	. 4588384 . 4322214 . 414163 . 4530513 1001986 = 7,690 = 10.79 = 0.0000 = 0.0070 = 1.9899
d3 d4 d5 d6 _cons  inear regress	.3159829 .3041159 .2780624 .3375526 1953678	.0728753 .0653509 .0694294 .0589198 .0485489 Robust Std. Err.	4.34 4.65 4.00 5.73 -4.02	0.000 0.000 0.000 0.000 Number F(5, 76 Prob > R-squar Root MS	.1731275 .1760103 .1419618 .2220538 2905369 of obs 90) F ed E	.4588384 .4322214 .414163 .4530513 1001986 = 7,690 = 10.79 = 0.0070 = 0.0070 = 1.9893
d3 d4 d5 d6 _cons .inear regress	.3159829 .3041159 .2780624 .3375526 1953678 sion Coef.	.0728753 .0653509 .0694294 .0589198 .0485489 Robust Std. Err. .0784498 .0843577	4.34 4.65 4.00 5.73 -4.02	0.000 0.000 0.000 0.000 Number F(5, 76 Prob > R-squar Root MS	.1731275 .1760103 .1419618 .2220538 2905369 of obs 90) F ed E	.4588384 .4322214 .414163 .4530513 1001986 = 7,69 = 10.7 = 0.000 = 0.007 = 1.989
d3 d4 d5 d6 _cons  .inear regress d2 d3 d4	.3159829 .3041159 .2780624 .3375526 1953678	.0728753 .0653509 .0694294 .0589198 .0485489 Robust Std. Err.	4.34 4.65 4.00 5.73 -4.02	0.000 0.000 0.000 0.000 Number F(5, 76 Prob > R-squar Root MS	.1731275 .1760103 .1419618 .2220538 2905369 of obs 90) F ed E	.4588384 .4322214 .414163 .4530513 1001986 = 7,69 = 10.7 = 0.000 = 0.007 = 1.989
d3 d4 d5 d6 _cons  Linear regress elceq d2 d3	.3159829 .3041159 .2780624 .3375526 1953678 sion Coef.	.0728753 .0653509 .0694294 .0589198 .0485489 Robust Std. Err. .0784498 .0843577	4.34 4.65 4.00 5.73 -4.02	0.000 0.000 0.000 0.000 Number F(5, 76 Prob > R-squar Root MS	.1731275 .1760103 .1419618 .2220538 2905369 of obs 90) F ed E	.4588384 .4322214 .414163 .4530513 1001986 = 7,690 = 10.79 = 0.0000 = 0.0070 = 1.9899
d3 d4 d5 d6 _cons  Linear regress elceq d2 d3 d4	.3159829 .3041159 .2780624 .3375526 1953678 sion  Coef3893387 .4733838 .4071349	Robust Std. Err.  .0784498 .0843577 .0790293	4.34 4.65 4.00 5.73 -4.02 t 4.96 5.61 5.15	0.000 0.000 0.000 0.000 0.000 Number F(5, 76 Prob > R-squar Root MS	.1731275 .1760103 .1419618 .2220538 2905369 of obs 90) F ed E	.4588384 .4322214 .414163 .4530513 1001986 = 7,696 = 10.75 = 0.0006 = 0.0076 = 1.9893

Linear regress	sion			Number o	f obs =	7,696
				F(5, 769		8.70
				Prob > F		0.0000
				R-square		0.0054
				Root MSE		1.9493
		Robust				
autos	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.3361236	.078935	4.26	0.000	.1813894	. 4908577
d3	.396217	.0839253	4.72	0.000	.2317007	.5607334
d4	. 2958955	.0772984	3.83	0.000	.1443696	.4474215
d5	.3183001	.0787318	4.04	0.000	.1639643	.472636
d6	. 4595882	.0717416	6.41	0.000	.318955	.6002214
_cons	2432238	.0572447	-4.25	0.000	355439	1310086
Linear regress	sion			Number o		7,696
				F(5, 769	0) =	4.37
				Prob > F	=	0.0006
				R-square	d =	0.0027
				Root MSE	=	2.4932
		Robust				
	Coef.	Std. Err.	t	P> t	[95% Conf.	Intervall
aero		5141 2111		11 121	1000 00	
d2	.235626	.1007028	2.34	0.019	.038221	
						. 4330309
d2	. 235626	.1007028	2.34	0.019	.038221	. 4330309
d2 d3	.235626 .3350142	.1007028	2.34	0.019 0.001	.038221	.4330309 .5342042 .5363917
d2 d3 d4	.235626 .3350142 .3454699	.1007028 .1016135 .0973955	2.34 3.30 3.55	0.019 0.001 0.000	.038221 .1358241 .1545481	.4330309 .5342042 .5363917
d2 d3 d4 d5	.235626 .3350142 .3454699 .3129355	.1007028 .1016135 .0973955 .0980488	2.34 3.30 3.55 3.19	0.019 0.001 0.000 0.001	.038221 .1358241 .1545481 .1207332	.4330309 .5342042 .5363917 .5051378
d2 d3 d4 d5 d6 _cons	.235626 .3350142 .3454699 .3129355 .3995891 2007981	.1007028 .1016135 .0973955 .0980488 .093492	2.34 3.30 3.55 3.19 4.27	0.019 0.001 0.000 0.001 0.000 0.004	.038221 .1358241 .1545481 .1207332 .2163194 3377368	.4330309 .5342042 .5363917 .5051378 .5828589
d2 d3 d4 d5 d6 _cons	.235626 .3350142 .3454699 .3129355 .3995891 2007981	.1007028 .1016135 .0973955 .0980488 .093492	2.34 3.30 3.55 3.19 4.27	0.019 0.001 0.000 0.001 0.000 0.004	.038221 .1358241 .1545481 .1207332 .2163194 3377368	.4330309 .5342042 .5363917 .5051378 .5828589 0638595
d2 d3 d4 d5 d6	.235626 .3350142 .3454699 .3129355 .3995891 2007981	.1007028 .1016135 .0973955 .0980488 .093492	2.34 3.30 3.55 3.19 4.27	0.019 0.001 0.000 0.001 0.000 0.004 Number o	.038221 .1358241 .1545481 .1207332 .2163194 3377368	.4330309 .5342042 .5363917 .5051378 .5828589 0638595
d2 d3 d4 d5 d6 _cons	.235626 .3350142 .3454699 .3129355 .3995891 2007981	.1007028 .1016135 .0973955 .0980488 .093492	2.34 3.30 3.55 3.19 4.27	0.019 0.001 0.000 0.001 0.000 0.004 Number o F(5, 769 Prob > F	.038221 .1358241 .1545481 .1207332 .2163194 3377368	.4330309 .5342042 .5363917 .5051378 .5828589 0638595
d2 d3 d4 d5 d6 _cons	.235626 .3350142 .3454699 .3129355 .3995891 2007981	.1007028 .1016135 .0973955 .0980488 .093492	2.34 3.30 3.55 3.19 4.27	0.019 0.001 0.000 0.001 0.000 0.004 Number of (5, 769 Prob > F	.038221 .1358241 .1545481 .1207332 .2163194 3377368	.4330309 .5342042 .5363917 .5051378 .5828589 0638595 7,690 12.49
d2 d3 d4 d5 d6 _cons	.235626 .3350142 .3454699 .3129355 .3995891 2007981	.1007028 .1016135 .0973955 .0980488 .093492	2.34 3.30 3.55 3.19 4.27	0.019 0.001 0.000 0.001 0.000 0.004 Number o F(5, 769 Prob > F	.038221 .1358241 .1545481 .1207332 .2163194 3377368	.4330309 .5342042 .5363917 .5051378 .5828589 0638595 7,696 12.49
d2 d3 d4 d5 d6 _cons	.235626 .3350142 .3454699 .3129355 .3995891 2007981	.1007028 .1016135 .0973955 .0980488 .093492 .0698569	2.34 3.30 3.55 3.19 4.27	0.019 0.001 0.000 0.001 0.000 0.004 Number of (5, 769 Prob > F	.038221 .1358241 .1545481 .1207332 .2163194 3377368	.4330309 .5342042 .5363917 .5051378 .5828589 0638595 7,696 12.49
d2 d3 d4 d5 d6 _cons	.235626 .3350142 .3454699 .3129355 .3995891 2007981	.1007028 .1016135 .0973955 .0980488 .093492 .0698569	2.34 3.30 3.55 3.19 4.27 -2.87	0.019 0.001 0.000 0.001 0.004 Number o F(5, 769 Prob > F R-square Root MSE	.038221 .1358241 .1545481 .1207332 .2163194 3377368	.4330309 .5342042 .5363917 .5051378 .5828589 0638595 7,690 12.49 0.0000 0.0078
d2 d3 d4 d5 d6 _cons Linear regress	.235626 .3350142 .3454699 .3129355 .3995891 2007981	.1007028 .1016135 .0973955 .0980488 .093492 .0698569	2.34 3.30 3.55 3.19 4.27 -2.87	0.019 0.001 0.000 0.001 0.004 Number of F(5, 769 Prob > FR-square Root MSE	.038221 .1358241 .1545481 .1207332 .2163194 3377368 of obs = 00000000000000000000000000000000000	.4330309 .5342042 .5363917 .5051378 .5828589 0638595 7,690 12.49 0.0000 0.0078 1.7472
d2 d3 d4 d5 d6 _cons Linear regress	.235626 .3350142 .3454699 .3129355 .3995891 2007981	.1007028 .1016135 .0973955 .0980488 .093492 .0698569 Robust Std. Err.	2.34 3.30 3.55 3.19 4.27 -2.87	0.019 0.001 0.000 0.001 0.004 Number of F(5, 769 Prob > F R-square Root MSE	.038221 .1358241 .1545481 .1207332 .2163194 3377368 of obs = (0) = (0	.4330309 .5342042 .5363917 .5051378 .5828589 0638595 7,690 12.49 0.0007 1.7473
d2 d3 d4 d5 d6 _cons Linear regress ships d2 d3	.235626 .3350142 .3454699 .3129355 .3995891 2007981 sion	.1007028 .1016135 .0973955 .0980488 .093492 .0698569 Robust Std. Err.	2.34 3.30 3.55 3.19 4.27 -2.87	0.019 0.001 0.000 0.001 0.004 Number of (5, 769) Prob > F R-square Root MSE	.038221 .1358241 .1545481 .1207332 .2163194 3377368 of obs = 000 = 00000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 00000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 00000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 00000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 00000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 00000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 00000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 00000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 00000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 00000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 00000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 00000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 00000 = 0000 = 00000 = 00000 = 00000 = 00000 = 00000 = 00000 = 000000	.4330309 .5342042 .5363917 .5051378 .5828589 0638595 7,690 12.49 0.0007 1.7472
d2 d3 d4 d5 d6 _cons Linear regress ships d2 d3 d4	.235626 .3350142 .3454699 .3129355 .3995891 2007981	.1007028 .1016135 .0973955 .0980488 .093492 .0698569 Robust Std. Err.	2.34 3.30 3.55 3.19 4.27 -2.87	0.019 0.001 0.000 0.001 0.004 Number of F(5, 769 Prob > F R-square Root MSE	.038221 .1358241 .1545481 .1207332 .2163194 3377368 of obs = (0) = (1	.4330309 .5342042 .5363917 .5051378 .5828589 0638595 7,690 12.49 0.0007 1.7472
d2 d3 d4 d5 d6 _cons Linear regress ships d2 d3	.235626 .3350142 .3454699 .3129355 .3995891 2007981 sion	.1007028 .1016135 .0973955 .0980488 .093492 .0698569 Robust Std. Err.	2.34 3.30 3.55 3.19 4.27 -2.87	0.019 0.001 0.000 0.001 0.004 Number of (5, 769) Prob > F R-square Root MSE	.038221 .1358241 .1545481 .1207332 .2163194 3377368 of obs = 000 = 00000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 00000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 00000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 00000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 00000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 00000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 00000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 00000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 00000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 00000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 00000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 00000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 0000 = 00000 = 0000 = 00000 = 00000 = 00000 = 00000 = 00000 = 00000 = 000000	.4330309 .5342042 .5363917 .5051378 .58285890638595  7,696 12.45 0.0006 0.0078 1.7472  Interval .4451712 .5467748 .5012722
d2 d3 d4 d5 d6 _cons Linear regress ships d2 d3 d4	.235626 .3350142 .3454699 .3129355 .3995891 2007981 sion  Coef3051088 .4046867 .3651024	.1007028 .1016135 .0973955 .0980488 .093492 .0698569 Robust Std. Err. .0714505 .0724839 .069465	2.34 3.30 3.55 3.19 4.27 -2.87	0.019 0.001 0.000 0.001 0.004 Number o F(5, 769 Prob > F R-square Root MSE P> t  0.000 0.000	.038221 .1358241 .1545481 .1207332 .2163194 3377368 of obs = (0) = (1	.4330309 .5342042 .5363917 .5051378 .5828589 0638595 7,696 12.45 0.0006 0.0078

Linear regress	sion			Number	of obs	=	7,696
Linear regress				F(5, 76		=	4.33
				Prob >		=	0.0006
				R-squar		=	0.0026
				Root MS		=	1.6195
				Noot 113	_	_	1.0133
		Robust					
mines	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
d2	.1194644	.0641121	1.86	0.062	0062	128	.2451416
d3	.2280688	.0665424	3.43	0.001	.0976	276	.3585101
<b>d4</b>	.2037054	.0631393	3.23	0.001	.0799	351	.3274757
d5	.1832703	.06397	2.86	0.004	. 0578	716	.308669
d6	.2450473	.0585175	4.19	0.000	.1303	371	.3597575
_cons	1213772	.0445689	-2.72	0.006	2087	443	03401
Linear regress	sion			Number		=	7,696
				F(5, 76		=	9.04
				Prob >	F	=	0.0000
				R-squar	ed	=	0.0057
				Root MS	E	=	2.0758
		Robust					
5001	Coof		+	D . I + I	[050	Conf	Intorvall
coal	Coef.	Std. Err.	t	P> t	[95%	Cont.	Interval]
d2	.1960889	.0818541	2.40	0.017	.0356	326	.3565451
d3	. 4242393	.0858399	4.94	0.000	. 2559	698	.5925088
d4	.3224912	.081086	3.98	0.000	.1635	405	.481442
d5	.3468805	.0827243	4.19	0.000	. 1847	184	.5090426
d6	.4797641	.0797904	6.01	0.000	.3233	533	.636175
_cons	2651095	.0588435	-4.51	0.000	3804	588	1497603
1 /	-1			Nombre	- f - h -		7.606
Linear regress	S10N				of obs	=	7,696
				F(5, 7)		=	10.69
				Prob >		=	0.0000
				R-squa		=	0.0065
				Root M	SE	=	1.3727
		Robust					
oil	Coef.	Std. Err.	t	P> t	[95%	Conf	. Interval]
d2	.2010375	.0567815	3.54	0.000	.0897	7303	.3123447
d3	.3102983	.057121	5.43	0.000	.1983	3255	. 422271
d4	.295695	.055548	5.32	0.000	.1868		.4045842
d5	.2236186	.0550594	4.06	0.000	.1156		.33155
d6	.3311515	.048407	6.84	0.000	. 2362		.4260424
_cons	1881377	.0397018	-4.74	0.000	265		1103114
	1	<b></b>			• •		

Linear regress	sion			Number o F(5, 769		7,696 10.47
				Prob > F	=	0.0000
				R-square		0.0063
				Root MSE		1.5462
		Robust				
util	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.2120842	.0610115	3.48	0.001	.092485	.3316834
d3	.3213221	.063991	5.02	0.000	.1958823	. 446762
d4	.3304577	.0622823	5.31	0.000	.2083675	. 452548
d5	.2847707	.0633195	4.50	0.000	.1606472	.4088942
d6	.3751179	.0553891	6.77	0.000	.2665401	.4836957
_cons	2218623	.0441046	-5.03	0.000	3083193	1354053
Linna	4			Normal	£ _ L _	T 405
Linear regress	10N			Number o		7,696
				F(5, 7690		2.89
				Prob > F	. =	0.0132
				R-square	<b>=</b>	0.0017
				Root MSE	=	1.006
		Robust				
telcm	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.0619582	.0396509	1.56	0.118	0157684	.1396849
d3	.076748	.0435971	1.76	0.078	0087142	.1622102
d4	.0935826	.0397455	2.35	0.019	.0156705	.1714946
d5	.0392085	.0394313	0.99	0.320	0380876	.1165046
d6	.1338521	.0385484	3.47	0.001	.0582867	.2094174
_cons	0379108	.0291944	-1.30	0.194	0951398	.0193182
Linear regress	510N			Number o		7,696
				F(5, 769		1.98
				Prob > F		0.0788
				R-square		0.0011
				Root MSE	=	3.1285
		Robust				
bussv	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.0487283	.1190139	0.41	0.682	1845714	.282028
d3	.2564481	.1213464	2.11	0.035	.018576	.4943201
d4	.2520064	.1131617	2.23	0.026	.0301786	.4738341
d5	.1992125	.1133673	1.76	0.079	0230184	.4214433
d6	.2546038	.1094881	2.33	0.020	.0399773	.4692304
_cons	1068232	.072832	-1.47	0.142	2495937	.0359473

Robust hardw Coef. Std. Err. t  d2 .152309 .0596819 2.55 d3 .2681844 .0637551 4.21 d4 .2923006 .0615245 4.75 d5 .1979724 .0591932 3.34	F(5, 769 Prob > I R-square Root MSI P> t	= = ed = E =	7,696 6.12 0.0000 0.0041 1.504
hardw Coef. Std. Err. t  d2 .152309 .0596819 2.55 d3 .2681844 .0637551 4.21 d4 .2923006 .0615245 4.75	Prob > F R-square Root MSE	= = ed = E =	0.0041
hardw Coef. Std. Err. t  d2 .152309 .0596819 2.55 d3 .2681844 .0637551 4.21 d4 .2923006 .0615245 4.75	Root MSE	=	
hardw         Coef.         Std. Err.         t           d2         .152309         .0596819         2.55           d3         .2681844         .0637551         4.21           d4         .2923006         .0615245         4.75	Root MSE	=	1.504
hardw         Coef.         Std. Err.         t           d2         .152309         .0596819         2.55           d3         .2681844         .0637551         4.21           d4         .2923006         .0615245         4.75	P> t		
hardw         Coef.         Std. Err.         t           d2         .152309         .0596819         2.55           d3         .2681844         .0637551         4.21           d4         .2923006         .0615245         4.75	P> t	1050 6 6	
d2 .152309 .0596819 2.55 d3 .2681844 .0637551 4.21 d4 .2923006 .0615245 4.75	P> t		
d3 .2681844 .0637551 4.21 d4 .2923006 .0615245 4.75		[95% Cont.	Interval]
d4 .2923006 .0615245 4.75	0.011	.0353161	.2693019
	0.000	.143207	.3931617
d5 1979724 9591932 3.34	0.000	.1716958	.4129055
45 13/3/24 .0331332 3.34	0.001	.0819376	.3140072
d6 .2340678 .053019 4.41	0.000	.1301362	.3379995
_cons  1419953 .0428706 -3.31	0.001	2260333	0579573
Linear regression	Number F(5, 76		7,696 5.43
	Prob >		0.0001
	R-squar		0.0032
	Root MS	SE =	2.1666
Robust			
	D . I + I	IOE% Conf	Intorvall
chips Coef. Std. Err. t	P> t	[95% CONT	. Interval]
d2 .1643526 .0858246 1.91	0.056	003887	.3325921
d3 .3016039 .089465 3.37	0.001	.1262282	.4769797
d4 .3199224 .0882537 3.63	0.000	.1469211	.4929237
d5 .263388 .0865218 3.04	0.002	.0937817	. 4329944
d6 .3774083 .0788155 4.79	0.000	.2229083	.5319082
_cons  1865102 .0617012 -3.02	0.003	3074614	065559
Linear regression		of obs =	•
	F(5, 7		
	Prob >		
	R-squa		0.0021
	Root M	SE =	1.5479
Robust		•	
labeq Coef. Std. Err. t	P> t	[95% Conf	. Interval]
d2 .1152797 .0628459 1.83	0.067	0079154	.2384748
d3 .2124852 .0660452 3.22	0.001	.0830187	.3419517
d4 .1655793 .063147 2.62	0.009	.041794	. 2893647
d5 .164503 .0644027 2.55	0.011	.0382561	.2907499
d6 .1992804 .0591439 3.37	0.001	.0833423	.3152184
	0.029		0104101
_cons  1027778 .0471198 -2.18	0.029	1951454	0104101

Linear regres	sion			Number		7,696
				F(5, 769		7.36
				Prob > I	F =	0.0000
				R-square		0.0050
				Root MSI	E =	1.3993
		Robust				
boxes	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.2205337	.0565439	3.90	0.000	.1096923	.3313751
d3	.282647	.0592575	4.77	0.000	.1664861	.3988079
d4	.2989727	.0554627	5.39	0.000	.1902506	.4076948
d5	.2223467	.0574091	3.87	0.000	.1098092	.334884
d6	.2521799	.0507242	4.97	0.000	.1527466	.351613
_cons	1688811	.0407791	-4.14	0.000	2488193	0889428
Linear regress	sion			Number o	f obs =	7,696
				F(5, 769	0) =	12.72
				Prob > F		0.0000
				R-square	d =	0.0081
				Root MSE		1.6801
	Τ					
		Robust				
trans	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.3013132	.0678906	4.44	0.000	.168229	.4343973
d3	.4152947	.0709137	5.86	0.000	.2762846	.5543048
d4	.4081306	.0669796	6.09	0.000	.2768323	.5394289
d5	.3354512	.0699069	4.80	0.000	.1984147	.4724877
d6	.4648087	.0618518	7.51	0.000	.3435623	.5860551
_cons	2915962	.0496044	-5.88	0.000	3888344	1943581
				Number	of abo	7.60
Linear regres	sion			Number o		7,696
Linear regres	sion			F(5, 769	90) =	6.90
Linear regres	sion			F(5, 769 Prob > 1	90) = F =	6.90 0.000
_inear regres	sion			F(5, 769 Prob > 1 R-square	90) = F = ed =	6.90 0.000 0.003
inear regres	sion			F(5, 769 Prob > 1	90) = F = ed =	6.90 0.000 0.003
Linear regres	sion	Robust		F(5, 769 Prob > 1 R-square	90) = F = ed =	6.90 0.0000 0.003
Linear regres	sion Coef.	Robust Std. Err.	t	F(5, 769 Prob > 1 R-square	90) = = = = = = = = = = = = = = = = = = =	6.90 0.0000 0.003 2.524
			t 2.34	F(5, 769 Prob > I R-square Root MSI	90) = = = = = = = = = = = = = = = = = = =	6.90 0.0000 0.003 2.524
whlsl	Coef.	Std. Err.		F(5, 769 Prob > I R-square Root MSI	90) = F = ed = E =	6.90 0.000 0.003 2.524 Interval
whlsl d2	Coef. .2289367	.0978352	2.34	F(5, 769 Prob > I R-square Root MSE P> t  0.019	90) = = = = = = = = = = = = = = = = = = =	6.90 0.0000 0.003 2.524 Interval .4207202 .5530180
whlsl d2 d3	Coef. .2289367 .3441664	.0978352 .1065424	2.34	F(5, 769 Prob > I R-square Root MSI P> t  0.019 0.001	90) = = = = = = = = = = = = = = = = = = =	6.90 0.0000 0.003 2.524 Interval .420720 .5530180 .569042
whlsl d2 d3 d4	Coef. .2289367 .3441664 .3687609	.0978352 .1065424 .1021701	2.34 3.23 3.61	F(5, 769 Prob > I R-square Root MSE P> t  0.019 0.001 0.000	90) = = = = = = = = = = = = = = = = = = =	

Linear regres	sion			Number		=	7,696
				F(5, 76		=	8.90
				Prob >		=	0.0000
				R-squar		=	0.0057
				Root MS	E	=	1.2802
		Robust					
rtail	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
d2	. 1333994	.0517002	2.58	0.010	.0320	528	. 2347459
d3	.2610361	.0545066	4.79	0.000	.1541	884	.3678838
d4	.259212	.051337	5.05	0.000	.1585	776	.3598465
d5	.2068609	.051582	4.01	0.000	.1057	461	.3079756
d6	.2748173	.0466887	5.89	0.000	.1832	947	.3663399
_cons	1549296	.0373531	-4.15	0.000	2281	518	0817073
Linear regress	sion			Number		=	7,69
				F(5, 76		=	7.5
				Prob >		=	0.000
				R-squar		=	0.004
				Root MS	SE	=	1.581
		Robust					
meals	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval
d2	.059109	.0645536	0.92	0.360	0674	1337	.185651
d3	.227969	.0678763	3.36	0.001	.0949	129	.361025
<b>d4</b>	. 2563844	.0636299	4.03	0.000	.1316	5525	.381116
d5	. 159247	.0644722	2.47	0.014	.032	2864	.2856
d6	.308406	.0614161	5.02	0.000	.1886	137	.428798
_cons	1360485	.0479062	-2.84	0.005	2299	577	042139
_inear regress	sion			Number		=	7,696
				F(5, 76		=	5.37
				Prob >	F	=	0.0001
				R-squar	ed	=	0.0036
				Root MS	E	=	1.8043
		Robust					
			t	P> t	[95%	Conf.	Interval]
banks	Coef.	Std. Err.		<u> </u>			
banks d2	Coef.	.071814	2.65	0.008	.0495	084	.3310584
					.0495		
d2	.1902834	.071814	2.65	0.008		422	. 456437
d2 d3	.1902834 .3051396	.071814	2.65	0.008	.1538	422 156	. 456437 . 4492059
d2 d3 d4	.1902834 .3051396 .3086107	.071814 .0771818 .0717223	2.65 3.95 4.30	0.008 0.000 0.000	.1538 .1680	422 156 759	.3310584 .456437 .4492059 .3888005

Linear regress	ion			Number	of obs =	7,69
				F(5, 76	90) =	5.0
				Prob >	F =	0.000
				R-squar	ed =	0.003
				Root MS		
		Robust				
insur	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval
d2	.1636183	.0687179	2.38	0.017	.0289125	. 298324
d3	.2570329	.072246	3.56	0.000	.1154111	.398654
d4	.3019103	.0718281	4.20	0.000	.1611077	.442712
d5	.2397958	.0681852	3.52	0.000	.1061342	.373457
d6	.2717493	.0644911	4.21	0.000	.1453292	.398169
_cons	1644523	.0498062	-3.30	0.001	2620859	066818
_inear regress	ion			Number	of obs =	7,696
				F(5, 769	90) =	9.29
				Prob > 1	=	0.0000
				R-square	ed =	0.0057
				Root MSI	=	3.117
rlest	Coof	Robust	_	Ds.1+1	[OE% Conf	Intorvali
rtest	Coef.	Std. Err.	t	P> t	[95% (011)	. Interval]
d2	.091845	.1213677	0.76	0.449	1460688	.3297587
	.5008955	.1323722	3.78	0.000	.2414099	.760381
d3					.1283916	.6234107
d3 d4	.3759011	.1262628	2.98	0.003	.1203910	.0234107
	.3759011 .4291836	.1262628 .1216169	2.98 3.53	0.003 0.000	.1907814	
d4						.6675858
d4 d5	.4291836	.1216169	3.53	0.000	.1907814	. 6675858 . 9483629
d4 d5 d6 _cons	.4291836 .7053417 2997027	.1216169 .1239732	3.53 5.69	0.000 0.000 0.001	.1907814 .4623205 4781091	.6675858 .9483629 1212962
d4 d5 d6 _cons	.4291836 .7053417 2997027	.1216169 .1239732	3.53 5.69	0.000 0.000 0.001	.1907814 .4623205 4781091	.6675858 .9483629 1212962 7,696
d4 d5 d6 _cons	.4291836 .7053417 2997027	.1216169 .1239732	3.53 5.69	0.000 0.000 0.001 Number o	.1907814 .4623205 4781091 f obs = 0) =	.6675858 .9483629 1212962 7,696 10.98
d4 d5 d6 _cons	.4291836 .7053417 2997027	.1216169 .1239732	3.53 5.69	0.000 0.000 0.001 Number o F(5, 769 Prob > F	.1907814 .4623205 4781091 f obs = 0) = =	.6675858 .9483629 1212962 7,696 10.98 0.0000
d4 d5 d6 _cons	.4291836 .7053417 2997027	.1216169 .1239732	3.53 5.69	0.000 0.001 Number o F(5, 769 Prob > F R-square	.1907814 .4623205 4781091 f obs = 0) = d = d	.6675858 .9483629 1212962 7,696 10.98 0.0000 0.0070
d4 d5 d6 _cons	.4291836 .7053417 2997027	.1216169 .1239732	3.53 5.69	0.000 0.000 0.001 Number o F(5, 769 Prob > F	.1907814 .4623205 4781091 f obs = 0) = =	.6675858 .9483629 1212962 7,696 10.98 0.0000
d4 d5 d6 _cons	.4291836 .7053417 2997027	.1216169 .1239732	3.53 5.69	0.000 0.001 Number o F(5, 769 Prob > F R-square	.1907814 .4623205 4781091 f obs = 0) = d = d	.6675858 .9483629 1212962 7,696 10.98 0.0000 0.0070
d4 d5 d6 _cons	.4291836 .7053417 2997027	.1216169 .1239732 .0910111	3.53 5.69	0.000 0.001 Number o F(5, 769 Prob > F R-square	.1907814 .4623205 4781091 f obs = 0) = d = d	7,696 10.98 0.0000 1.995
d4 d5 d6 _cons	.4291836 .7053417 2997027	.1216169 .1239732 .0910111	3.53 5.69 -3.29	0.000 0.001 Number o F(5, 769 Prob > F R-square Root MSE	.1907814 .4623205 4781091 f obs = 0) = = d = =	7,696 10.98 0.000 1.995
d4 d5 d6 _cons Linear regress	.4291836 .7053417 2997027 ion	.1216169 .1239732 .0910111 Robust Std. Err.	3.53 5.69 -3.29	0.000 0.001 Number o F(5, 769 Prob > F R-square Root MSE	.1907814 .4623205 4781091 f obs = 0) = d = = = = = = = = = = = = = = = = =	.6675858 .9483629 1212962 7,696 10.98 0.0000 0.0070 1.995
d4 d5 d6 _cons Linear regress	.4291836 .7053417 2997027 ion	.1216169 .1239732 .0910111 Robust Std. Err.	3.53 5.69 -3.29	0.000 0.001 Number o F(5, 769 Prob > F R-square Root MSE	.1907814 .4623205 4781091 f obs = 0) = d = = = = = = = = = = = = = = = = =	.6675858 .9483629 1212962 7,696 10.98 0.0000 0.0070 1.995
d4 d5 d6 _cons Linear regress fin d2 d3	.4291836 .7053417 2997027 ion Coef. .293649 .4345487	.1216169 .1239732 .0910111 Robust Std. Err. .0780926 .0846564	3.53 5.69 -3.29 t 3.76 5.13	0.000 0.001 Number o F(5, 769 Prob > F R-square Root MSE P> t  0.000 0.000	.1907814 .4623205 4781091 f obs = 0) = = d = = = = = = = = = = = = = = = =	.6675858 .9483629 1212962 7,696 10.98 0.0000 0.0070 1.995 Interval]
d4 d5 d6 _cons Linear regress fin d2 d3 d4	.4291836 .7053417 2997027 ion Coef. .293649 .4345487 .4829804	Robust Std. Err0780926 .0846564 .0816881	3.53 5.69 -3.29 t 3.76 5.13 5.91	0.000 0.001 Number o F(5, 769 Prob > F R-square Root MSE P> t  0.000 0.000	.1907814 .4623205 4781091 f obs = 0) = = d = = = = = = = = = = = = = = = =	.6675858 .9483629 1212962 7,696 10.98 0.0000 0.0070 1.995 Interval] .4467318 .6004984 .6431114

# Table 1(Post):

Linear regress	sion			Number	of obs	=	16,465
				F(4, 16	460)	=	13.95
				Prob >	F	=	0.0000
				R-squar	ed	=	0.0034
				Root MS	E	=	1.3791
		Robust					
agric	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
d2	.0654272	.0350322	1.87	0.062	0032	397	.134094
d3	.1807874	.0356747	5.07	0.000	.1108	611	.2507136
d4	.1196567	.0352133	3.40	0.001	.0506	348	.1886785
d5	.2286532	.0344895	6.63	0.000	.16	105	.2962563
_cons	0760019	.0260409	-2.92	0.004	1270	449	0249589
Linear regres			=	16,465			
				F(4, 16460) =			9.17
				Prob >		=	0.0000
				R-squar		=	0.0025
				Root MS	SE	=	.83297
		Robust					
food	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
d2	.0951768	.0211636	4.50	0.000	. 053	6938	.1366598
d3	.1176997	.0212201	5.55	0.000		6106	.1592935
d4	.0908214	.0216748	4.19	0.000	.0483	3364	.1333063
d5	.1060274	.0213286	4.97	0.000	.0642	2211	.1478337
_cons	0317343	.015969	-1.99	0.047	0630	9353	0004334
Linear regress	sion			Number	of obs	=	16,465
29.20				F(4, 16		=	10.82
				Prob >		=	0.0000
				R-squar		=	0.0028
				Root MS		=	1.061
		Robust					
beer	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
beer d2	Coef.		t 3.64	P> t  0.000	.0450		
		Std. Err.				528	. 1499239
d2	.0974883	.0267514	3.64	0.000	. 0450	)528 .353	.1499239
d2 d3	.0974883	.0267514 .0271021	3.64 5.88	0.000	.0450 .1061 .0567	)528 .353	.1499239 .2123813 .1637108 .2033353

Linear regres	sion			Number F(4, 16		=	16,465 0.90
				Prob >		=	0.4646
				R-squar		=	0.0002
				Root MS		=	1.2878
				Noot 113	_	_	1.2070
		Robust					
smoke	Coef.	Std. Err.	t	P> t	[95% (	Conf.	Interval]
d2	.0032123	.0326309	0.10	0.922	06074	79	.0671724
d3	.0390705	.0334542	1.17	0.243	02650		.1046443
d4	0051593	.0330343	-0.16	0.876	069	91	.0595915
d5	0174218	.0329129	-0.53	0.597	08193		.047091
_cons	.0619277	.0247052	2.51	0.012	.01350	29	.1103526
Linone rooms	cion			Numbar	of obs		16 465
Linear regres	2 1011			Number of obs = $F(4, 16460)$ =		16,465 9.42	
				Prob >		=	0.0000
				R-squar		=	0.0000
				Root MS		=	1.4918
				Nooc III	, _		2.4520
		Robust					
toys	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
d2	.1451349	.0390859	3.71	0.000	.0685	223	. 2217475
d2 d3	.1451349	.0390859	3.71 5.36	0.000	.0685		
						665	.2852383
d3	.2089024	.0389447	5.36	0.000	.1325	665 938	.2852383 .2446158
d3 d4	.2089024 .1668548	.0389447 .0396718	5.36 4.21	0.000 0.000	.1325 .0890	665 938 073	.2217475 .2852383 .2446158 .2865363 0448398
d3 d4 d5 _cons	.2089024 .1668548 .2118218 1033481	.0389447 .0396718 .0381175	5.36 4.21 5.56	0.000 0.000 0.000 0.001	.1325 .0890 .1371 1618	665 938 073 564	.2852383 .2446158 .2865363 0448398
d3 d4 d5	.2089024 .1668548 .2118218 1033481	.0389447 .0396718 .0381175	5.36 4.21 5.56	0.000 0.000 0.000 0.001	.1325 .0890 .1371 1618	665 938 073 564 =	.2852383 .2446158 .2865363 0448398
d3 d4 d5 _cons	.2089024 .1668548 .2118218 1033481	.0389447 .0396718 .0381175	5.36 4.21 5.56	0.000 0.000 0.000 0.001 Number F(4, 16	.1325 .0890 .1371 1618 of obs	665 938 073 564 = =	.2852383 .2446158 .2865363 0448398 16,465 12.82
d3 d4 d5 _cons	.2089024 .1668548 .2118218 1033481	.0389447 .0396718 .0381175	5.36 4.21 5.56	0.000 0.000 0.001 Number F(4, 16 Prob >	.1325 .0890 .1371 1618 of obs 460)	665 938 073 564 = = =	.2852383 .2446158 .2865363 0448398 16,465 12.82 0.0000
d3 d4 d5 _cons	.2089024 .1668548 .2118218 1033481	.0389447 .0396718 .0381175	5.36 4.21 5.56	0.000 0.000 0.000 0.001 Number F(4, 16	.1325 .0890 .1371 1618 of obs .460) F	665 938 073 564 = =	.2852383 .2446158 .2865363 0448398 16,465 12.82
d3 d4 d5 _cons	.2089024 .1668548 .2118218 1033481	.0389447 .0396718 .0381175 .0298495	5.36 4.21 5.56	0.000 0.000 0.001 Number F(4, 16 Prob > R-squar	.1325 .0890 .1371 1618 of obs .460) F	665 938 073 564 = = = =	.2852383 .2446158 .2865363 0448398 16,465 12.82 0.0000 0.0034
d3 d4 d5 _cons	.2089024 .1668548 .2118218 1033481	.0389447 .0396718 .0381175	5.36 4.21 5.56	0.000 0.000 0.001 Number F(4, 16 Prob > R-squar	.1325 .0890 .1371 1618 of obs .460) F	665 938 073 564 = = = =	.2852383 .2446158 .2865363 0448398 16,465 12.82 0.0000 0.0034
d3 d4 d5 _cons	.2089024 .1668548 .2118218 1033481	.0389447 .0396718 .0381175 .0298495	5.36 4.21 5.56 -3.46	0.000 0.000 0.001 Number F(4, 16 Prob > R-squar Root MS	.1325 .0890 .1371 1618 of obs .460) F	665 938 073 564 = = = = =	.2852383 .2446158 .2865363 0448398 16,465 12.82 0.0000 0.0034 1.5301
d3 d4 d5 _cons Linear regress	.2089024 .1668548 .2118218 1033481	.0389447 .0396718 .0381175 .0298495 Robust Std. Err.	5.36 4.21 5.56 -3.46	0.000 0.000 0.001 Number F(4, 16 Prob > R-squar Root MS	.1325 .0890 .1371 1618 of obs .460) F	665 938 073 564 = = = = =	.2852383 .2446158 .2865363 0448398 16,465 12.82 0.0000 0.0034 1.5301 Interval]
d3 d4 d5 _cons  Linear regress  fun	.2089024 .1668548 .2118218 1033481 sion	.0389447 .0396718 .0381175 .0298495 Robust Std. Err.	5.36 4.21 5.56 -3.46	0.000 0.000 0.001 Number F(4, 16 Prob > R-squar Root MS	.1325 .0890 .1371 1618 of obs .460) F ed .E	665 938 073 564 = = = = = = 1	.2852383 .2446158 .2865363 0448398 16,465 12.82 0.0000 0.0034 1.5301 Interval] .2165501 .3303208
d3 d4 d5 _cons  Linear regress  fun d2 d3	.2089024 .1668548 .2118218 1033481 sion Coef. .1379817 .2515477	.0389447 .0396718 .0381175 .0298495 Robust Std. Err. .0400837 .0401881	5.36 4.21 5.56 -3.46 t 3.44 6.26	0.000 0.000 0.001 Number F(4, 16 Prob > R-squar Root MS P> t  0.001 0.000	.1325 .0890 .1371 1618 of obs .460) Feed .E	665 938 073 564 = = = = = = 200nf.	.2852383 .2446158 .2865363 0448398 16,465 12.82 0.0000 0.0034 1.5301

Linear regres	sion			Number F(4, 16 Prob > R-squar Root MS	460) = F = ed =	16,465 9.67 0.0000 0.0028 1.1764
books	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2 d3 d4 d5 _cons	.1051551 .1717775 .1401295 .1652567 0678472	.0308492 .0311367 .0315999 .0306363 .0240955	3.41 5.52 4.43 5.39 -2.82	0.001 0.000 0.000 0.000 0.005	.0446872 .1107462 .0781904 .1052063 1150771	.165623 .2328087 .2020687 .2253071 0206173
Linear regress	sion			Number F(4, 16 Prob > R-squar Root MS	460) = F = ed =	16,465 3.16 0.0133 0.0008 1.027
hshld	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2 d3 d4 d5 _cons	.057765 .0928041 .0421451 .0531178 0021814	.0270595 .0265867 .0263852 .0262331 .0201252	2.13 3.49 1.60 2.02 -0.11	0.033 0.000 0.110 0.043 0.914	.0047256 .0406913 0095728 .001698 0416289	.1108045 .1449169 .093863 .1045376 .0372662
Linear regres	sion			Number F(4, 1 Prob > R-squa Root M	F = red =	8.87 0.0000 0.0023
clths	Coef.	Robust Std. Err.	t	P> t	[95% Conf	. Interval]
d2 d3 d4 d5 _cons	.0907495 .1484539 .1254128 .1494761 0578282	.029153 .0290477 .0295804 .0287369 .0217795	3.11 5.11 4.24 5.20 -2.66	0.002 0.000 0.000 0.000 0.008	.0336064 .0915173 .067432 .0931486 1005183	.1478926 .2053905 .1833936 .2058035 015138

Linear regres	sion			Number of obs = F(4, 16460) = Prob > F = R-squared = Root MSE =		16,465 12.63 0.0000 0.0032 1.1867	
medeq	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]	
d2 d3 d4 d5 _cons	.1167028 .2116866 .1297892 .1374029 0639125	.0302166 .0300026 .0306306 .0302405 .022511	3.86 7.06 4.24 4.54 -2.84	0.000 0.000 0.000 0.000 0.005	.057475 .1528784 .0697498 .0781283 1080365	.1759307 .2704949 .1898285 .1966775 0197885	
Linear regres	sion			Number o F(4, 164 Prob > F R-square Root MSE	60) = =	16,465 8.50 0.0000 0.0024 1.0733	
drugs	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]	
d2 d3 d4 d5 _cons	.1162666 .1577033 .107621 .1200081 0454566	.0280159 .0279999 .0278991 .0274777 .0211725	4.15 5.63 3.86 4.37 -2.15	0.000 0.000 0.000 0.000 0.032	.0613524 .1028204 .0529357 .0661488 0869569	.1711807 .2125862 .1623063 .1738674 0039562	
Linear regress	sion			Number o F(4, 164 Prob > F R-square Root MSE	60) = =	16,465 8.91 0.0000 0.0025 1.1393	
chems	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]	
d2 d3 d4 d5 _cons	.1197312 .157034 .1181125 .1585525 0656246	.0299541 .029937 .0303158 .0291566 .0229488	4.00 5.25 3.90 5.44 -2.86	0.000 0.000 0.000 0.000 0.004	.0610179 .0983543 .0586903 .1014024 1106067	.1784446 .2157137 .1775347 .2157027 0206425	

Linear regres:	sion			Number of F(4, 1646 Prob > F R-squared Root MSE	0) = =	16,465 12.65 0.0000 0.0033 1.23
txtls	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.1115568	.03114	3.58	0.000	.050519	.1725946
d3	.1625639	.0315242	5.16	0.000	.100773	.2243547
d4	.1787832	.0319071	5.60	0.000	.1162419	.2413245
d5	.2038001	.0316098	6.45	0.000	.1418415	.2657587
_cons	086655	.0236213	-3.67	0.000	1329554	0403547
. reg bldmt d2	2 d3 d4 d5, r	obust				
Linear regress	sion			Number of		16,465
				F(4, 1646	(0) =	11.19
				Prob > F	=	0.0000
				R-squared	=	0.0030
				Root MSE	=	1.1087
		Robust			_	
bldmt	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.1056851	.0288287	3.67	0.000	.0491777	.1621925
d3	.1613716	.028761	5.61	0.000	.104997	.2177462
d4	.1423426	.0295215	4.82	0.000	.0844773	.2002079
d5	.1708427	.0281866	6.06	0.000	.115594	.2260914
_cons	0688269	.0219698	-3.13	0.002	1118901	0257637
Linear regress	ion			Number of	obs =	16,465
				F(4, 1646	0) =	17.85
				Prob > F	=	0.0000
				R-squared	=	0.0048
				Root MSE	=	1.4658
		Robust				
cnstr	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.1731054	.0383475	4.51	0.000	.0979401	.2482707
d3	.2763262	.0382526	7.22	0.000	.2013469	.3513054
d4	.2562552	.0381403	6.72	0.000	.1814961	.3310143
d5	.2647633	.0368515	7.18	0.000	.1925304	.3369963
_cons	1487159	.0286993	-5.18	0.000	2049696	0924622

Linear regress	sion			Number o		16,465
				F(4, 164		= 14.76
				Prob > F		9.0000
				R-square		0.0039
				Root MSE	E =	1.484
		Robust				
steel	Coef.	Std. Err.	t	P> t	[95% Cont	f. Interval]
d2	.1684614	.039127	4.31	0.000	.0917682	.2451545
d3	.2263913	.039421	5.74	0.000	.1491219	.3036607
d4	.1702319	.0390561	4.36	0.000	.0936777	.2467861
d5	.2797679	.037559	7.45	0.000	.2061483	.3533876
_cons	1321243	.0297772	-4.44	0.000	1904907	0737578
Linear regress	sion			Number		= 16,465
				F(4, 16	460)	= 10.18
				Prob >	F	= 0.0000
				R-squar	ed	= 0.0028
				Root MS	E	= 1.1855
b	C	Robust		D. Lat	[050 6	£ Tut
mach	Coef.	Std. Err.	t	P> t	[95% Con	f. Interval]
d2	.112472	.030884	3.64	0.000	.051936	.173008
d3	.1740337	.031226	5.57	0.000	.1128273	.2352402
d4	.1336027	.0314793	4.24	0.000	.0718998	.1953055
d5	.1731445	.0302372	5.73	0.000	.1138763	.2324126
_cons	0718675	.0237214	-3.03	0.002	1183641	0253709
14,000,000,000				Numban	of abo	16 465
Linear regress	sion			Number o		
Linear regress	sion			F(4, 164	460) =	7.14
Linear regress	sion			F(4, 164 Prob > F	460) = F =	7.14 0.0000
Linear regress	sion			F(4, 164 Prob > F R-square	460) = F = ed =	7.14 0.0000 0.0019
Linear regress	sion			F(4, 164 Prob > F	460) = F = ed =	7.14 0.0000 0.0019
Linear regress	sion	Robust		F(4, 164 Prob > F R-square	460) = F = ed =	7.14 0.0000 0.0019
Linear regress	Coef.	Robust Std. Err.	t	F(4, 164 Prob > F R-square	460) = F = ed = E =	7.14 0.0000 0.0019
			t 3.89	F(4, 164 Prob > F R-square Root MSE	460) = F = ed = E =	7.14 0.0000 0.0019 1.2985
elceq	Coef.	Std. Err.		F(4, 164 Prob > F R-square Root MSE	460) = F = E = E = E = E = E = E = E = E = E	7.14 0.0000 0.0019 1.2985
elceq d2	Coef. .1305807	.033565	3.89	F(4, 164 Prob > F R-square Root MSE P> t	(95% Conf	7.14 0.0000 0.0019 1.2985
elceq d2 d3	Coef. .1305807 .1607261	.033565 .0334688	3.89 4.80	F(4, 164 Prob > F R-square Root MSE P> t  0.000 0.000	(95% Conf	7.14 9.0000 9.0019 1.2985 7. Interval] .1963717 .2263285

Linear regress	sion			Number o F(4, 164 Prob > F R-square Root MSE	60) = = d =	16,465 3.56 0.0066 0.0010 1.3504
autos	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2 d3 d4 d5 _cons	.0771529 .1268918 .0655305 .0969928 0302917	.0351454 .035101 .0353726 .0341757 .0264905	2.20 3.62 1.85 2.84 -1.14	0.028 0.000 0.064 0.005 0.253	.0082641 .0580901 0038036 .0300047 082216	.1460418 .1956936 .1348646 .1639809 .0216326
Linear regress	sion			Number F(4, 16 Prob > R-squar Root MS	460) = F = ed =	16,465 14.05 0.0000 0.0041 1.3123
aero	Coef.	Robust Std. Err.	t	P> t	[95% Conf	. Interval]
d2 d3 d4 d5 _cons	.17575 .2304941 .1733 .2323231 1050412	.0347825 .0348435 .0344808 .0341843 .026768	5.05 6.62 5.03 6.80 -3.92	0.000 0.000 0.000 0.000 0.000	.1075725 .162197 .1057139 .1653182 1575093	.2439274 .2987912 .240886 .299328 0525731
Linear regres	sion			Number F(4, 16 Prob > R-squar Root MS	460) = F = ed =	16,465 8.91 0.0000 0.0023 1.3781
ships	Coef.	Robust Std. Err.	t	P> t	[95% Conf	. Interval]
d2 d3 d4 d5 _cons	.0933596 .1482607 .1540525 .1914376 0693215	.0352216 .035788 .0349744 .0346469 .0261632	2.65 4.14 4.40 5.53 -2.65	0.008 0.000 0.000 0.000 0.008	.0243215 .0781123 .0854989 .123526	.1623978 .2184091 .2226061 .2593493 0180388

Linear regres	sion			Number F(4, 16 Prob > R-squar Root MS	460) = F = ed =	12.44 0.0000 0.0033
mines	Coef.	Robust Std. Err.	t	P> t	[95% Conf	. Interval]
d2 d3 d4 d5 _cons	.1160575 .2152796 .1950513 .2338667 1064268	.0385181 .0392429 .0386451 .0371322 .0293127	3.01 5.49 5.05 6.30 -3.63	0.003 0.000 0.000 0.000 0.000	.0405578 .1383593 .1193027 .1610836 1638828	.1915572 .2921998 .2707999 .3066498 0489707
Linear regress	sion			Number of F(4, 164 Prob > I R-square Root MSI	460) = F = ed =	9.66 0.0000 0.0024
coal	Coef.	Robust Std. Err.	t	P> t	[95% Conf	. Interval]
d2 d3 d4 d5 _cons	.1131464 .2424603 .2043663 .2999314 1194388	.0542373 .0554021 .0548637 .0530311 .0406196	2.09 4.38 3.72 5.66 -2.94	0.037 0.000 0.000 0.000 0.003	.0068354 .1338662 .0968274 .1959847 1990575	.2194573 .3510543 .3119051 .403878 0398201
Linear regres	sion			Number of F(4, 164 Prob > F R-square Root MSE	160) = = = ed =	16,465 11.51 0.0000 0.0031 1.2302
oil	Coef.	Robust Std. Err.	t	P> t	[95% Conf	. Interval]
d2 d3 d4 d5 _cons	.1424849 .1863145 .1265303 .1948479 0814426	.0319239 .0327697 .0320511 .0310439 .0243309	4.46 5.69 3.95 6.28 -3.35	0.000 0.000 0.000 0.000 0.001	.0799106 .1220824 .0637066 .1339985 1291338	.2050592 .2505466 .189354 .2556973 0337514

Linear regres	sion			Number F(4, 16 Prob > R-squar Root MS	460) = F = ed =	4.21 0.0021 0.0010
util	Coef.	Robust Std. Err.	t	P> t	[95% Conf	. Interval]
d2 d3 d4 d5 _cons	.0195345 .0450505 .0374535 .0742133 .0063887	.0204123 .0204284 .020588 .0197667 .0154419	0.96 2.21 1.82 3.75 0.41	0.339 0.027 0.069 0.000 0.679	0204758 .0050086 0029012 .0354684 0238791	.0595447 .0850924 .0778081 .1129582 .0366565
Linear regress	sion			Number of F(4, 164 Prob > F R-square Root MSE	460) = F = ed =	6.20 0.0001
telcm	Coef.	Robust Std. Err.	t	P> t	[95% Conf	. Interval]
d2 d3 d4 d5 _cons	.0833672 .1019565 .0837027 .1264526 0355739	.0273396 .0271995 .0267298 .0260297 .0204616	3.05 3.75 3.13 4.86 -1.74	0.002 0.000 0.002 0.000 0.082	.0297786 .0486426 .0313093 .0754315 0756808	.1369558 .1552704 .136096 .1774736 .004533
Linear regress	sion			Number of F(4, 164) Prob > FR-square Root MSE	160) = = = ed =	16,465 19.51 0.0000 0.0054 1.0276
bussv	Coef.	Robust Std. Err.	t	P> t	[95% Conf	. Interval]
d2 d3 d4 d5 _cons	.1280364 .1982542 .1714388 .2140883 0975301	.0268113 .0268976 .0274725 .026601 .0207444	4.78 7.37 6.24 8.05 -4.70	0.000 0.000 0.000 0.000 0.000	.0754833 .145532 .1175897 .1619474 1381914	.1805894 .2509764 .225288 .2662293 0568689

Linear regres	sion			Number F(4, 16 Prob > R-squar Root MS	460) = F = ed =	16,465 1.97 0.0962 0.0005 1.535
hardw	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2 d3 d4 d5 _cons	.0508713 .1038124 .0294884 .0301484 .0142359	.0397753 .0396832 .0388856 .0380244 .029038	1.28 2.62 0.76 0.79 0.49	0.201 0.009 0.448 0.428 0.624	0270927 .026029 0467316 0443836 0426817	.1288353 .1815957 .1057084 .1046804 .0711535
Linear regress	sion			Number of F(4, 164 Prob > F R-square Root MSE	460) = = = ed =	16,465 7.14 0.0000 0.0019 1.51
chips	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2 d3 d4 d5 _cons	.0972177 .2056837 .1145864 .1193681 0563094	.0382109 .0387993 .0383146 .0371379 .0279642	2.54 5.30 2.99 3.21 -2.01	0.011 0.000 0.003 0.001 0.044	.0223203 .1296328 .0394855 .0465738 1111224	.1721152 .2817346 .1896872 .1921625 0014965
Linear regress	sion			Number F(4, 16 Prob > R-squar Root MS	460) = F = ed =	16,465 7.28 0.0000 0.0019 1.3569
labeq	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2 d3 d4 d5 _cons	.0994002 .1653664 .1137485 .163439 0531167	.034909 .0350606 .0350255 .0344322 .0261666	2.85 4.72 3.25 4.75 -2.03	0.004 0.000 0.001 0.000 0.042	.0309748 .0966438 .0450947 .0959481 104406	.1678256 .234089 .1824022 .2309298 0018274

Linear regress	sion			Number		,
				F(4, 164	460) =	9.44
				Prob > I	F =	0.0000
				R-square	ed =	0.0025
				Root MS	=	1.1714
		Robust				
boxes	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval]
d2	.1046354	.0305231	3.43	0.001	.0448068	.1644641
d3	.1613989	.0302518	5.34	0.000	.1021021	.2206957
d4	.1156129	.0310577	3.72	0.000	.0547364	.1764893
d5	.1654961	.0298532	5.54	0.000	.1069806	.2240115
_cons	0605675	.0231539	-2.62	0.009	1059517	0151834
Linear regress	ion			Number o		16,465
				F(4, 164		20.45
				Prob > F	=	0.0000
				R-square	d =	0.0056
				Root MSE	=	1.1493
		Robust				
trans	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval]
d2	.1607705	.0299144	5.37	0.000	.102135	.219406
d3	.240532	.0301072	7.99	0.000	.1815185	.2995454
d4	.1946188	.0302757	6.43	0.000	.1352751	.2539624
d5	.2315356	.028976	7.99	0.000	.1747395	.2883316
_cons	120967	.0226763	-5.33	0.000	1654149	0765191
Linear regress	sion			Number		,
				F(4, 16		
				Prob > 1		
				R-square		= 0.0051
				Root MSI	E =	1.0124
		Robust				
whlsl	Coef.	Robust Std. Err.	t	P> t	[95% Cont	f. Interval]
whlsl d2	Coef.		t 4.34	P> t	[95% Cont	f. Interval]
		Std. Err.				
d2	.1148814	.0264453	4.34	0.000	.0630458	.166717 .2410325
d2 d3	.1148814	.0264453 .0266396	4.34	0.000	.0630458	.166717

Linear regress	ion			Number o	of obs	=	16,465
				F(4, 164	160)	=	9.54
				Prob > F	•	=	0.0000
				R-square	ed	=	0.0026
				Root MSE		=	1.0501
		Robust					
rtail	Coef.	Std. Err.	t	P> t	[95% C	onf.	Interval]
d2	.1116396	.0273789	4.08	0.000	. 05797	41	.1653051
d3	.1547749	.0270572	5.72	0.000	.10173	98	.2078099
d4	.1283139	.02747	4.67	0.000	.07446	97	.1821582
d5	.1347963	.0267535	5.04	0.000	.08235	64	.1872361
_cons	0556658	.0205741	-2.71	0.007	09599	33	0153384
							_
Linear regress	ion			Number	of obs	=	16,465
				F(4, 16	460)	=	11.34
				Prob >	F	=	0.0000
				R-squar	ed	=	0.0030
				Root MS	E	=	1.196
_		Robust					
meals	Coef.	Std. Err.	t	P> t	[95%	Conf	Interval]
d2	.0971492	.0305505	3.18	0.001	.0372	668	.1570316
d3	.1682285	.0314287	5.35	0.000	.1066	249	.2298321
d4	.1575337	.0311388	5.06	0.000	.0964	982	.2185691
d5	.1800958	.030401	5.92	0.000	.1205	066	.2396851
_cons	0661129	.0233354	-2.83	0.005	1118	529	0203729
Linear regress	ion			Number	of obs	=	16,465
				F(4, 164	460)	=	6.64
				Prob > I	F	=	0.0000
				R-square	ed	=	0.0018
				Root MS	Ē	=	1.2863
		Data :					
		Robust					
banks	Coef.	Robust Std. Err.	t	P> t	[95% (	Conf.	Interval]
banks d2	Coef.		t 3.71	P> t	[95% (		Interval]
		Std. Err.				22	
d2	. 1269327	Std. Err.	3.71	0.000	. 05991	22	.1939533
d2 d3	.1269327	.0341923 .0331305	3.71 4.87	0.000	.05991	22 261 554	.1939533

Linear regress	sion			Number	of obs	=	16,465
				F(4, 16	460)	=	7.71
				Prob >	F	=	0.0000
				R-squar	ed	=	0.0022
				Root MS	E	=	1.1489
		Robust					
insur	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
d2	.1155748	.030563	3.78	0.000	. 05	5668	.1754815
d3	.1263147	.0297192	4.25	0.000	.068	0618	.1845676
d4	.1244072	.0305572	4.07	0.000	.064	5118	.1843027
d5	.159148	.0296527	5.37	0.000	.101	0255	.2172705
_cons	0590203	.0231928	-2.54	0.011	104	4806	01356
Linear regress	sion			Number		=	16,465
				F(4, 16		=	24.93
				Prob >		=	0.0000
				R-squar	ed	=	0.0063
				Root MS	E	=	1.4432
		Robust					
rlest	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
d2	.1266293	.0370167	3.42	0.001	.0540	726	.199186
d3	.241215	.0373042	6.47	0.000	.1686	9948	.3143353
d4	.2415751	.0383822	6.29	0.000	.1663	3418	.3168083
d5	.3369871	.0365751	9.21	0.000	. 2652	2961	.4086782
_cons	1568199	.0282528	-5.55	0.000	212	1985	1014413
Linear regress	sion			Number		=	16,465
				F(4, 16		=	13.82
				Prob >		=	0.0000
				R-squar	ed	=	0.0038
				Root MS	E	=	1.3177
		Robust					
fin	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
d2	.1683186	.0347701	4.84	0.000	.1001		.2364718
d3	.2114028	.0345214	6.12	0.000	. 1437		.2790683
d4	.1868677	.0343509	5.44	0.000	.1195		.2541991
						- 40	2077451
d5	.2322999 1081072	.0333885 .0261214	6.96 -4.14	0.000 0.000	.1668 1593		.2977451 0569065

# *Table 1.1 (Whole):*

#### . reg agric d, robust

\_cons

.0905479

.0103592

. reg agric a							
Linear regress	sion			Number of	ohs	=	24,161
				F(1, 24159		=	46.15
				Prob > F		=	0.0000
				R-squared		=	0.0020
				Root MSE		=	1.4919
		Robust					
agric	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
d	1721033	.0253346	-6.79	0.000 -	2217	607	1224459
_cons	.0745988	.0105546	7.07	0.000	.0539	111	.0952865
. reg food d,	robust						
Linear regress	sion			Number of	obs	=	24,161
J				F(1, 24159	9)	=	63.72
				Prob > F		=	0.0000
				R-squared		=	0.0028
				Root MSE		=	.91821
		Robust					
food	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
d	1264176	.0158363	-7.98	0.000 -	1574	578	0953774
_cons	.0669862	.0064643	10.36	0.000	.0543	3158	.0796565
. reg beer d,	robust						
Linear regress	sion			Number of	obs	=	24,161
				F(1, 24159	<b>)</b> )	=	66.94
				Prob > F		=	0.0000
				R-squared		=	0.0027
				Root MSE		=	1.4529
		Robust					
beer	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
d	1965791	.0240268	-8.18	0.000	243	8673	1494851

8.74

0.000

.0702432

## . reg smoke d, robust

\_cons

.1042663 .0125498

Linear regress	sion			Number of		24,161
				F(1, 24159	=	4.53
				Prob > F	=	0.0333
				R-squared	=	0.0002
				Root MSE	=	1.1916
		Robust				
smoke	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d	0446838	.0209902	-2.13		085826	0035417
_cons	.0610218	.0083312	7.32	0.000	.0446922	.0773515
. reg toys d,	robust					
Linear regress	sion			Number of	obs =	24,161
				F(1, 24159	=	38.66
				Prob > F	=	0.0000
				R-squared	=	0.0016
				Root MSE	=	2.1398
		Robust				
toys	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d _cons	2203516 .0875493	.0354406 .0152501	-6.22 5.74	0.000 - 0.000	.2898174 .0576581	1508859 .1174405
. reg fun d,	robust					
Linear regress	sion			Number of		24,161
				F(1, 24159	=	75.96
				Prob > F	=	0.0000
				R-squared	=	0.0035
				Root MSE	=	1.7928
		Robust			•	
fun	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d	2742167	.0314641	-8.72	0.000 -	.3358882	2125451

8.31

0.000

.0796678

# . reg books d, robust

Linear regress	sion			Number of (F(1, 24159) Prob > F R-squared Root MSE		24,161 53.29 0.0000 0.0024 1.5632
		Robust				
books	Coef.	Std. Err.	t	P> t	[95% Conf.	<pre>Interval]</pre>
d _cons	1989919 .0804607	.0272599 .010966	-7.30 7.34		252423 .0589667	1455608 .1019548
. reg hshld d	, robust					
Linear regress	sion			Number of		24,161
				F(1, 24159	) =	25.93
				Prob > F	=	0.0000
				R-squared	=	0.0011
				Root MSE	=	1.1581
habld.	Conf	Robust		Do I to I	[050 Canf	Totaniall
hshld	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval
d _cons	1014131 .0594343	.019916 .0081609	-5.09 7.28		.1404498 .0434384	0623764 .0754302
. reg clths d	, robust					
Linear regress	sion			Number of	obs =	24,161
				F(1, 24159	) =	39.48
				Prob > F	=	0.0000
				R-squared	=	0.0018
				Root MSE	=	1.1351
		Robust				
clths	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d _cons	1254494 .0627847	.0199657 .0079395	-6.28 7.91		.1645835 .0472227	0863154 .0783467

#### . reg medeq d, robust

Linear regress	ion			Number of ob	s =	24,161
•				F(1, 24159)	=	48.15
				Prob > F	=	0.0000
				R-squared	=	0.0016
				Root MSE	=	1.5879
		Robust				
medeq	Coef.	Std. Err.	t	P> t  [9	5% Conf.	Interval]
d	1658729	.0239042	-6.94		127266	1190193
_cons	. 0846748	.0115957	7.30	0.000 .0	519466	.1074031
. reg drugs d,	robust					
Linear regress	ion			Number of ob	s =	24,161
				F(1, 24159)	=	48.32
				Prob > F	=	0.0000
				R-squared	=	0.0022
				Root MSE	=	1.1369
		Robust				
drugs	Coef.	Std. Err.	t	P> t  [9	5% Conf.	Interval]
d _cons	137874 .0745076	.0198352 .0079737	-6.95 9.34		767523 588786	0989958 .0901366
. reg chems d,	robust					
Linear regress	ion			Number of ob	s =	24,161
				F(1, 24159)	=	62.45
				Prob > F	=	0.0000
				R-squared	=	0.0029
				Root MSE	=	1.27
		Robust				
chems	Coef.	Std. Err.	t	P> t  [9	Conf	<pre>Interval]</pre>

-7.90

9.06

0.000

0.000

-.2210546

.0629893

-.1331914

.097773

.0224134

.0088731

-.177123

.0803812

d

\_cons

#### . reg txtls d, robust

Linear regress	sion			Number of obs F(1, 24159) Prob > F R-squared Root MSE	= = =	24,161 75.95 0.0000 0.0035 1.3042
txtls	Coef.	Robust Std. Err.	t	P> t  [95	% Conf.	Interval]
d _cons	1983492 .0777941	.0227593 .0091469	-8.72 8.50		29587 98656	1537396 .0957226
. reg bldmt d	, robust					
Linear regress	sion			Number of obs	=	24,161
				F(1, 24159)	=	68.97
				Prob > F R-squared	=	0.0000 0.0032
				Root MSE	=	1.2458
bldmt	Coef.	Robust Std. Err.	t	P> t  [95	% Conf.	Interval]
d _cons	1837242 .0766303	.0221234	-8.30 8.82	0.00022	70874 96051	140361 .0936556
. reg cnstr d	, robust					
Linear regress	sion			Number of obs	=	24,161
				F(1, 24159)	=	96.70
				Prob > F	=	0.0000
				R-squared	=	0.0041
				Root MSE	=	1.9952
cnstr	Coef.	Robust Std. Err.	t	P> t  [95	% Conf.	Interval]
d _cons	3326061 .1093796	.0338227 .014122	-9.83 7.75		89006 16997	2663116 .1370595

## . reg steel d, robust

cg steet u						
Linear regress	sion			Number of	obs =	24,161
				F(1, 24159		84.59
				Prob > F	=	0.0000
				R-squared	=	0.0038
				Root MSE	=	1.6636
		Robust				
steel	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d	2668713	.0290167	-9.20	0.000 -	3237457	2099968
_cons	.0895631	.0116696	7.67	0.000	.0666899	.1124362
. reg mach d,	robust					
Linear regress	sion			Number of		24,161
				F(1, 24159	9) =	61.91
				Prob > F	=	0.0000
				R-squared	=	0.0028
				Root MSE	=	1.3643
		Robust				
mach	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d	1882983	.0239314	-7.87	0.000 -	2352053	1413912
_cons	.0808186	.0095523	8.46	0.000	.0620955	.0995417
. reg elceq d	, robust					
Linear regress	sion			Number of	obs =	24,161
				F(1, 24159	9) =	69.82
				Prob > F	=	0.0000
				R-squared	=	0.0031
				Root MSE	=	1.553
elceq	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
	- 2244002	0260652	_0 36		2771470	_ 1710225
d	2244902 0037560	.0268653	-8.36 8.58		2771479 .0723476	1718325
_cons	.0937569	.0109228	8.58	0.000	.0/234/0	.1151662

#### . reg autos d, robust

Linear regress	sion			Number of obs	=	24,161
_				F(1, 24159)	=	38.88
				Prob > F	=	0.0000
				R-squared	=	0.0018
				Root MSE	=	1.567
		Robust				
autos	Coef.	Std. Err.	t	P> t  [95%	Conf.	Interval]
d _cons	1708022 .0791099	.0273922 .0109833	-6.24 7.20	0.000224 0.000 .057	4926 5819	1171117 .100638
. reg aero d,	robust					
Linear regress	sion			Number of obs	=	24,161
				F(1, 24159)	=	61.60
				Prob > F	=	0.000
				R-squared	=	0.0027
				Root MSE	=	1.7758
2050	Coef.	Robust Std. Err.	t	D>  +   [050	Conf	Interval]
aero	coer.	Sta. Err.	ι .	P> t  [95%	Coni.	Intervati
d _cons	2387886 .1061351	.0304247 .0125282	-7.85 8.47	0.000298 0.000 .081	4228 5792	1791543 .1306911
. reg ships d	, robust					
Linear regress	sion			Number of obs	=	24,161
Linear regress				F(1, 24159)	=	66.71
-Inear regres:						0.0006
inear regres:				Prob > F	=	0.0000
-incar regres:				Prob > F R-squared	=	0.0036
Linear regres:						
Linear regres:		Robust		R-squared	=	0.003

-8.17

7.81

0.000

0.000

-.2646389 -.1622039

.1034315

.0619311

-.2134214 .0261306

.0105865

.0826813

d \_cons

## . reg mines d, robust

\_cons

		.0226011	-8.58	0.000 -	2382034	1496044
oil	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
				Root MSE	_	1.2777
				R-squared	=	0.0034
				F(1, 24159 Prob > F	) = =	73.61 0.0006
inear regres	21011			Number of		24,161
reg oil d,				Number of	a ha	24 161
d _cons	2536474 .0922034	.0366611 .0148302	-6.92 6.22	0.000 - 0.000	3255054 .0631352	1817894 .1212715
coal	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
				ROOT MSE	_	2.1112
				R-squared Root MSE	=	0.0022 2.1112
				Prob > F	=	0.0006
				F(1, 24159		47.87
inear regres	sion			Number of		24,161
reg coal d,	robust					
d _cons	1909157 .0801779	.0267161 .0106601	-7.15 7.52	0.000 0.000	243281 .0592835	1385505 .1010723
mines	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval
		Robust				
				Root MSE	=	1.5227
				R-squared	=	0.0023
				Prob > F	=	0.0006
				F(1, 24159	9) =	51.07

9.16

0.000

.0642109

.099179

.0089201

# . reg util d, robust

\_cons

.0848593

.014316

. reg utit u,	TODUSE					
Linear regress	sion			Number of ob	s =	24,161
•				F(1, 24159)	=	41.78
				Prob > F	=	0.0000
				R-squared	=	0.0018
				Root MSE	=	1.0867
		Robust				
util	Coef.	Std. Err.	t	P> t  [9	5% Conf.	Interval]
d _cons	1198352 .060406	.0185394 .0076767	-6.46 7.87		561735 453593	0834968 .0754527
. reg telcm d,	, robust					
Linear regress	sion			Number of ob	s =	24,161
•				F(1, 24159)	=	25.66
				Prob > F	=	0.0000
				R-squared	=	0.0012
				Root MSE	=	1.0237
		Robust				
telcm	Coef.	Std. Err.	t	P> t  [9	5% Conf.	Interval]
d _cons	0925258 .0562781	.0182642 .0071255	-5.07 7.90		283247 423116	0567269 .0702445
. reg bussv d,	, robust					
Linear regress	sion			Number of ob	s =	24,161
				F(1, 24159)	=	39.66
				Prob > F	=	0.0000
				R-squared	=	0.0013
				Root MSE	=	1.9589
		Robust				
bussv	Coef.	Std. Err.	t	P> t  [9	5% Conf.	Interval]
d	1850692	.029387	-6.30	0.0002	426696	1274687

5.93

0.000

.0567991

# . reg hardw d, robust

				Nombre of	- 6 -	24 161
Linear regress	sion			Number of		24,161
				F(1, 24159		15.85
				Prob > F	=	0.0001
				R-squared	=	0.0007
				Root MSE	=	1.5257
		Robust				
hardw	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d	105018	.026381	-3.98	0.000 -	.1567263	0533097
_cons	.0742035	.010732	6.91	0.000	.053168	.0952389
. reg chips d,	robust					
Linear regress	sion			Number of	obs =	24,161
				F(1, 24159	) =	36.56
				Prob > F	=	0.0000
				R-squared	=	0.0016
				Root MSE	=	1.7466
		Robust				
chips	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
d	1779863	.0294353	-6.05	0.000 -	.2356813	1202912
_cons	.0841325	.0123844	6.79	0.000	.0598582	.1084067
. reg labeq d,	robust					
Linear regress				Number of	obs =	24,161
Linear regress				Number of F(1, 24159		24,161 33.45
Linear regress						
Linear regress				F(1, 24159	) =	33.45
Linear regress				F(1, 24159 Prob > F	) = =	33.45 0.0000
Linear regress				F(1, 24159 Prob > F R-squared	) = = = =	33.45 0.0000 0.0016
	sion	Robust		F(1, 24159 Prob > F R-squared Root MSE	) = = = = =	33.45 0.0000 0.0016 1.4206
Linear regress		Robust Std. Err.	t	F(1, 24159 Prob > F R-squared Root MSE	) = = = =	33.45 0.0000 0.0016 1.4206
	sion		t -5.78	F(1, 24159 Prob > F R-squared Root MSE	) = = = = =	33.45 0.0000 0.0016 1.4206

# . reg boxes d, robust

Linear regress	sion			Number of		=	24,161
				F(1, 24159	))	=	60.39
				Prob > F		=	0.0000
				R-squared		=	0.0028
				Root MSE		=	1.2487
		Robust					
boxes	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
d	1713611	.0220512	-7.77		.214	5827	1281395
_cons	.0795605	.008723	9.12	0.000	.062	4629	.0966582
. reg trans d	, robust						
Linear regress	sion			Number of	obs	=	24,161
Linear regress	72011			F(1, 24159		=	119.95
				Prob > F	,	=	0.0000
				R-squared		=	0.0055
				Root MSE		=	1.342
		Robust					
trans	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
d	2578827	.0235463	-10.95		30		2117305
_cons	.0877135	.0093951	9.34	0.000	.069	2985	.1061285
. reg whlsl d	, robust						
Linear regress	sion			Number of	obs	=	24,161
				F(1, 24159	)	=	61.85
				Prob > F		=	0.0000
				R-squared		=	0.0024
				Root MSE		=	1.6526
		Robust					
whlsl	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
d	2112692	.0268645	-7.86		. 263		1586131
_cons	.0781961	.0118402	6.60	0.000	.054	9884	.101403

# . reg rtail d, robust

\_cons

.0844478

.0103149

Linear regress	sion			Number of o	bs =	24,161
Linear regress	51011			F(1, 24159)	=	64.47
				Prob > F	=	0.0000
				R-squared	=	0.0030
				Root MSE	=	1.1288
		Robust				
rtail	Coef.	Std. Err.	t	P> t  [	95% Conf.	Interval]
d	1592003	.0198273	-8.03		1980631	1203375
_cons	.074911	.0078999	9.48	0.000 .	0594267	.0903954
. reg meals d,	, robust					
Linear regress	sion			Number of o	bs =	24,161
				F(1, 24159)	=	48.64
				Prob > F	=	0.0000
				R-squared	=	0.0023
				Root MSE	=	1.3316
		Robust				
meals	Coef.	Std. Err.	t	P> t  [	95% Conf.	Interval]
d	1640238	.0235192	-6.97	0.000:	2101228	1179247
_cons	. 0777444	.0093013	8.36	0.000 .	0595134	.0959755
. reg banks d,	, robust					
Linear regress	sion			Number of o	bs =	24,161
				F(1, 24159)	=	46.76
				Prob > F	=	0.0000
				R-squared	=	0.0021
				Root MSE	=	1.4713
		Robust				
banks	Coef.	Std. Err.	t	P> t  [	95% Conf.	Interval]
d	17577	.0257041	-6.84	0.000:	2261516	1253884

8.19

0.000

.06423

#### . reg insur d, robust

49 37	Robust Std. Err. .0363198 .0150257 Robust Std. Err.	t -7.95 6.04	P> t   0.000 0.000  Number of F(1, 24159 Prob > F R-squared Root MSE  P> t	359 .0613	9964	Interval]2175859 .120205  24,161 92.45 0.0000 0.0042 1.5662
49	Std. Err.	-7.95	0.000 0.000 Number of F(1, 24159 Prob > F R-squared	359 .0613	9964 3025 = = = =	2175859 .120205 24,161 92.45 0.0000 0.0042
49	Std. Err.	-7.95	0.000 0.000 Number of F(1, 24159 Prob > F	359 .0613	9964 3025	2175859 .120205 24,161 92.45 0.0000
49	Std. Err.	-7.95	0.000 0.000 Number of F(1, 24159	359 .0613	9964 3025 = =	2175859 .120205
49	Std. Err.	-7.95	0.000 0.000 Number of	359 .0613	9964	2175859 .120205
49	Std. Err.	-7.95	0.000	359 .0613	9964 3025	2175859 .120205
49	Std. Err.	-7.95	0.000	359	9964	2175859
49	Std. Err.	-7.95	0.000	359	9964	2175859
f.		t	P> t	[95%	Conf.	Interval]
			Root MSE		=	2.1275
			R-squared		=	0.0028
			Prob > F	•	=	0.0000
			Number of F(1, 24159		=	24,161 63.22
66	.0095699	7.87	0.000	.0565	5991	.0941141
79	.0238867	-6.90	0.000 -	. 2115	5983	1179596
f.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
			ROOT MSE		=	1.3656
					=	0.0022
					=	0.0000
				))	=	47.59
					F(1, 24159) Prob > F R-squared	Prob > F = R-squared =

# Table 1.1 (Pre):

## . reg agric D1, robust

Linear regression	Number of obs	=	7,696
	F(1, 7694)	=	19.56
	Prob > F	=	0.0000
	R-squared	=	0.0025
	Root MSE	=	1.7068

agric	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	2298997	.0519858	-4.42	0.000	3318059	1279934
_cons	.0793285	.0213353	3.72	0.000	.0375054	.1211515

# . reg food D1, robust

Linear regression	Number of obs	=	7,696
	F(1, 7694)	=	30.82
	Prob > F	=	0.0000
	R-squared	=	0.0042
	Root MSE	=	1.0778

food	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	1870284	.0336885	-5.55	0.000	253067	1209897
_cons	.0592428	.0133842	4.43	0.000	.0330061	.0854794

## . reg beer D1, robust

Number of obs	=	7,696
F(1, 7694)	=	32.96
Prob > F	=	0.0000
R-squared	=	0.0042
Root MSE	=	2.0527
	F(1, 7694) Prob > F R-squared	F(1, 7694) = Prob > F = R-squared =

beer	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	. Interval]
D1	3569507	.0621777	-5.74	0.000	4788358	2350655
_cons	.1187582	.0256928	4.62	0.000	.0683933	.1691231

## . reg smoke D1, robust

D1 _cons	4531867 .1088205	.0720226 .0277971	-6.29 3.91	0.000 0.000	594 .054		3120027 .1633104
fun	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
				Root MSE		=	2.2522
				R-square	d	=	0.0056
				Prob > F		=	0.0000
				F(1, 769		=	39.59
Linear regress	sion			Number o	f obs	=	7,696
. reg fun D1,	robust						
D1 _cons	3092402 .1037473	.0916623 .0390304	-3.37 2.66	0.001 0.008	4889 .027		1295572 .1802574
toys	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
		Robust					
				Root MSE		=	3.1005
						=	0.0014
				Prob > F		=	0.0007
				F(1, 769		=	11.38
Linear regress	sion			Number o	f obs	=	7,696
. reg toys D1,	robust						
_cons	.0486195	.0118471	4.10	0.000	.025	3961	.071843
D1	1447932	.0295631	-4.90	0.000	202	7449	0868415
smoke	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
				Root MSE		=	.95231
				Prob > F R-square		=	0.0000 0.0032
				F(1, 769		=	23.99
				-/4	• •		

## . reg books D1, robust

Linear regress	sion			Number of F(1, 7694) Prob > F R-squared Root MSE		7,696 23.35 0.0000 0.0032 2.1697
books	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1 _cons	3299114 .0862964	.0682796 .0268953	-4.83 3.21	0.000 0.001	463758 .0335743	1960648 .1390184
. reg hshld Di	l, robust					
Linear regress	sion			Number of		7,696
				F(1, 7694)	=	22.18
				Prob > F	=	0.0000
				R-squared Root MSE	=	0.0028
				KOOL MSE	_	1.3972
		Robust				
hshld	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1 _cons	1997266 .059531	.0424053 .0174798	-4.71 3.41	0.000 - 0.001	.2828526 .0252659	1166007 .0937961
. reg clths Di	l, robust					
Linear regress	sion			Number of	obs =	7,696
_				F(1, 7694)	=	10.95
				Prob > F	=	0.0009
				R-squared	=	0.0016
				Root MSE	=	1.1298
		Robust				
clths	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1 _cons	1211871 .0465862	.0366144 .0138918	-3.31 3.35	0.001 - 0.001	.1929613 .0193544	0494129 .0738179

## . reg medeq D1, robust

Linear regress	sion			Number of F(1, 7694 Prob > F R-squared Root MSE	1)	= = =	7,696 14.38 0.0002 0.0012 2.214
medeq	Coef.	Robust Std. Err.	t	P> t	[95% (	Conf.	Interval]
D1 _cons	2076407 .0837831	.0547495 .0288075	-3.79 2.91	0.000 0.004	31496 .02731		1003168 .1402537
. reg drugs Di	l, robust						
Linear regress	sion			Number of	fobs	=	7,696
				F(1, 7694	1)	=	19.62
				Prob > F		=	0.0000
				R-squared	t	=	0.0025
				Root MSE		=	1.262

drugs	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	1706142	.0385225	-4.43	0.000	2461287	0950997
_cons	.0630477	.0157665	4.00	0.000	.0321411	.0939543

## . reg chems D1, robust

\_cons

.0963088

Linear	regress	ion			Number of F(1, 7694 Prob > F R-squared Root MSE	1)	= = = =	7,696 32.60 0.0000 0.0044 1.5115
	chems	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
	D1	2698456	.0472645	-5.71	0.000	3624	1968	1771944

5.13

0.000

.0595178

.1330998

# . reg txtls D1, robust

\_cons

.1418464

.0349877

Linear regress	ion			Number of		7,696
				F(1, 7694)	=	37.48
				Prob > F	=	0.0000
				R-squared	=	0.0053
				Root MSE	=	1.4494
		Robust			_	
txtls	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	2831175	.0462466	-6.12	0.000 -	.3737734	1924616
_cons	.0789	.0179003	4.41	0.000	.0438105	.1139894
. reg bldmt D1	, robust					
Linear regress	ion			Number of	obs =	7,696
				F(1, 7694)	=	32.92
				Prob > F	=	0.0006
				R-squared	=	0.0048
				Root MSE	=	1.4969
		Robust				
bldmt	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	2792479	.0486666	-5.74		.3746476	1838482
_cons	.0777142	.0183879	4.23	0.000	.0416689	.1137596
. reg cnstr D1	, robust					
Linear regress	ion			Number of		7,696
				F(1, 7694)		40.01
				Prob > F	=	0.0000
				R-squared	=	0.0053
				Root MSE	=	2.809
		Robust				
cnstr	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	548959	.086788	-6.33	0.000 -	.7190871	378831
I I						

4.05

0.000

.0732609

## . reg steel D1, robust

Linear regress	sion			Number of F(1, 7694) Prob > F R-squared Root MSE		= = =	7,696 43.41 0.0000 0.0056 1.993
steel	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	4005277 .1117093	.0607941 .0249033	-6.59 4.49	0.000 0.000	.062		2813547 .1605266
. reg mach D1,	robust						
Linear regress	sion			Number of	obs	=	7,696
				F(1, 7694)	)	=	29.18
				Prob > F		=	0.0000
				R-squared		=	0.0040
				Root MSE		=	1.6837
mach	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	2854161 .0900483	.0528396 .0208864	-5.40 4.31	0.000 0.000	38 .049		1818361 .1309914
. reg elceq Di	l, robust						
Linear regress	sion			Number of	obs	=	7,696
•				F(1, 7694)	)	=	46.76
				Prob > F		=	0.0000
				R-squared		=	0.0064
				Root MSE		=	1.9892
elceq	Coef.	Robust Std. Err.	t	P> t	[050-	Conf	Interval]
		Stu. EII.		1/14	1330	COIII.	Intervat]
D1 _cons	4302294 .116583	.0629149 .0246246	-6.84 4.73	0.000 - 0.000	.553 .068		3068991 .164854

# . reg autos D1, robust

Linear regress	sion			Number of ob F(1, 7694) Prob > F R-squared Root MSE	s = = = = =	7,696 33.43 0.0000 0.0047 1.9495
autos	Coef.	Robust Std. Err.	t	P> t  [9	5% Conf.	Interval]
D1 _cons	3590325 .1158087	.0620924 .0240876	-5.78 4.81		807504 685904	2373145 .1630269
. reg aero D1	, robust					
Linear regress	sion			Number of ob	s =	7,696
				F(1, 7694)	=	17.97
				Prob > F	=	0.0000
				R-squared	=	0.0023
				Root MSE	=	2.493
aero	Coef.	Robust Std. Err.	t	P> t  [9	5% Conf	Interval]
D1 _cons	324053 .1232549	.0764543	-4.24 3.96	0.0004	739243 622717	1741818 .1842381
. reg ships Di	l, robust					
Linear regress	sion			Number of ob	s =	7,696
				F(1, 7694)	=	45.17
				Prob > F	=	0.0000
				R-squared	=	0.0064
				Root MSE	=	1.748
		Robust				
ships	Coef.	Std. Err.	t	P> t  [9	5% Conf.	Interval]
D1 _cons	3763719 .0940558	.055999 .0215634	-6.72 4.36		861451 517856	2665987 .136326

## . reg mines D1, robust

	sion			Number of		7,696
				F(1, 7694)		15.85
				Prob > F	=	0.0001
				R-squared	=	0.0020
				Root MSE	=	1.6196
	Conf	Robust		Do Let	[050 Conf	Tata 200211
mines	Coef.	Std. Err.	t	P> t	[95% Conf.	intervati
D1 _cons	1948985 .0735213	.0489562 .0202821	-3.98 3.62	0.000 0.000	290866 .033763	0989309 .1132797
. reg coal D1,	, robust					
Linear regress	sion			Number of	obs =	7,696
Linear regress	31011			F(1, 7694)		29.87
				Prob > F	=	0.0000
				R-squared	=	0.0039
				Root MSE	=	2.0771
		Robust				
coal	Coef.	Std. Err.	t	P> t	[95% Conf.	<pre>Interval]</pre>
D1 _cons	3512376 .0861281	.0642624 .0258631	-5.47 3.33	0.000 -	.4772094 .0354294	2252659 .1368267
	3512376 .0861281			0.000 -		
cons	3512376 .0861281 robust			0.000 -	.0354294	.1368267
_cons	3512376 .0861281 robust			0.000 - 0.001	.0354294 obs =	
cons	3512376 .0861281 robust			0.000 - 0.001	.0354294 obs =	7,696
cons	3512376 .0861281 robust			0.000 - 0.001 Number of F(1, 7694)	.0354294  obs = =	.1368267 7,696 39.41
cons	3512376 .0861281 robust			0.000 - 0.001 Number of F(1, 7694) Prob > F	.0354294  obs = = = =	7,696 39.41 0.0000
cons	3512376 .0861281 robust	.0258631		0.000 - 0.001 Number of F(1, 7694) Prob > F R-squared	.0354294  obs = = = = = =	7,696 39.41 0.0000 0.0054
cons	3512376 .0861281 robust			0.000 - 0.001 Number of F(1, 7694) Prob > F R-squared Root MSE	.0354294  obs = = = = = =	7,696 39.41 0.0000 0.0054 1.3732
_cons . reg oil D1, Linear regress	3512376 .0861281 robust	.0258631 Robust	3.33	0.000 - 0.001  Number of F(1, 7694) Prob > F R-squared Root MSE	.0354294  obs = = = = = = =	7,696 39.41 0.0000 0.0054 1.3732

#### . reg util D1, robust

D1

\_cons

-.2012248

.0944017

. reg util D1,	, robust						
Linear regress	sion			Number of	obs	=	7,696
-				F(1, 7694)		=	39.72
				Prob > F		=	0.0000
				R-squared		=	0.0053
				Root MSE		=	1.5466
		Robust					
util	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	3031867	.0481042	-6.30	0.000 -	. 3974	4841	2088893
_cons	.0813244	.0192305	4.23	0.000	.0436	6273	.1190215
. reg telcm Di	l, robust						
Linear regress	sion			Number of	obs	=	7,696
				F(1, 7694)		=	6.32
				Prob > F		=	0.0119
				R-squared		=	0.0009
				Root MSE		=	1.0061
		Robust					
telcm	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	0798133	.0317368	-2.51		142		0176005
_cons	.0419025	.0124641	3.36	0.001	. 0174	4695	. 0663354
. reg bussv Di	l, robust						
Linear regress	sion			Number of	obs	=	7,696
				F(1, 7694)		=	5.85
				Prob > F		=	0.0156
				R-squared		=	0.0006
				Root MSE		=	3.1285
		Robust					
bussv	Coef.	Std. Err.	t	P> t	[95%	Conf.	<pre>Interval]</pre>

-2.42

2.35

0.016

0.019

-.364296

.0155387

.083188

.0402306

-.0381537

#### . reg hardw D1, robust

D1

\_cons

-.1709392

.0681614

.0507814

.0189638

	,					
Linear regress	sion			Number of obs	=	7,696
				F(1, 7694)	=	23.98
				Prob > F	=	0.0000
				R-squared	=	0.0032
				Root MSE	=	1.5044
		Robust				
hardw	Coef.	Std. Err.	t	P> t  [959	s Conf.	Interval]
D1	2290224	.0467645	-4.90		6937	1373512
_cons	.0870271	.0187081	4.65	0.000 .050	3541	.1237001
. reg chips DI	l, robust					
Linear regress	sion			Number of obs	=	7,696
				F(1, 7694)	=	17.71
				Prob > F	=	0.0000
				R-squared	=	0.0024
				Root MSE	=	2.167
		Robust				
chips	Coef.	Std. Err.	t	P> t  [959	conf.	Interval]
D1	2832693	.0673167	-4.21	0.00041	52283	1513102
_cons	.0967591	.0269532	3.59	0.000 .043	39235	.1495948
. reg labeq Di	l, robust					
Linear regress	sion			Number of obs	=	7,696
-				F(1, 7694)	=	11.33
				Prob > F	=	0.0008
				R-squared	=	0.0017
				Root MSE	=	1.5478
		Robust				
labeq	Coef.	Std. Err.	t	P> t  [959	conf.	Interval]

-3.37

3.59

0.001

0.000

-.2704845

.0309873

-.0713939

## . reg boxes D1, robust

Linear	regression Number	of obs =	7,696
	F(1, 76	94) =	33.28
	Prob >	F =	0.0000
	R-squar	ed =	0.0046
	Root MS	E =	1.3992

boxes	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	2555249	.0442942	-5.77	0.000	3423536	1686962
_cons	.0866438	.0173177	5.00	0.000	.0526964	.1205912

## . reg trans D1, robust

Prob > F = 0.000 R-squared = 0.007	Linear regression	Number of obs	=	7,696
R-squared = 0.007		F(1, 7694)	=	50.84
		Prob > F	=	0.0000
Root MSE = 1.680		R-squared	=	0.0072
		Root MSE	=	1.6805

trans	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	3832572	.0537534		0.000	4886286	2778858
_cons	.091661	.0207392		0.000	.0510066	.1323153

## . reg whlsl D1, robust

Linear regression	Number of obs	=	7,696
	F(1, 7694)	=	19.36
	Prob > F	=	0.0000
	R-squared	=	0.0023
	Root MSE	=	2.5255

whlsl	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	3263392	.0741609		0.000	4717146	1809637
_cons	.0808149	.0318399		0.011	.0184	.1432298

## . reg rtail D1, robust

D1 _cons	2704104 .1038454	.0569946	-4.74 4.65	0.000 - 0.000	.38213		1586854 .1476447
banks	Coef.	Robust Std. Err.	t	P> t	[95% C	onf.	Interval]
				Root MSE		=	1.8043
				R-squared		=	0.0031
				Prob > F		=	0.0000
				F(1, 7694)		=	22.51
Linear regres	sion			Number of		=	7,696
. reg banks D	1, robust						
D1 _cons	1998675 .0638189	.0516803 .0194175	-3.87 3.29	0.000 - 0.001	.30117 .02575		0985601 .1018825
meals	Coef.	Std. Err.	t	P> t	[95% C	onf.	Interval]
		Robust					
				Root MSE		=	1.5827
				R-squared		=	0.0001
				Prob > F		=	14.96 0.0001
Linear regres	sion			Number of F(1, 7694)		=	7,696
. reg meals D	l, robust						
_cons	.0711701	.015849	4.49	0.000	.04010	19	.1022384
D1	2260997	.0405674	-5.57	0.000	3056	23	1465765
rtail	Coef.	Robust Std. Err.	t	P> t	[95% C	onf.	Interval]
				Root MSE		=	1.2808
				R-squared		=	0.0043
				F(1, 7694) Prob > F		=	31.06 0.0000
				E/4 7004\			21 44

## . reg insur D1, robust

Linear regression				Number of of f(1, 7694) Prob > F R-squared Root MSE	obs = = = = = = =	7,696 20.58 0.0000 0.0028 1.7407
insur	Coef.	Robust Std. Err.	t	P> t  [	95% Conf.	Interval]
D1 _cons	2463064 .0818542	.0542877 .0216284	-4.54 3.78		3527251 0394565	1398878 .1242518
. reg rlest D	l, robust					
Linear regress	sion			Number of o	obs =	7,696
				F(1, 7694)	=	17.57
				Prob > F	=	0.0000
				R-squared	=	0.0024
				Root MSE	=	3.1214
rlest	Coef.	Robust Std. Err.	t	P> t  [	95% Conf.	Interval]
D1 _cons	4143318 .1146292	.0988472	-4.19 2.97	0.000	6080993	2205643 .1903492
. reg fin D1,	robust					
Linear regress	sion			Number of o	obs =	7,696
				F(1, 7694)	=	43.85
				Prob > F	=	0.0000
				R-squared	=	0.0060
				Root MSE	=	1.9955
		Robust				
fin	Coef.	Std. Err.	t	P> t  [	95% Conf.	Interval]
D1 _cons	416927 .105229	.0629648 .0247184	-6.62 4.26		5403552 0567742	2934988 .1536838

# *Table 1.1 (Post):*

## . reg agric D1, robust

Linear regression	Number of obs	=	16,465
	F(1, 16463)	=	26.93
	Prob > F	=	0.0000
	R-squared	=	0.0018
	Root MSE	=	1.3801

agric					[95% Conf.	Interval]
D1	1483203	.028582	-5.19	0.000	204344	0922966
_cons	.0723184	.0117865	6.14	0.000	.0492155	.0954213

## . reg food D1, robust

Linear regression	Number of obs	=	16,465
	F(1, 16463)	=	34.40
	Prob > F	=	0.0000
	R-squared	=	0.0023
	Root MSE	=	.83295

food	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1		.0174677	-5.87	0.000	1366926	0682154
_cons		.0070822	9.99	0.000	.0568378	.0846017

## . reg beer D1, robust

Linear regression	Number of obs	=	16,465
	F(1, 16463)	=	34.84
	Prob > F	=	0.0000
	R-squared	=	0.0023
	Root MSE	=	1.0612

beer	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	1294255	.0219283		0.000	1724075	0864436
_cons	.0769461	.0090704		0.000	.0591672	.0947251

#### . reg smoke D1, robust

fun

D1

\_cons

Coef.

-.2013476

.1020705

Std. Err.

.0328645

.0128996

_inear regress	ion			Number of	obs	=	16,465
				F(1, 1646		=	0.04
				Prob > F	-,	=	0.8510
				R-squared		=	0.0000
				Root MSE		=	1.2878
		Robust					
smoke	Coef.	Std. Err.	t	P> t	[95% C	onf.	Interval]
D1	005074	.0270201	-0.19	0.851	05803	63	.0478883
_cons	.0670017	.0109476	6.12	0.000	.04554	32	.0884603
	_						
. reg toys D1,	robust						
Linear regress	ion			Number of	obs	=	16,465
				F(1, 1646	3)	=	32.00
				Prob > F		=	0.0000
				R-squared		=	0.0023
				Root MSE		=	1.4919
		Robust					
toys	Coef.	Std. Err.	t	P> t	[95% C	onf.	Interval]
D1	1830874	.0323673	-5.66	0.000	24653	808	1196441
_cons	.0797393	.0125223	6.37	0.000	.05519	42	.1042844
. reg fun D1,	robust						
Linear regress	ion			Number of		=	16,465
				F(1, 1646 Prob > F	3)	=	37.54
				R-squared		=	0.0000
				R-squared		=	0.0027 1.5306
				NOOL FISE		-	1.5500
		Robust					
_							

t

-6.13

7.91

P>|t|

0.000

0.000

[95% Conf. Interval]

-.1369296

.1273551

-.2657656

## . reg books D1, robust

Linear regress	sion			Number of ob	s =	16,465
				F(1, 16463)	=	31.29
				Prob > F	=	0.0000
				R-squared	=	0.0024
				Root MSE	=	1.1765
		Robust				
books	Coef.	Std. Err.	t	P> t  [9	5% Conf.	Interval]
D1	1454942	.0260102	-5.59		196477	0945115
_cons	.0776471	.0098	7.92	0.000 .	058438	.0968561
. reg hshld D1	robust					
. reg nsncu Di	i, Tobust					
Linear regress	sion			Number of ob	s =	16,465
				F(1, 16463)	=	7.89
				Prob > F	=	0.0056
				R-squared	=	0.0006
				Root MSE	=	1.0271
		Robust				
hshld	Coef.	Std. Err.	t	P> t  [9	5% Conf.	Interval]
D1	0615691	.0219144	-2.81	0.0051	045237	0186145
_cons	.0593877	.0086771	6.84	0.000 .0	423797	.0763957
. reg clths D1	l, robust					
Linear regress	ion			Number of ob	s =	16,465
Linear regress	51011			F(1, 16463)	s – =	29.04
				Prob > F	=	0.0000
				R-squared	=	0.0020
				Root MSE	=	1.1375
				ROOT MISE	_	1.13/3
		Robust				
clths	Coef.	Std. Err.	t	P> t  [9	5% Conf.	Interval]
D1	1284232	.0238301	-5.39	0.0001	751326	0817137
_cons	.070595	.0096753	7.30	0.000 .0	516304	.0895596

## . reg medeq D1, robust

chems

\_cons

**D1** 

Linear regress	sion			Number of		=	16,465
				F(1, 1646	3)	=	36.45
				Prob > F		=	0.0000
				R-squared		=	0.0024
				Root MSE		=	1.187
		Robust					
medeq	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	1490173 .0851048	.0246809	-6.04 8.41	0.000 0.000	197	3945 5261	1006401 .1049486
	.0031040	.0101239	0.41	0.000	.00.	3201	.1049400
. reg drugs Di	l, robust						
Linear regress	sion			Number of	obs	=	16,465
_				F(1, 1646	3)	=	29.71
				Prob > F		=	0.0000
				R-squared		=	0.0021
				Root MSE		=	1.0733
		Robust					
drugs	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	1254896	.0230235	-5.45	0.000	170	6182	080361
_cons	.0800331	.0090493	8.84	0.000	.062	2954	.0977707
. reg chems Di	l robust						
. reg chems D.	i, Tobust						
Linear regress	sion			Number of		=	16,465
				F(1, 1646	3)	=	30.98
				Prob > F		=	0.0000
				R-squared		=	0.0023
				Root MSE		=	1.1394

Robust

Std. Err.

.024852

.0095432

t

-5.57

7.62

P>|t|

0.000

0.000

[95% Conf. Interval]

-.0896134

.0914072

-.1870388

.0539958

Coef.

-.1383261

## . reg txtls D1, robust

3	sion			Number of obs F(1, 16463)	=	16,465 40.27
				Prob > F	=	0.0000
				R-squared	=	0.0027
				Root MSE	=	1.2302
txtls	Coef.	Robust Std. Err.	t	P> t  [95%	s Conf.	Interval]
D1 _cons	163916 .0772609	.02583 .0104558	-6.35 7.39	0.000214 0.000 .056	15455 67663	1132864 .0977555
. reg bldmt D	1, robust					
Linear regres	sion			Number of obs	=	16,465
				F(1, 16463)	=	36.87
				Prob > F	=	0.0000
				R-squared	=	0.0026
				Root MSE	=	1.1088
		Robust				
bldmt	Coef.	Std. Err.	t	P> t  [95%	conf.	Interval]
D1 _cons	1449346 .0761077	.0238693 .0093358	-6.07 8.15	0.000191 0.000 .057	.7209 /8086	0981483 .0944069
	.0761077					
_cons	.0761077 1, robust					
_cons	.0761077 1, robust			0.000 .057	8086	.0944069
_cons	.0761077 1, robust			0.000 .057	<b>*</b> 8086	16,465
_cons	.0761077 1, robust			0.000 .057  Number of obs F(1, 16463)	28086 = =	.0944069 16,465 60.16
_cons	.0761077 1, robust			0.000 .057  Number of obs F(1, 16463) Prob > F	# 8086 = = = =	.0944069 16,465 60.16 0.0000
_cons	.0761077 1, robust	.0093358		0.000 .057  Number of obs F(1, 16463) Prob > F R-squared	**************************************	16,465 60.16 0.0000 0.0042
_cons	.0761077 1, robust			Number of obs F(1, 16463) Prob > F R-squared Root MSE	**************************************	16,465 60.16 0.0000 0.0042
_cons	.0761077 1, robust	.0093358	8.15	0.000 .057  Number of obs F(1, 16463) Prob > F R-squared Root MSE  P> t  [95% 0.000303	= = = = = = = = = = = = = = = = = = =	.0944069 16,465 60.16 0.0000 0.0042 1.4662

## . reg steel D1, robust

Linear regress	sion			Number of ob F(1, 16463) Prob > F R-squared Root MSE	s = = = = =	16,465 42.75 0.0000 0.0031 1.4844
steel	Coef.	Robust Std. Err.	t	P> t  [9	5% Conf.	Interval]
D1 _cons	2110094 .0788851	.0322724 .0124494	-6.54 6.34		742667 054483	1477521 .1032873
. reg mach D1,	robust					
Linear regress	sion			Number of ob	s =	16,465
				F(1, 16463)	=	33.21
				Prob > F	=	0.0000
				R-squared	=	0.0024
				Root MSE	=	1.1857
		Robust				
mach	Coef.	Std. Err.	t	P> t  [9	5% Conf.	Interval]
D1 _cons	1482359 .0763684	.0257227 .0099524	-5.76 7.67		986551 568606	0978167 .0958762
. reg elceq DI	l, robust					
Linear regress	sion			Number of ob	s =	16,465
3				F(1, 16463)	=	25.75
				Prob > F	=	0.0000
				R-squared	=	0.0018
				Root MSE	=	1.2985
		Robust		P. Ital	Fo. 6 6	T-1
elceq	Coef.	Std. Err.	t	P> t  [9	5% Conf.	Interval]
D1 _cons	1393681 .0827511	.027467 .0110058	-5.07 7.52		932064 611786	0855298 .1043236

# . reg autos D1, robust

Linear regress	sion			Number of	obs =	16,465
				F(1, 16463	) =	10.11
				Prob > F	=	0.0015
				R-squared	=	0.0007
				Root MSE	=	1.3504
	Γ					
		Robust				
autos	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	0917071	.0288392	-3.18	0.001	148235	0351791
_cons	.0614154	.0114052	5.38	0.000	.03906	.0837707
	•					
. reg aero D1	, robust					
Linear regress	sion			Number of		16,465
				F(1, 16463	) =	49.24
				Prob > F	=	0.0000
				R-squared	=	0.0037
				Root MSE	=	1.3124
		Robust				
aero	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	2029219	.0289176	-7.02	0.000 -	.2596035	1462403
_cons	.0978807	.0109469	8.94	0.000	.0764236	.1193378
. reg ships Di	l sobust					
Linear regress	sion			Number of		16,465
				F(1, 16463	) =	26.10
				Prob > F	=	0.0000
				R-squared	=	0.0017
				Root MSE	=	1.3784
		Dobust				
ships	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
	1465186	.0286795	-5.11	0.000 -	.2027334	0903037
D1	1403100	.0200793	-3.11	0.000 -	. 202/334	0903037

## . reg mines D1, robust

\_cons

.081066

.010365

linoon manus	-ion			Number of	oho =	16 465
Linear regress	510N			Number of ( F(1, 16463		16,465 35.56
				Prob > F	) = =	0.0000
				R-squared	_	0.0026
				Root MSE	=	1.4753
				KOOT HISE	_	1.4755
		Robust				
mines	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	1898142	.0318293	-5.96	0.000	252203	1274253
_cons	.0833874	.0124107	6.72	0.000	.0590611	.1077138
. reg coal D1,	, robust					
inear regress	sion			Number of	obs =	16,465
				F(1, 16463	) =	23.28
				Prob > F	=	0.0000
				R-squared	=	0.0016
				Root MSE	=	2.1267
		Robust				
coal	Coef.	Std. Err.	t	P>   t	[95% Conf.	Interval]
D1 _cons	2145714 .0951326	.0444672 .0181021	-4.83 5.26		301732 .0596505	1274108 .1306147
reg oil D1,	robust					
_inear regress	sion			Number of		16,465
				F(1, 16463		37.76
				Prob > F	=	0.0000
				R-squared	=	0.0027
				Root MSE	=	1.2303
		Robust				
oil	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	1625086	.0264447	-6.15	0.000	214343	1106743

7.82

0.000

.0607494

## . reg util D1, robust

Linear regression	Number of obs	=	16,465
	F(1, 16463)	=	6.85
	Prob > F	=	0.0089
	R-squared	=	0.0005
	Root MSE	=	.78226

util	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	0439313	.0167896	-2.62	0.009	0768407	011022
_cons	.05032	.0065939	7.63	0.000	.0373952	.0632449

#### . reg telcm D1, robust

Linear regression	Number of obs	=	16,465
	F(1, 16463)	=	19.75
	Prob > F	=	0.0000
	R-squared	=	0.0014
	Root MSE	=	1.0318

telcm	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	0987833	.0222266	-4.44	0.000	1423497	0552168
_cons	.0632094	.0086845	7.28	0.000	.0461868	.0802319

## . reg bussv D1, robust

Linear regression	Number of obs	=	16,465
	F(1, 16463)	=	62.68
	Prob > F	=	0.0000
	R-squared	=	0.0046
	Root MSE	=	1.0279

bussv	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	1777886	.0224561	-7.92	0.000	221805	1337721
_cons	.0802584	.0086039	9.33	0.000	.0633938	.097123

## . reg hardw D1, robust

\_cons

.0823041

.0115195

•						
Linear regress	sion			Number of		16,465
				F(1, 16463	) =	2.85
				Prob > F	=	0.0913
				R-squared	=	0.0002
				Root MSE	=	1.5351
		Robust			_	
hardw	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	0537845	.0318546	-1.69	0.091 -	.1162231	.008654
_cons	.0680204	.0131022	5.19	0.000	.0423388	.0937021
. reg chips Di	l, robust					
Linear regress	sion			Number of	obs =	16,465
				F(1, 16463	) =	19.00
				Prob > F	=	0.000
				R-squared	=	0.0012
				Root MSE	=	1.5103
		Robust				
chips	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1 _cons	1343539 .0780445	.0308209 .0129642	-4.36 6.02		.1947662 .0526332	0739417 .1034557
. reg labeq Di	l, robust					
Linear regress	sion			Number of	obs =	16,465
				F(1, 16463	) =	22.44
				Prob > F	=	0.000
				R-squared	=	0.0015
				Root MSE	=	1.357
		Robust				
labeq	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	1354208	.0285878	-4.74	0.000	191456	0793856

7.14

0.000

.0597247

## . reg boxes D1, robust

. reg boxes ba	.,					
Linear regress	sion			Number of	obs =	16,46
,				F(1, 16463		29.5
				Prob > F	=	0.000
				R-squared	=	0.002
				Root MSE	=	1.171
		Robust				
boxes	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval
D1 _cons	1367128 .0761453	.0251686 .0098717	-5.43 7.71	0.000 - 0.000	1860459 .0567958	087379 .095494
. reg trans D1	l, robust					
Linear regress	sion			Number of	obs =	16,46
				F(1, 16463	3) =	70.3
				Prob > F	=	0.000
				R-squared	=	0.005
				Root MSE	=	1.149
		Robust				
trans	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval
D1	2067773	.0246588	-8.39	0.000 -	2551111	158443
_cons	.0858102	.0096921	8.85	0.000	.0668127	.104807
. reg whlsl D1	l, robust					
Linear regress	sion			Number of	obs =	16,46
				F(1, 16463	3) =	56.1
				Prob > F	=	0.000
				R-squared	=	0.004
				Root MSE	=	1.012
		Robust				
whlsl	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval

0.000

0.000

-7.49

9.05

-.2074696

.0602626

-.121413

.0936042

-.1644413

.0769334

D1

\_cons

.021952

#### . reg rtail D1, robust

Linear regress	ion			Number of F(1, 164 Prob > F R-square Root MSE	163) = ed	= = =	16,465 34.91 0.0000 0.0025 1.0501
rtail	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	1323806 .0767147	.0224039	-5.91 8.65	0.000 0.000	176 .059	2946 3242	0884666 .0941053
. reg meals D1							
Linear regress	ion			Number o		=	16,465
				F(1, 164 Prob > F		=	35.05
				R-square		=	0.0000 0.0024
				Root MSE		=	1.1962
		Robust					
meals	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	1505716 .0844587	.0254333 .0101197	-5.92 8.35	0.000 0.000	200 .06	4236 4623	1007196 .1042945
. reg banks D1	, robust						
Linear regress	ion			Number o	of obs	=	16,465
,				F(1, 164		=	24.31
				Prob > F		=	0.0000
				R-square	he	=	0.0017
				it square	- u	_	0.0017

banks				P> t		
D1	1359289	.0275664	-4.93	0.000	1899619	0818959
_cons	.075095	.0108479	6.92		.053832	.0963581

## . reg insur D1, robust

Linear regress	sion			Number of F(1, 1646 Prob > F R-squared Root MSE	3)	= = = =	16,465 27.33 0.0000 0.0020 1.1489
insur	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	131244 .0722237	.0251051 .0096155	-5.23 7.51	0.000 0.000	180 .053		0820354 .0910712
. reg rlest Di	l, robust						
Linear regress	sion			Number of	obs	=	16,465
				F(1, 1646	3)	=	58.83
				Prob > F		=	0.0000
				R-squared		=	0.0041
				Root MSE		=	1.4447
rlest	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	2360619 .079242	.0307769	-7.67 6.49	0.000	296 .055		1757359 .1031792
. reg fin D1,	robust						
Linear regress	sion			Number of	obs	=	16,465
3				F(1, 1646	3)	=	49.47
				Prob > F		=	0.0000
				R-squared		=	0.0035
				Root MSE		=	1.3177
fin	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
				**   *			
D1 _cons	1995999 .0914927	.0283771 .0110931	-7.03 8.25	0.000 0.000	25 .069		1439778 .1132364

## Table 2 (Whole):

#### . reg agric TOM, robust

TOM

\_cons

.123843

.0319555

.022487

.010548

. reg agric it							
Linear regress	sion			Number of	obs	=	24,161
-				F(1, 24159	)	=	14.10
				Prob > F		=	0.0002
				R-squared		=	0.0006
				Root MSE		=	1.493
		Robust					
agric	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
TOM _cons	.093312 .0260511	.0248483 .0106255	3.76 2.45		.0446		.1420162
. reg food TOM	M, robust						
_inear regress	sion			Number of	obs	=	24,161
				F(1, 24159		=	41.33
				Prob > F		=	0.0000
				R-squared		=	0.0016
				R-squared Root MSE		=	0.0016 .91876
		Robust		•			
food	Coef.	Robust Std. Err.	t	Root MSE	[95%	=	.91876
food TOM _cons	Coef. .0963137 .0262727		t 6.43 4.00	P> t  0.000	[95% .0669 .0133	= Conf.	.91876 Interval]
TOM _cons	.0963137 .0262727	Std. Err.	6.43	P> t  0.000	.0669	= Conf.	.91876 Interval]
TOM _cons	.0963137 .0262727	Std. Err.	6.43	P> t  0.000	.0669	= Conf.	.91876 Interval] .1256792 .0391618
TOM _cons	.0963137 .0262727	Std. Err.	6.43	P> t  0.000 0.000	.0669 .0133	Conf. 9483 3836	.91876 Interval] .1256792 .0391618
TOM _cons	.0963137 .0262727	Std. Err.	6.43	P> t  0.000 0.000  Number of	.0669 .0133	= Conf. 9483 3836	.91876 Interval] .1256792 .0391618
TOM _cons	.0963137 .0262727	Std. Err.	6.43	P> t  0.000 0.000  Number of F(1, 24159	.0669 .0133	= Conf. 9483 3836	
ТОМ	.0963137 .0262727	Std. Err.	6.43	P> t  0.000 0.000  Number of F(1, 24159 Prob > F	.0669 .0133	= Conf. 9483 3836	.91876 Interval] .1256792 .0391618
TOM _cons	.0963137 .0262727	Std. Err.	6.43	P> t  0.000 0.000  Number of F(1, 24159 Prob > F R-squared	.0669 .0133	= Conf. 9483 3836	.91876 Interval .1256792 .0391618 24,161 30.33 0.0006 0.0011

5.51

3.03

0.000

0.002

.079767

.0112807

.1679189

## . reg smoke TOM, robust

Linear regress	sion			Number of	obs	=	24,161
				F(1, 24159	)	=	42.72
				Prob > F		=	0.0000
				R-squared		=	0.0017
				Root MSE		=	1.1907
		Robust					
smoke	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
том	.1284091	.0196469	6.54	0.000	.089	8999	.1669183
_cons	.0294617	.0084948	3.47	0.001	.012	B113	.046112
	_						
. reg toys TOM	1, robust						
Linear regress	sion			Number of		=	24,161
				F(1, 24159	)	=	12.23
				Prob > F		=	0.0005
				R-squared		=	0.0005
				Root MSE		=	2.141
		Robust					
toys	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
ТОМ	.117787	.0336769	3.50	0.000	.051	7782	.1837958
_cons	.025698	.0154672	1.66	0.097 -	.004	5188	.0560147
. reg fun TOM,	robust						
Linear regress	sion			Number of	obs	=	24,161
				F(1, 24159		=	25.20
				Prob > F	,	=	0.0000
				R-squared		=	0.0010
				Root MSE		=	1.795
				NOOT HOL			11755
		Robust					
fun	Coef.	Std. Err.	t	P> t	[95%	Conf.	<pre>Interval]</pre>
TOM	. 1474792	.0293793	5.02	0.000	.089	9894	.2050644
_cons	.0271318	.0128348	2.11	0.035	.001	9748	.0522888

## . reg books TOM, robust

Linear regress	sion			Number of F(1, 24159 Prob > F		= =	24,161 4.45 0.0350
				R-squared		=	0.0002
				Root MSE		=	1.565
		Robust					
books	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
ТОМ	.0532091	.025236	2.11	0.035	.00	3745	.1026732
_cons	.0342773	.0112345	3.05	0.002	.01	2257	.0562975
. reg hshld T(	OM, robust						
Linear regress	sion			Number of	obs	=	24,161
				F(1, 24159	)	=	30.76
				Prob > F		=	0.0000
				R-squared		=	0.0012
				Root MSE		=	1.1581
		Robust					
hshld	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
TOM	.1021323	.018414	5.55	0.000	.066	0397	.1382249
_cons	.0222489	.0083441	2.67	0.008	.00	5894	.0386038
. reg clths TO	OM, robust						
Linear regress	sion			Number of	obs	=	24,161
				F(1, 24159	)	=	36.06
				Prob > F		=	0.0000
				R-squared		=	0.0015
				Root MSE		=	1.1353
		Robust					
		Std. Err.	t	P> t	[95%	Conf.	Interval]
clths	Coef.	Stu. Liii.					
clths TOM _cons	.112222 .0193544	.018688	6.01	0.000 0.017	. 075	5924 3469	.1488517

## . reg medeq TOM, robust

Prob > F		sion			Number of		=	24,161
R-squared						))	=	17.59
Root MSE					Prob > F		=	
medeq         Coef.         Std. Err.         t         P> t          [95% Conf. Interval]           TOM .0979368 .0233509cons         .0364285 .0116557 .0133807 .0592744           . reg drugs TOM, robust         .0364285 .0116557 .0133807 .0592744           . reg drugs TOM, robust         .0000 .0000 .0000 .0000 .0000 .0000 .0000 .0000 .0000 .0000 .0000 .0000 .0000 .0000 .0000 .0000 .0000 .00000 .00000 .00000 .00000 .00000 .00000 .00000 .0000 .0000 .00000 .00000 .0000 .0000 .0000 .00000 .0000 .0000 .0000 .00000 .0							=	0.0006
Medeq					Root MSE		=	1.5887
Medeq			Robust					
cons	medeq	Coef.		t	P> t	[95%	Conf.	Interval]
. reg drugs TOM, robust  Linear regression  Number of obs = 24,161 F(1, 24159) = 29.76 Prob > F = 0.0000 R-squared = 0.0012 Root MSE = 1.1374   drugs  Coef. Std. Err. t P> t  [95% Conf. Interval]  TOM	ТОМ	.0979368		4.19		.052	1676	.143706
Number of obs	_cons	.0364285	.0116557	3.13	0.002	.013	5827	.0592744
F(1, 24159)	. reg drugs T(	OM, robust						
Prob > F	Linear regress	sion			Number of	obs	=	24,161
R-squared = 0.0012 Root MSE = 1.1374  drugs					F(1, 24159	))	=	29.76
Root MSE					Prob > F		=	0.0000
Robust   TOM					R-squared		=	0.0012
TOM					Root MSE		=	1.1374
TOM								
cons	drugs	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
Linear regression $ \begin{array}{ccccccccccccccccccccccccccccccccccc$								
F(1, 24159) = 38.01 $Prob > F = 0.0000$ $R-squared = 0.0015$ $Root MSE = 1.2708$ $Chems$								.1412802 .0461427
F(1, 24159) = 38.01 $Prob > F = 0.0000$ $R-squared = 0.0015$ $Root MSE = 1.2708$ $Chems$	_cons	.0303056						
R-squared = $0.0015$ Root MSE = $1.2708$ Robust  chems Coef. Std. Err. t P> t  [95% Conf. Interval]	_cons	.0303056 DM, robust			0.000	.014	4685	
Root MSE = 1.2708  Robust  chems Coef. Std. Err. t P> t  [95% Conf. Interval]	_cons	.0303056 DM, robust			0.000 Number of	.014	4685 =	.0461427
Robust  chems Coef. Std. Err. t P> t  [95% Conf. Interval]	_cons	.0303056 DM, robust			0.000 Number of F(1, 24159	.014	4685 = = =	24,161
chems Coef. Std. Err. t P> t  [95% Conf. Interval]	_cons	.0303056 DM, robust			0.000 Number of F(1, 24159 Prob > F	.014	4685 = = = =	.0461427 24,161 38.01
chems Coef. Std. Err. t P> t  [95% Conf. Interval]	_cons	.0303056 DM, robust			0.000 Number of F(1, 24159 Prob > F R-squared	.014	= = = = =	.0461427 24,161 38.01 0.0000 0.0015
TOM .1281681 .0207881 6.17 0.000 .0874222 .1689141	_cons	.0303056 DM, robust	.0080799		0.000 Number of F(1, 24159 Prob > F R-squared	.014	= = = = =	.0461427 24,161 38.01 0.0000 0.0015
	_cons . reg chems TC	.0303056  DM, robust sion	.0080799	3.75	Number of F(1, 24159 Prob > F R-squared Root MSE	.014	= = = = = =	.0461427 24,161 38.01 0.0000 0.0015 1.2708
_cons	_cons . reg chems TC Linear regress	.0303056  DM, robust sion  Coef1281681	Robust Std. Err.	t 6.17	Number of F(1, 24159 Prob > F R-squared Root MSE	.014	= = = = Conf.	.0461427 24,161 38.01 0.0000 0.0015 1.2708

#### . reg txtls TOM, robust

Linear regress	ion			Number of F(1, 24159 Prob > F R-squared Root MSE		24,161 33.13 0.0000 0.0014 1.3056
txtls	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
TOM _cons	.1259934 .0184857	.0218883 .0092721	5.76 1.99	0.000 0.046	.083091 .0003119	.1688957 .0366595
. reg bldmt TO	)M, robust					
Linear regress	ion			Number of F(1, 24159		24,161 45.34
				Prob > F	=	0.0000
				R-squared	=	0.0017
				Root MSE	=	1.2468
bldmt	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
TOM	. 1333797	.0198095	6.73	0.000	.094552	. 1722075
_cons	.0186608	.0089844	2.08	0.038	.0010507	.0362708
		.0089844	2.08			.0362708
_cons	DM, robust	.0089844	2.08	0.038	.0010507	
_cons	DM, robust	.0089844	2.08	0.038	.0010507	24,161
_cons	DM, robust	.0089844	2.08	0.038	.0010507	
_cons	DM, robust	.0089844	2.08	0.038 Number of F(1, 24159	.0010507  obs =	24,161 21.55
_cons	DM, robust	.0089844	2.08	0.038  Number of F(1, 24159 Prob > F	.0010507  obs = 0) = = =	24,161 21.55 0.0000
_cons	DM, robust	Robust		Number of F(1, 24159 Prob > F R-squared Root MSE	obs = = = = = =	24,161 21.55 0.0000 0.0008 1.9985
_cons	DM, robust		2.08	0.038  Number of F(1, 24159 Prob > F R-squared	.0010507  obs = = = = = =	24,161 21.55 0.0000 0.0008 1.9985
_cons . reg cnstr TO	DM, robust	Robust		Number of F(1, 24159 Prob > F R-squared Root MSE	obs = = = = = =	24,161 21.55 0.0000 0.0008 1.9985

## . reg steel TOM, robust

Linear regress	ion			Number of	obs	=	24,161
-				F(1, 24159	)	=	45.76
				Prob > F		=	0.0000
				R-squared		=	0.0019
				Root MSE		=	1.6653
		Robust					
steel	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
TOM _cons	.1877978 .0064402	.0277621 .0118458	6.76 0.54		.1333		.2422132 .0296586
. reg mach TOM	rohust						
. reg maen ron	, 10005						
Linear regress	ion			Number of		=	24,161
				F(1, 24159	)	=	41.36
				Prob > F		=	0.0000
				R-squared		=	0.0016
				Root MSE		=	1.3652
		Robust					
mach	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
TOM _cons	.1417294 .0204908	.0220374 .0097975	6.43 2.09	0.000 0.037	.0985	5347 1287	.1849241 .0396945
. reg elceq TO	M, robust						
Linear regress	ion			Number of	obs	=	24,161
				F(1, 24159	)	=	26.75
				Prob > F		=	0.0000
				R-squared		=	0.0011
				Root MSE		=	1.5546
		Robust					
elceq	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
TOM _cons	.1314846 .0286542	.0254236 .0111181	5.17 2.58	0.000 0.010	.0816	5527 5862	.1813164

#### . reg autos TOM, robust

Linear regress	sion			Number of ob F(1, 24159) Prob > F R-squared Root MSE	s = = = = =	24,161 52.47 0.0000 0.0021 1.5667
autos	Coef.	Robust Std. Err.	t	P> t  [9	5% Conf.	Interval]
TOM _cons	.1848761 .0141412	.0255234 .0112165	7.24 1.26		348487 078439	.2349036 .0361262
. reg aero TOM	1, robust					
Linear regress	sion			Number of ob F(1, 24159) Prob > F R-squared Root MSE	s = = = = =	24,161 27.66 0.0000 0.0011 1.7772
aero	Coef.	Robust Std. Err.	t	P> t  [9	5% Conf.	Interval]
TOM _cons	.1537264 .0343628	.0292321 .0126902	5.26 2.71		964298 094892	.2110231
. reg ships TO	DM, robust					
Linear regress	sion			Number of ob F(1, 24159) Prob > F R-squared Root MSE	s = = = = =	24,161 32.32 0.0000 0.0013 1.5078
ships	Coef.	Robust Std. Err.	t	P> t  [9	5% Conf.	Interval]
TOM _cons	.1420076 .0176944	.0249803 .0107444	5.68 1.65		930446 033652	.1909706 .038754

## . reg mines TOM, robust

Linear regress	sion			Number of	obs =	24,161
				F(1, 24159	9) =	25.79
				Prob > F	=	0.0000
				R-squared	=	0.0010
				Root MSE	=	1.5237
		Robust				
mines	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval]
TOM _cons	.1265013 .0221407	.0249078 .0108984	5.08 2.03	0.000 0.042	.0776804 .0007792	.1753222 .0435021
. reg coal TOM	1, robust					
Linear regress	sion			Number of	obs =	24,161
				F(1, 24159	9) =	22.30
				Prob > F	=	0.0000
				R-squared	=	0.0009
				Root MSE	=	2.1125
		Robust				
coal	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval]
TOM _cons	.1672453 .0152456	.0354156 .0150028	4.72 1.02	0.000 0.310 -	.0978285 0141607	.236662
. reg oil TOM,	robust					
Linear regress	sion			Number of	obs =	24,161
				F(1, 24159	9) =	37.95
				Prob > F	=	0.0000
				R-squared	=	0.0016
				Root MSE	=	1.2789
		Robust				
oil	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval]
ТОМ	.1312287	.0213034	6.16	0.000	.0894728	.1729846
_cons	.0222494	.0090994	2.45	0.014	.0044141	.0400847
_						

#### . reg util TOM, robust

TOM

\_cons

.096051

.0334349

.0290525

.0143523

. reg utile ron							
Linear regress	ion			Number of	obs	=	24,161
				F(1, 24159	)	=	30.38
				Prob > F		=	0.0000
				R-squared		=	0.0012
				Root MSE		=	1.087
		Robust					
util	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
том	.0962911	.0174686	5.51	0.000	.0620	<b>0516</b>	.1305305
_cons	.0209041	.0078106	2.68	0.007	.005	5948	.0362135
. reg telcm TO	M, robust						
inear regress	ion			Number of	obs	=	24,161
				F(1, 24159	)	=	40.06
				Dook - E			0.0000
				Prob > F		=	0.000
				R-squared		=	0.0016
		Robust		R-squared		=	0.0016
telcm	Coef.	Robust Std. Err.	t	R-squared	[95%	=	0.0016
telcm TOM _cons	Coef. .1078046 .0196909		t 6.33 2.70	R-squared Root MSE	[95% .0744 .0054	= = Conf.	0.0016 1.0234
TOM _cons	.1078046 .0196909	.017033	6.33	R-squared Root MSE P> t  0.000	.0744	= = Conf.	0.0016 1.0234 Interval
TOM _cons	.1078046 .0196909	.017033	6.33	R-squared Root MSE P> t  0.000	.0744	= = Conf.	0.0016 1.0234 Interval
TOM _cons	.1078046 .0196909	.017033	6.33	R-squared Root MSE P> t  0.000 0.007	.0744 .0054	= = Conf. 4188 4142	0.0016 1.0234 Interval] .1411904 .0339675
TOM _cons	.1078046 .0196909	.017033	6.33	R-squared Root MSE  P> t   0.000 0.007  Number of F(1, 24159 Prob > F	.0744 .0054	= = Conf. 4188 4142	0.0016 1.0234 Interval] .1411904 .0339675
TOM _cons	.1078046 .0196909	.017033	6.33	R-squared Root MSE  P> t   0.000 0.007  Number of F(1, 24159 Prob > F R-squared	.0744 .0054	= = = Conf. 4188 4142	0.0016 1.0234 Interval .1411904 .0339675 24,161 10.93 0.0009
ТОМ	.1078046 .0196909	.017033	6.33	R-squared Root MSE  P> t   0.000 0.007  Number of F(1, 24159 Prob > F	.0744 .0054	Conf. 4188 4142	0.0016 1.0234 Interval] .1411904 .0339675
TOM _cons . reg bussv TO	.1078046 .0196909	.017033	6.33	R-squared Root MSE  P> t   0.000 0.007  Number of F(1, 24159 Prob > F R-squared	.0744 .0054	= = = = = = = = = = = = = = = = = = =	0.0016 1.0234 Interval .1411904 .0339679 24,163 10.93 0.0009

0.001

0.020

.0391063

.0053035

.1529957

.0615662

3.31

## . reg hardw TOM, robust

Linear regress	sion			Number of o F(1, 24159) Prob > F R-squared Root MSE		24,161 13.63 0.0002 0.0006 1.5258
hardw	Coef.	Robust Std. Err.	t	P> t  [	95% Conf.	Interval]
TOM _cons	.0958512 .0374996	.02596 .0107888	3.69 3.48		0449679 0163529	.1467345
. reg chips T(	OM, robust					
Linear regress	sion			Number of o	bs =	24,161
				F(1, 24159)	=	38.92
				Prob > F	=	0.0000
				R-squared	=	0.0015
				Root MSE	=	1.7466
chips	Coef.	Robust Std. Err.	t	P> t  [	95% Conf.	Interval]
TOM _cons	.1751085 .0196231	.0280675 .01255	6.24 1.56	0.000 .	1200945 0049757	.2301225
. reg labeq TO	OM, robust					
Linear regress	sion			Number of o	bs =	24,161
Linear regress	2011			F(1, 24159)		24.95
				Prob > F	=	0.0000
				R-squared	=	0.0010
				Root MSE	=	1.421
		Robust				
labeq	Coef.	Std. Err.	t	P> t  [	95% Conf.	Interval]
TOM _cons	.1160694 .029961	.0232366 .0101627	5.00 2.95		0705242 0100414	.1616146 .0498807

#### . reg boxes TOM, robust

Linear regress	sion			Number of o F(1, 24159) Prob > F R-squared Root MSE		24,161 39.75 0.0000 0.0015 1.2495
boxes	Coef.	Robust Std. Err.	t	P> t  [	[95% Conf.	Interval]
TOM _cons	.1267447 .025066	.0201022 .0089754	6.31 2.79		0873432 0074738	.1661462 .0426583
. reg trans TO	)M, robust					
Linear regress	sion			Number of of f(1, 24159) Prob > F R-squared Root MSE		24,161 50.59 0.0000 0.0020 1.3444
trans	Coef.	Robust Std. Err.	t	P> t	95% Conf.	Interval]
TOM _cons	.1551526 .0121791	.0218126 .0096352	7.11 1.26		1123985 0067064	.1979066 .0310647
. reg whlsl TO	)M, robust					
Linear regress	sion			Number of o F(1, 24159) Prob > F R-squared Root MSE		24,161 31.78 0.0000 0.0011 1.6537
whlsl	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
TOM _cons	.1439574 .0132492	.0255367 .0120003	5.64 1.10		0939039 0102722	.1940109 .0367705

# . reg rtail TOM, robust

Linear regress	sion			Number of F(1, 24159 Prob > F R-squared Root MSE		= = = =	24,161 45.80 0.0000 0.0018 1.1295
rtail	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
TOM _cons	.1247962 .0230018	.0184398	6.77 2.85	0.000 0.004	.08	8653 1613	.1609394
. reg meals TO	OM, robust						
Linear regress	sion			Number of		=	24,161
				F(1, 24159	9)	=	26.74
				Prob > F		=	0.0000 0.0010
				R-squared Root MSE		=	1.3324
meals	Coef.	Robust Std. Err.	t	P> t	[Q5%	Conf	Interval]
TOM _cons	.1112412	.0215109	5.17	0.000	.069	0784	.153404
. reg banks TO	)M, robust						
Linear regress	sion			Number of	obs	=	24,161
				F(1, 24159	)	=	30.86
				Prob > F		=	0.0000
				R-squared		=	0.0012
				Root MSE		=	1.472
hank-	Conf	Robust		D- 1+1	[050	Conf	Into rus 11
banks	Coef.	Std. Err.	t	P> t	[95%	Cont.	Interval]
TOM _cons	.1319561 .0281963	.0237545 .0105648	5.55 2.67	0.000 0.008	.085 .007		.1785164 .0489039

## . reg insur TOM, robust

Linear regress	sion			Number of F(1, 24159 Prob > F R-squared Root MSE		= = = =	24,161 33.31 0.0000 0.0012 1.3662
insur	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
TOM _cons	.1250437 .022379	.0216652 .0098499	5.77 2.27	0.000 0.023	.0825		.1675088 .0416854
. reg rlest TO	M, robust						
Linear regress	sion			Number of F(1, 24159 Prob > F R-squared Root MSE		= = = =	24,161 25.83 0.0000 0.0010 2.1293
rlest	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
TOM _cons	.1750394 .0059342	.0344422	5.08 0.39	0.000 0.698	.1075 0240		.2425483
. reg fin TOM,	robust						
Linear regress	sion			Number of F(1, 24159 Prob > F R-squared Root MSE		= = = =	24,161 39.35 0.0000 0.0015 1.5683
fin	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
TOM _cons	.159718 .0186987	.0254599 .0112382	6.27	0.000 0.096	.109		.2096211

# Table 2 (Pre):

#### . reg agric D1, robust

Linear regress	sion			Number		=	7,696
				F(1, 76		=	4.02
				Prob >		=	0.0449
				R-squar		=	0.0005
				Root MS	E	=	1.7085
		Robust					
agric	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.10553	.052601	2.01	0.045	.002		.2086424
_cons	.0239286	.0212998	1.12	0.261	017	8249	.065682
. reg food D1,	robust						
Linear regress	sion			Number	of obs	=	7,696
				F(1, 76	94)	=	23.30
				Prob >	F	=	0.0000
				R-squar	ed	=	0.0028
				Root MS	E	=	1.0785
food	Coef.	Robust Std. Err.		D. I.t.I	[050	Conf	Tata muall
1000	coer.	Sta. Err.	t	P> t	[93%	Coni.	Interval]
		.0318477	4.83		.091	3063	.2161667
D1	.1537365	.03104//	4.03	0.000			
D1 _cons	.1537365 .0030947	.0135751	0.23	0.000	023		.0297057
	.0030947						
_cons	.0030947				023		
_cons	.0030947			0.820	023	5162	.0297057
_cons	.0030947			0.820 Number	023	=	.0297057 7,696
_cons	.0030947			0.820 Number F(1, 76	023! of obs 94) F	= = =	.0297057 7,696 13.95
_cons	.0030947			0.820 Number F(1, 76 Prob >	023! of obs 94) F	= = = =	7,696 13.95 0.0002
_cons	.0030947			0.820 Number F(1, 76 Prob > R-squar	023! of obs 94) F	= = = = =	7,696 13.95 0.0002 0.0015
_cons	.0030947	.0135751		0.820 Number F(1, 76 Prob > R-squar	023! of obs 94) F ed E	= = = = = =	7,696 13.95 0.0002 0.0015
_cons . reg beer D1,	.0030947	.0135751	0.23	Number F(1, 76 Prob > R-squar Root MS	023! of obs 94) F ed E	= = = = Conf.	7,696 13.95 0.0002 0.0015 2.0554

#### . reg smoke D1, robust

D1 _cons	.234176 0046537	.0675351 .0283227	3.47 -0.16	0.001 0.869	.101 060		.3665632 .0508664
fun	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
				Root MSI	E	=	2.2569
				R-square		=	0.0015
				Prob > I		=	0.0005
				F(1, 769	94)	=	12.02
Linear regress				Number	of obs	=	7,696
. reg fun D1,	robust						
D1 _cons	.1617023 .0260047	.0898099 .0392089	1.80 0.66	0.072 0.507	0143 0508		.3377541 .1028648
toys	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
				Root MSI	<b>E</b>	=	3.1021
				R-square		=	0.0004
				Prob > I		=	0.0718
				F(1, 769	94)	=	3.24
_inear regress	ion			Number	of obs	=	7,696
. reg toys D1,	robust						
D1 _cons	.1330173 .0028665	.0291063 .0118969	4.57 0.24	0.000 0.810	.07! 020	5961 4547	.1900736 .0261876
smoke			t	P> t			
ama ka	Coef.	Robust Std. Err.		D. I.t.I	[OFO.	Conf	Interval]
				Root MSI	Ē	=	.95256
				R-square		=	0.0027
				Prob > 1		=	0.0000
	sion			F(1, 769	of obs	=	7,696 20.89

#### . reg books D1, robust

	sion			Number of c F(1, 7694) Prob > F	=	7,696 1.21 0.2712
					=	
				R-squared	=	0.0001
				Root MSE	=	2.173
		Robust				
books	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.0718274	.0652796	1.10		0561385	.1997933
_cons	.0197888	.027246	0.73	0.468	.0336208	.0731985
. reg hshld Di	l, robust					
Linear regress	sion			Number of o	obs =	7,696
Linear regress	,1011			F(1, 7694)	=	12.80
				Prob > F	=	0.0003
				R-squared	=	0.0014
				Root MSE	=	1.3982
		Robust				
hshld	Coef.	Std. Err.	t	P> t  [	[95% Conf.	Interval]
D1	.1432766	.040045	3.58	0.000 .	.0647776	.2217756
_cons	.0029814	.0177111	0.17		.0317372	.0376999
	.0029814	. 0177111			.0317372	.0376999
_cons	.0029814 1, robust	.0177111				7,696
_cons	.0029814 1, robust	.0177111		0.866		
_cons	.0029814 1, robust	.0177111		0.866	obs =	7,696
_cons	.0029814 1, robust	.0177111		0.866  Number of c	obs = =	7,696 11.11
_cons	.0029814 1, robust	.0177111		0.866  Number of c F(1, 7694) Prob > F	obs = = = =	7,696 11.11 0.0009
_cons	.0029814 1, robust			Number of of F(1, 7694) Prob > F R-squared	obs = = = = =	7,696 11.11 0.0009 0.0013
_cons	.0029814 1, robust	Robust Std. Err.		Number of of F(1, 7694) Prob > F R-squared Root MSE	obs = = = = = =	7,696 11.11 0.0009 0.0013
_cons . reg clths D1 Linear regress	.0029814 1, robust	Robust	0.17	Number of of F(1, 7694) Prob > F R-squared Root MSE	obs = = = = = =	7,696 11.11 0.0009 0.0013 1.1299

## . reg medeq D1, robust

D1 _cons	.1665891 .0243106	.0462744 .0189012	3.60 1.29		758787 912741	.2572995 .0613621
chems	Coef.	Robust Std. Err.	t	P> t  [9:	5% Conf.	Interval]
				Root MSE	=	1.5136
				R-squared	=	0.0017
				Prob > F	=	0.0003
Linear regress	2101			Number of obs F(1, 7694)	5 = =	7,696 12.96
. reg chems Di				Number of ob		7 606
D1 _cons	.1351902 .0126522	.0401409 .0156143	3.37 0.81		056503 L79562	.2138773 .0432605
drugs						
drugs	Coef.	Robust Std. Err.	t	D>  +  [0]	E& Conf	Interval]
				Root MSE	=	1.2626
				R-squared	=	0.0016
				Prob > F	=	0.0008
				F(1, 7694)	=	11.34
Linear regress	sion			Number of ob	s =	7,696
. reg drugs D:	l, robust					
_cons	.0211149	.0286903	0.74		351259	.0773557
D1	.1727147	.0557222	3.10	0.002 .00	534839	. 2819455
medeq	Coef.	Robust Std. Err.	t	P> t  [9:	5% Conf.	Interval]
				ROOT MSL	_	2.2144
				R-squared Root MSE	=	0.0008 2.2144
				Prob > F	=	0.0019
				F(1, 7694)	=	9.61
Linear regress	31011			Number of ob	5 =	7,696

## . reg txtls D1, robust

Linear regress	sion			Number of o F(1, 7694) Prob > F R-squared Root MSE	obs = = = = = =	7,696 12.38 0.0004 0.0016 1.4521
txtls	Coef.	Robust Std. Err.	t	P> t  [	[95% Conf.	Interval]
D1 _cons	.1556033 .0064907	.0442189 .0181506	3.52 0.36		.0689223 .0290895	.2422843
. reg bldmt Di	l, robust					
Linear regress	sion			Number of o	obs =	7,696
				F(1, 7694)	=	16.92
				Prob > F	=	0.0000
				R-squared	=	0.0018
				Root MSE	=	1.4991
bldmt	Coef.	Robust Std. Err.	t	P> t  [	[95% Conf.	Interval]
D1 _cons	.1742349	.0423525	4.11	0.000 .	.0912125	.2572573
. reg cnstr Di	l, robust					
Linear regress	sion			Number of o	obs =	7,696
				F(1, 7694)	=	10.10
				Prob > F	=	0.0015
				R-squared	=	0.0012
				Root MSE	=	2.8147
		Robust				
cnstr	Coef.	Std. Err.	t	P> t  [	[95% Conf.	Interval]
D1 _cons	.2665303 .0071879	.0838801 .0353565	3.18 0.20		. 1021025 . 0621204	.4309581 .0764962

#### . reg steel D1, robust

Linear regress	sion		F(1, 769 Prob > F R-square		Number of F(1, 7694) Prob > F R-squared Root MSE		7,696 16.60 0.0000 0.0024 1.9962
steel	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]	
D1 _cons	.2629943 .0022764	.0645506 .0245748	4.07 0.09	0.000 0.926	.1364575 045897	.3895311	
. reg mach D1,	, robust						
Linear regress	sion			Number of F(1, 7694) Prob > F R-squared Root MSE		7,696 18.83 0.0000 0.0022 1.6851	
mach	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]	
D1 _cons	.2162845 .007354	.0498481	4.34 0.35	0.000 0.729	.1185687 034208	.3140003 .0489161	
. reg elceq Di	l, robust						
Linear regress	sion			Number of F(1, 7694) Prob > F R-squared Root MSE		7,696 12.11 0.0005 0.0014 1.9942	
elceq	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]	
D1 _cons	.2055105 .0115994	.0590665 .0250829	3.48 0.46	0.001 0.644 -	.0897241 0375699	.3212968	

## . reg autos D1, robust

Linear regress	sion			Number of obs F(1, 7694) Prob > F R-squared Root MSE	= = =	7,696 18.64 0.0000 0.0022 1.9519
autos	Coef.	Robust Std. Err.	t	P> t  [95%	conf.	Interval]
D1 _cons	.2479959 .0157143	.0574342 .0245869	4.32 0.64	0.000 .135 0.523032	4092 4827	.3605826 .0639112
. reg aero D1,	robust					
Linear regress	sion			Number of obs F(1, 7694)	=	7,696 10.96
				Prob > F	=	0.0009
				R-squared	=	0.0015
				Root MSE	=	2.4941
aero	Coef.	Robust Std. Err.	t	P> t  [95%	conf.	Interval]
D1 _cons	.2591677 .027146	.0783006 .0309434	3.31 0.88	0.001 .105 0.380033	66772 85116	.4126583
. reg ships D1	, robust					
Linear regress	ion			Number of obs	=	7,696
				F(1, 7694)	=	13.26
				Prob > F	=	0.0003
				R-squared	=	0.0017
				Root MSE	=	1.7521
ships	Coef.	Robust Std. Err.	t	P> t  [95%	conf.	Interval]
D1 _cons	.1958257 0004037	.0537869 .0218585	3.64 -0.02	0.000 .090 0.985043	3888 2524	.3012626 .0424449

#### . reg mines D1, robust

Linear regress	sion			Number of obs F(1, 7694) Prob > F R-squared Root MSE	= = =	7,696 14.05 0.0002 0.0016 1.6199
mines	Coef.	Robust Std. Err.	t	P> t  [95%	conf.	Interval]
D1 _cons	.1767119 .0123168	.0471372 .020453	3.75 0.60	0.000 .084 0.547027	13101 77766	.2691137 .0524101
. reg coal D1,	robust					
Linear regress	sion			Number of obs	=	7,696
				F(1, 7694)	=	7.14
				Prob > F	=	0.0076
				R-squared =		0.0009
				Root MSE	=	2.0803
	Conf	Robust		D-  +  [050	Cant	Tota musli
coal	Coef.	Std. Err.	t	P> t  [95%	6 CONT.	Interval]
D1 _cons	.1676672 .0004379	.0627585 .0260595	2.67 0.02	0.008 .044 0.987056	16435 16459	.2906909 .0515217
. reg oil D1,	robust					
Linear regress	sion			Number of obs	=	7,696
				F(1, 7694)	=	25.65
				Prob > F	=	0.0000
				R-squared	=	0.0034
				Root MSE	=	1.3745
		Robust				
oil	Coef.	Std. Err.	t	P> t  [95%	conf.	Interval]
D1 _cons	.2169365 .0025699	.0428353 .0170851	5.06 0.15	0.000 .132 0.880036	9677 9216	.3009053

## . reg util D1, robust

Linear regress	sion			Number of obs = F(1, 7694) = Prob > F = R-squared = Root MSE =		7,696 10.86 0.0010 0.0014 1.5496
util	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1 _cons	.1547477 .005722	.0469476 .0193928	3.30 0.30		.0627176 .0322931	.2467777 .0437372
. reg telcm D1	l, robust					
Linear regress	sion			Number of of F(1, 7694) Prob > F R-squared Root MSE	obs = = = = = = = = = = = = = = = = = = =	7,696 12.80 0.0003 0.0016 1.0058
telcm	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1 _cons	.1080926 .0110078	.0302171 .0126106	3.58 0.87		.0488587 .0137124	.1673264 .0357279
. reg bussv Dl	l, robust					
Linear regress	sion			Number of of F(1, 7694) Prob > F R-squared Root MSE	obs = = = = = =	7,696 1.66 0.1974 0.0002 3.1292
bussv	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1 _cons	.1097614 .043073	.0851481	1.29		057152 .0353907	.2766749 .1215366

## . reg hardw D1, robust

Linear regress	ion			Number of obs F(1, 7694) Prob > F	= =	7,696 7.42 0.0065
				R-squared Root MSE	=	0.0010 1.506
		Robust				
hardw	Coef.	Std. Err.	t	P> t  [95	% Conf.	Interval]
D1	.1320924	.0485088	2.72	0.006 .03	70019	.2271828
_cons	.0274379	.0185594	1.48	0.13900	89435	.0638193
. reg chips D1	., robust					
Linear regress	ion			Number of obs	=	7,696
				F(1, 7694)	=	13.60
				Prob > F	=	0.0002
				R-squared	=	0.0015
				Root MSE	=	2.1679
		Robust				
chips	Coef.	Std. Err.	t	P> t  [95	% Conf.	Interval]
D1	.2264494	.0614103	3.69	0.000 .10	60685	.3468302
_cons	.0127624	.0275227	0.46	0.64304	11895	.0667144
. reg labeq D1	, robust					
Linear regress	ion			Number of obs	=	7,696
				F(1, 7694)	=	10.22
				Prob > F	=	0.0014
				R-squared	=	0.0012
				Root MSE	=	1.5482
		Robust				
	Coef.	Std. Err.	t	P> t  [95	% Conf.	Interval]
labeq						

#### . reg boxes D1, robust

Linear regress	sion		Number of obs F(1, 7694) Prob > F R-squared Root MSE			7,696 19.12 0.0000 0.0023 1.4008
boxes	Coef.	Robust Std. Err.	t	P> t  [9	5% Conf.	Interval]
D1 _cons	.1833275 .0142919	.0419253 .0175794	4.37 0.81		011424 201684	. 2655126 . 0487523
. reg trans Di	l, robust					
Linear regress	sion			Number of ob F(1, 7694)	7,696 13.11	
				F(1, 7694) = Prob > F =		0.0003
				R-squared	=	0.0016
				Root MSE	=	1.6852
trans	Coef.	Robust Std. Err.	t	P> t  [9:	5% Conf.	Interval]
D1 _cons	.1799877 0013571	.0497092 .0212159	3.62 -0.06	0.000 .0	825441 429461	.2774313
. reg whisi Di				Number of ob F(1, 7694)	=	7,696 10.36
				Prob > F R-squared Root MSE	= =	0.0013 0.0011 2.527
whlsl	Coef.	Robust Std. Err.	t	P> t  [9	5% Conf.	Interval]

3.22

-0.34

0.001

0.735

.0897802

-.0737821

.3694915

.052074

.2296359

-.010854

.071345

.0321017

D1

\_cons

#### . reg rtail D1, robust

Linear regress	sion	Number of obs F(1, 7694) Prob > F R-squared Root MSE		= = =	7,696 20.98 0.0000 0.0025 1.2819	
rtail	Coef.	Robust Std. Err.	t	P> t  [959	⊌ Conf.	Interval]
D1 _cons	.1746765 .0051165	.0381333 .0161088	4.58 0.32		99925 54612	.2494281 .0366941
. reg meals Di	l, robust					
Linear regress	sion			Number of obs F(1, 7694) Prob > F R-squared Root MSE	= = = =	7,696 15.18 0.0001 0.0019 1.5829
meals	Coef.	Robust Std. Err.	t	P> t  [959	⊌ Conf.	Interval]
D1 _cons	.1863146	.0478141 .0198225	3.90 0.01	0.000 .092 0.991038	25859 36355	.2800433
. reg banks Di	l, robust					
Linear regress	sion			Number of obs F(1, 7694) Prob > F R-squared Root MSE	= = =	7,696 10.83 0.0010 0.0013 1.8059
banks	Coef.	Robust Std. Err.	t	P> t  [959	⊌ Conf.	Interval]
D1 _cons	.178113 .0298727	.054128 .0226549	3.29 1.32	0.001 .072 0.187014	20073 15371	.2842187

## . reg insur D1, robust

Linear regress	sion			Number of obs F(1, 7694) Prob > F R-squared Root MSE		= = = =	7,696 9.49 0.0021 0.0011 1.7421
insur	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.1557857 .015528	.0505715 .0220074	3.08 0.71	0.002 0.480	.056 027		.2549197 .0586685
. reg rlest Di	l, robust						
Linear regress	sion			Number of	obs	=	7,696
				F(1, 7694	)	=	14.87
				Prob > F		=	0.0001
				R-squared		=	0.0019
				Root MSE		=	3.1222
rlest	Coef.	Robust Std. Err.	+	D>  +	[05%	Conf	Interval]
	coer.	Sta. Err.	t	P> t	[95%	coni.	Intervati
D1 _cons	.366172 0139348	.0949488 .0390383	3.86 -0.36	0.000 0.721	.1800 090		.5522975 .0625909
. reg fin D1,	robust						
Linear regress	sion			Number of	obs	=	7,696
				F(1, 7694		=	14.52
				Prob > F		=	0.0001
				R-squared		=	0.0018
				Root MSE		=	1.9997
		Robust					
fin	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
fin D1	Coef.		t 3.81	P> t	[95% .112		Interval]

## Table 2 (Post):

#### . reg agric D1, robust

Linear regress	sion			F(1, 16463) = Prob > F = R-squared =		= = =	16,465 10.23 0.0014 0.0006 1.3809
agric	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.0882479 .0270769	.0275918 .0119355	3.20 2.27	0.001 0.023	.034	1649 3682	.1423309
. reg food D1,	, robust						
Linear regress	sion			Number of F(1, 16463 Prob > F R-squared Root MSE		= = =	16,465 18.59 0.0000 0.0011 .83345
food	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.0714139 .0374747	.0165614 .0072164	4.31 5.19	0.000 0.000	.038		.1038761 .0516195
. reg beer D1,	, robust						
Linear regress	sion			Number of F(1, 16463 Prob > F R-squared Root MSE		= = = =	16,465 17.25 0.0000 0.0010 1.0619
beer	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.0867934 .0356015	.0208984 .0092213	4.15 3.86	0.000 0.000	.045		.1277565 .0536762

#### . reg smoke D1, robust

Linear regression	Number of obs	=	16,465
	F(1, 16463)	=	24.63
	Prob > F	=	0.0000
	R-squared	=	0.0014
	Root MSE	=	1.2869

smoke	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.1243504	.0250571	4.96	0.000	.0752358	.173465
_cons	.0423152	.0112108	3.77	0.000	.0203409	.0642895

#### . reg toys D1, robust

Linear regression	Number of obs	=	16,465
	F(1, 16463)	=	11.46
	Prob > F	=	0.0007
	R-squared	=	0.0007
	Root MSE	=	1.4931

toys	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.1002465	.0296082	3.39	0.001	.0422111	.1582818
_cons	.0255497	.0129359	1.98	0.048	.0001939	.0509056

## . reg fun D1, robust

Linear regression	Number of obs	=	16,465
	F(1, 16463)	=	12.88
	Prob > F	=	0.0003
	R-squared	=	0.0008
	Root MSE	=	1.532

fun	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.1101527	.030694	3.59	0.000	.0499891	.1703163
_cons	.0424938	.0132308	3.21	0.001	.0165601	.0684275

#### . reg books D1, robust

Linear regress	sion			Number of		=	16,465
				F(1, 16463 Prob > F	3)	=	3.66 0.0557
				R-squared		=	0.0002
				Root MSE		=	1.1778
		Robust					
books	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.0445548	.023286	1.91		001		.0901979
_cons	.0412795	.0102137	4.04	0.000	.021	2597	.0612994
. reg hshld D1	l, robust						
Linear regress	sion			Number of	obs	=	16,465
				F(1, 16463	3)	=	17.60
				Prob > F		=	0.0000
				R-squared		=	0.0010
				Root MSE		=	1.0268
		Robust					
hshld	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.0840696	.0200403	4.20	0.000	. 044	7885	.1233507
_cons	.031561	.0089393	3.53	0.000	.014	0391	.0490829
. reg clths D1	l, robust						
Linear regress	sion			Number of	obs	=	16,465
				F(1, 16463	3)	=	24.58
				Prob > F		=	0.0000
				R-squared		=	0.0015
				Root MSE		=	1.1378
		Robust					
	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
clths							
clths D1 _cons	.1114118	.0224729	4.96 2.51	0.000 0.012	.067		.155461

## . reg medeq D1, robust

Linear regress	sion			Number of F(1, 16463		=	16,465 8.20
				Prob > F	,	=	0.0042
				R-squared		=	0.0005
				Root MSE		=	1.1882
		Robust					
medeq	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.06675	.0233123	2.86	0.004	.021		.1124446
_cons	.0438296	.0103278	4.24	0.000	.023	5861	.0640732
. reg drugs Di	l, robust						
Linear regress	sion			Number of	obs	=	16,465
_				F(1, 16463	)	=	17.93
				Prob > F		=	0.0000
				R-squared		=	0.0011
				Root MSE		=	1.0739
		Robust					
drugs	Coef.	Std. Err.	t	P> t	[95%	Conf.	<pre>Interval]</pre>
D1	. 089965	.0212461	4.23	0.000	.048	3204	.1316097
_cons	.0388375	.0093106	4.17	0.000	.020	5878	.0570872
. reg chems Di	l, robust						
Linear regress	sion			Number of	obs	=	16,465
				F(1, 16463	)	=	25.55
				Prob > F		=	0.0000
				R-squared		=	0.0015
				Root MSE		=	1.1398
		Robust					
chems	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.1127781	.0223107	5.05	0.000	.069	0467	. 1565095
_cons	.0246964	.0099142	2.49	0.013	.005	2635	.0441294

#### . reg txtls D1, robust

Linear regress	sion			Number of F(1, 16463 Prob > F R-squared Root MSE		= = = =	16,465 20.56 0.0000 0.0013 1.2311
txtls	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.1131502 .0242829	.0249521 .0105929	4.53	0.000 0.022	.064		.162059
. reg bldmt D1	l, robust						
Linear regress	sion			Number of	obs	=	16,465
				F(1, 16463	3)	=	28.21
				Prob > F		=	0.0000
				R-squared Root MSE		=	0.0017 1.1094
				ROOT HISE		_	1.1094
		Robust					
bldmt	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.1157253 .0262747	.0217897 .0096393	5.31 2.73	0.000 0.006	.073		.1584356 .0451687
. reg cnstr DI	l, robust						
Linear regress	sion			Number of	obs	=	16,465
				F(1, 16463	3)	=	11.94
				Prob > F		=	0.0006
				R-squared		=	0.0007
				Root MSE		=	1.4687
		Robust					
cnstr	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.1019954 .0278326	.0295218 .0126709	3.45 2.20	0.001 0.028	.044		.1598614

## . reg steel D1, robust

Linear regress	sion			Number of o		16,465
				F(1, 16463)		29.75
				Prob > F	=	0.0000
				R-squared	=	0.0017
				Root MSE	=	1.4854
		Robust				
steel	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.1573723	.0288526	5.45	0.000	.100818	.2139266
_cons	.0084525	.0129499	0.65	0.514	.0169307	.0338358
. reg mach D1,	, robust					
Linear regress	sion			Number of o	obs =	16,465
				F(1, 16463)		22.59
				Prob > F	=	0.0000
				R-squared	=	0.0013
				Root MSE	=	1.1863
		Robust				
mach	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.1108131	.0233172	4.75	0.000 .	.0651089	.1565173
_cons	.0268398	.0103058	2.60		.0066393	.0470403
. reg elceq Di	l, robust					
Linear regress	sion			Number of o	obs =	16,465
Linear regress	sion			Number of of F(1, 16463)		16,465 14.59
Linear regress	510N					•
Linear regress	sion			F(1, 16463)	=	14.59
Linear regress	sion			F(1, 16463) Prob > F	= =	14.59 0.0001
Linear regress	sion	Robust		F(1, 16463) Prob > F R-squared	= = =	14.59 0.0001 0.0009
Linear regress	Coef.	Robust Std. Err.	t	F(1, 16463) Prob > F R-squared Root MSE	= = =	14.59 0.0001 0.0009 1.2991
			t 3.82 3.30	F(1, 16463) Prob > F R-squared Root MSE  P> t	= = =	14.59 0.0001 0.0009 1.2991

## . reg autos D1, robust

Linear regress	sion			Number of F(1, 16463 Prob > F R-squared Root MSE		34.76 0.0000 0.0022
autos	Coef.	Robust Std. Err.	t	P> t	[95% Conf	. Interval]
D1 _cons	.1597593 .0133809	.0270954 .0116462	5.90 1.15	0.000 0.251 -	.1066493 0094469	.2128692
. reg aero D1,	robust					
Linear regress	sion			Number of	obs =	16,465
_				F(1, 16463	3) =	
				Prob > F	=	0.0000
				R-squared	=	0.0011
				Root MSE	=	1.3141
aero	Coef.	Robust Std. Err.	t	P> t	[95% Con1	f. Interval]
D1 _cons	.1109487 .0378507	.0257022 .0114328	4.32 3.31	0.000 0.001	.0605697 .0154411	.1613278 .0602602
. reg ships Di	l, robust					
Linear regress	sion			Number of	obs =	16,465
				F(1, 16463		
				Prob > F	=	0.0000
				R-squared	=	0.0011
				Root MSE	=	1.3788
		Robust				
ships	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval]
D1 _cons	.1189727 .0264413	.0274341 .011933	4.34	0.000 0.027	.0651989 .0030513	.1727466 .0498313

#### . reg mines D1, robust

Linear regress	sion			Number of	obs =	16,465
				F(1, 16463	=	13.00
				Prob > F	=	0.0003
				R-squared	=	0.0008
				Root MSE	=	1.4766
		Robust				
mines	Coef.	Std. Err.	t	P> t	[95% Conf.	<pre>Interval]</pre>
D1 _cons	.1055987 .0268886	.0292921 .0127918	3.61 2.10	0.000 0.036	.048183 .0018152	.1630144 .0519619
. reg coal D1	, robust					
Linear regress	sion			Number of	obs =	16,465
				F(1, 16463	=	15.01
				Prob > F	=	0.0001
				R-squared	=	0.0009
				Root MSE	=	2.1274
		Robust				
coal	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1 _cons	.165843 .0224023	.0428067 .0183475	3.87 1.22	0.000 0.222 -	.0819373 .0135607	.2497487 .0583652
. reg oil D1,	robust					
Linear regress	sion			Number of	obs =	16,465
				F(1, 16463	=	15.30
				Prob > F	=	0.0001
				R-squared	=	0.0009
				Root MSE	=	1.2314
		Robust				
oil	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.0953063	.0243644	3.91	0.000	.0475494	.1430632
_cons	.0317606	.0106764	2.97	0.003	.0108338	.0526874

#### . reg util D1, robust

D1

\_cons

.0913698

.0287767

.0206405

.0088907

. reg util D1	, robust						
Linear regres:	sion			Number of	obs	=	16,465
				F(1, 16463	)	=	22.11
				Prob > F		=	0.0000
				R-squared		=	0.0013
				Root MSE		=	.78195
		Robust					
util	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.0716437	.0152366	4.70		.041		.101509
_cons	.0282417	.0068106	4.15	0.000	.014	8921	.0415912
. reg telcm D:	1, robust						
Linear regress	sion			Number of	obs	=	16,465
_				F(1, 16463	)	=	27.01
				Prob > F		=	0.0000
				R-squared		=	0.0017
				Root MSE		=	1.0316
		Robust					
telcm	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.1069661 .0238874	.020582 .0089211	5.20 2.68	0.000 0.007	.066	6231 6401	.1473091 .0413738
. reg bussv D	1, robust						
Linear regres	sion			Number of		=	16,465
				F(1, 16463	)	=	19.60
				Prob > F		=	0.0000
				R-squared		=	0.0012
				Root MSE		=	1.0296
		Robust					
bussv	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
	I						

4.43

3.24

0.000

0.001

.0509122

.0113501

.1318273 .0462034

#### . reg hardw D1, robust

Linear regression	Number of obs	=	16,465
	E/1 16462\	_	6 05

F(1, 16463) = 6.85 Prob > F = 0.0089 R-squared = 0.0004 Root MSE = 1.535

hardw	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.0805165	.0307731	2.62	0.009	.0201978	.1408352
_cons	.0423625	.0132535	3.20	0.001	.0163842	.0683408

#### . reg chips D1, robust

Linear regression Number of obs = 16,465

Number of obs = 16,465 F(1, 16463) = 25.71 Prob > F = 0.0000 R-squared = 0.0016 Root MSE = 1.51

chips	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.1540007	.0303734	5.07	0.000	.0944654	.2135359
_cons	.0229388	.0130243	1.76	0.078	0025902	.0484679

#### . reg labeq D1, robust

Linear regression Number of obs = 16,465

Number of obs = 16,465 F(1, 16463) = 14.63 Prob > F = 0.0001 R-squared = 0.0009 Root MSE = 1.3575

labeq	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.1021454	.0267015	3.83	0.000	.0498076	.1544831
_cons	.0368833	.0117905	3.13	0.002	.0137727	.0599939

## . reg boxes D1, robust

\_cons

.0248983

.0087263

Linear regress	ion			Number of	obs =	16,465
				F(1, 16463	3) =	21.01
				Prob > F	=	0.0000
				R-squared	=	0.0012
				Root MSE	=	1.1721
		Robust				
boxes	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.1032141	.0225188	4.58	0.000	.0590748	.1473533
_cons	.0302732	.0102502	2.95	0.003	.0101817	.0503647
. reg trans D1	., robust					
Linear regress	ion			Number of	obs =	16,465
				F(1, 16463	3) =	39.44
				Prob > F	=	0.0000
				R-squared	=	0.0024
				Root MSE	=	1.151
		Robust				
trans	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1 _cons	.1440909 .0187212	.022944 .0099565	6.28 1.88	0.000 0.060 -	.0991182 0007946	.1890636 .038237
		.0033303		0.000		.030237
. reg whlsl D1	., robust					
Linear regress	ion			Number of		16,465
				F(1, 16463		27.48
				Prob > F	=	0.0000
				R-squared	=	0.0017
				Root MSE	=	1.014
		Robust				
whlsl	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.1076781	.0205419	5.24	0.000	.0674137	.1479425

2.85

0.004

.0077938

.0420028

## . reg rtail D1, robust

Linear regress	sion			Number of F(1, 16463 Prob > F R-squared Root MSE		= = =	16,465 24.83 0.0000 0.0015 1.0506
rtail	Coef.	Robust Std. Err.	t	P> t	[95% 0	Conf.	Interval]
D1 _cons	.1033542 .0316458	.0207423 .009115	4.98 3.47	0.000 0.001	.0626		.1440114
. reg meals Di	l, robust						
Linear regress	sion			Number of	obs	=	16,465
				F(1, 16463	()	=	11.68
				Prob > F		=	0.0006
				R-squared		=	0.0007
				Root MSE		=	1.1973
meals	Coef.	Robust Std. Err.	t	P> t	[95% 0	Conf.	Interval]
D1 _cons	.0789465 .0405598	.0231048 .0104577	3.42 3.88	0.001 0.000	.03365		.1242344
. reg banks D	l, robust						
Linear regress	sion			Number of	ohs	=	16,465
				F(1, 16463		=	20.63
				Prob > F		=	0.0000
				R-squared		=	0.0012
				Root MSE		=	1.2866
haales	Coof	Robust		Do 1+1	[OE0: C	`an£	Totage: 11
banks	Coef.	Std. Err.	t	P> t	195% (	.ont.	Interval]
D1 _cons	.113633 .0273861	.0250191 .0112122	4.54 2.44	0.000 0.015	.06459		.1626731 .0493632

## . reg insur D1, robust

Linear regress	sion			Number of F(1, 16463 Prob > F R-squared Root MSE		= = =	16,465 25.25 0.0000 0.0015 1.1492
insur	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.1121762 .0256901	.0223259 .0100178	5.02 2.56	0.000 0.010	.068		.1559374 .045326
. reg rlest Di	l, robust						
Linear regress	sion			Number of		=	16,465
				F(1, 16463 Prob > F	3)	=	11.44 0.0007
				R-squared		=	0.0007
				Root MSE		=	1.4472
rlest	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.0969312 .015537	.0286633 .0125426	3.38 1.24	0.001 0.215	.04	0748 0479	.1531144
. reg fin D1,	robust						
Linear regress	sion			Number of	obs	=	16,465
				F(1, 16463	3)	=	25.18
				Prob > F		=	0.0000
				R-squared		=	0.0015
				Root MSE		=	1.3191
fin	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.1293772 .0285846	.0257819 .0114786	5.02 2.49	0.000 0.013	.078		.1799124 .0510838

## Table 3 (Whole):

#### . reg agric D1, robust

Linear regress	sion			Number of F(1, 24429 Prob > F R-squared Root MSE		= = = =	24,431 12.50 0.0004 0.0004 2.3868
agric	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.1774944 .0744096	.0501996 .0160921	3.54 4.62	0.000 0.000	.079		.2758888 .1059511
. reg food D1,	, robust						
Linear regress	sion			Number of	obs	=	24,431
				F(1, 24429	)	=	47.46
				Prob > F		=	0.0000
				R-squared		=	0.0016
				Root MSE		=	. 95722
food	Conf	Robust		D. Iti	[050	Cant	T=+====11
food	Coef.	Std. Err.	t	P> t	[95%	CONT.	Interval]
D1 _cons	.139416 .0641499	.0202364 .0064508	6.89 9.94	0.000 0.000	.099		.1790807 .0767938
. reg beer D1,	, robust						
Linear regress	sion			Number of	obs	=	24,431
•				F(1, 24429	)	=	9.75
				Prob > F		=	0.0018
				R-squared		=	0.0003
				Root MSE		=	1.5018
		Robust					
beer	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.0985132 .0666951	.0315535 .010126	3.12 6.59	0.002 0.000	.036		.1603601 .0865428

#### . reg smoke D1, robust

fun	Coef.	Std. Err.	6.14	P> t  0.000	[95%	7769	.2863487
fun	Coof	Robust	+	D> I+ I	[05%	Conf	Intorvall
				Root MSE		=	1.6668
				R-squared		=	0.0013
				Prob > F		=	0.0000
				F(1, 24429	9)	=	37.73
Linear regress	sion			Number of		=	24,431
. reg fun D1,	robust						
_cons	.063257	.0144915	4.37	0.000	.034	8529	.0916612
D1	.1843641	.0461503	3.99	0.000	.093	9068	.2748214
toys	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
				Root MSE		=	2.1529
				R-squared		=	0.0006
				Prob > F		=	0.0001
				F(1, 24429	9)	=	15.90
_inear regress	sion			Number of	obs	=	24,431
. reg toys D1,	robust						
_cons	.070477	.0089986	7.83	0.000	.052		.0881149
D1	.1065336	.0282667	3.77	0.000	.051		.161938
smoke	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
				Root MSE		=	1.3354
				R-squared		=	0.0005
				Prob > F		=	0.0002
Linear regress	, 1011			F(1, 24429		=	14.20
Linear regress	sion			Number of		=	24,431

#### . reg books D1, robust

Linear regress	sion			Number of F(1, 24429 Prob > F R-squared Root MSE		= = = =	24,431 13.99 0.0002 0.0005 1.5861
books	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.125109 .0644646	.0334511	3.74 6.03	0.000 0.000	.0595		.1906752 .0854191
. reg hshld Di	l, robust						
Linear regress	sion			Number of	obs	=	24,431
				F(1, 24429	)	=	63.43
				Prob > F		=	0.0000
				R-squared		=	0.0021
				Root MSE		=	1.2032
hahld	Conf	Robust		Do Let	[050	Conf	T=+====11
hshld	Coef.	Std. Err.	t	P> t	195%	Cont.	Interval]
D1 _cons	.1996551 .0570939	.0250683 .008118	7.96 7.03	0.000 0.000	.1505		.2487904 .0730058
. reg clths Di	l, robust						
Linear regress	sion			Number of	obs	=	24,431
,				F(1, 24429	)	=	58.66
				Prob > F		=	0.0000
				R-squared		=	0.0028
				Root MSE		=	1.2544
		Robust					
clths	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.2368804	.0309293	7.66	0.000	. 176	5257	.2975038
_cons	.0667	.0083236	8.01	0.000	.0503		.0830149

## . reg medeq D1, robust

D1

\_cons

.130252

.0643555

.0245589

.0081791

Inear regression  Number of F(1, 24429 Prob > F R-squared Root MSE  Robust  medeq  Coef. Std. Err. t P> t		= = =	24,43: 45.1( 0.000( 0.001) 1.505(
Prob > F R-squared Root MSE	9)	=	0.000 0.001
R-squared Root MSE		=	0.001
Root MSE Robust			
Robust		=	1.505
medea Coef. Std. Err. + Poltl			
	[95%	Conf.	Interval
D1 .2285559 .0340119 6.72 0.000	.161	8906	.2952213
_cons	0.000 .0397773		.079312
reg drugs D1, robust			
inear regression Number of	obs	=	24,43
F(1, 24429		=	27.6
Prob > F		=	0.000
R-squared		=	0.001
Root MSE		=	1.268
Robust			
drugs Coef. Std. Err. t P> t	[95%	Conf.	Interval
D1 .1454402 .0276478 5.26 0.000	.091	2489	.199631
_cons	.049	1576	.0825680
. reg chems D1, robust			
inear regression Number of	obs	=	24,43
F(1, 24429	)	=	28.13
Prob > F		=	0.000
R-squared		=	0.0009
Root MSE		=	1.209
Robust			
chems Coef. Std. Err. t P> t	[95%	Conf.	Interval

5.30

7.87

0.000

0.000

.082115

.0483239

.178389

.0803871

## . reg txtls D1, robust

	-4			Number of			24 421
Linear regress	510N			Number of		=	24,431
				F(1, 24429	,	=	39.39
				Prob > F		=	0.0000
				R-squared		=	0.0014
				Root MSE		=	1.3172
		Robust					
txtls	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	. 17827	.028405	6.28	0.000	.1225	945	.2339455
_cons	.0579461	.0088614	6.54	0.000	.0405	5772	.075315
. reg bldmt Di	l, robust						
Linear regress	sion			Number of		=	24,431
				F(1, 24429	)	=	56.05
				Prob > F		=	0.0000
				R-squared		=	0.0019
				Root MSE		=	1.1805
	Ι						
		Robust					
bldmt	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.1866524	.0249305	7.49	0.000	. 1377	7871	.2355177
_cons	.0624465	.0079563	7.85	0.000	. 0468	3515	.0780414
. reg cnstr Di	l. robust						
Linear regress	sion			Number of		=	24,431
				F(1, 24429	)	=	28.98
				Prob > F		=	0.0000
				R-squared		=	0.0014
				Root MSE		=	2.4838
		Robust					
cnstr	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.3351658	.0622605	5.38	0.000	.2131	L314	.4572003
	i						
_cons	.0787973	.0164492	4.79	0.000	.0465	5559	.1110388

## . reg steel D1, robust

D1	.1966723	.0295544	6.65 6.88	0.000	.138	7438	.2546008
elceq	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
				Root MSE		=	1.4274
				R-squared		=	0.0015
				Prob > F		=	0.0000
				F(1, 24429	))	=	44.28
Linear regress	sion			Number of		=	24,431
. reg elceq Di	l, robust						
D1 _cons	.1946281 .064432	.0279398	6.97 7.47	0.000 0.000	.047		.2493919 .0813422
mach	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
				Root MSE		=	1.2835
				R-squared		=	0.0018
				Prob > F		=	0.0000
				F(1, 24429	))	=	48.52
Linear regress	sion			Number of	obs	=	24,431
. reg mach D1,	robust						
_cons	.0588626	.0100251	5.87	0.000	.039		.0785125
D1	. 1870579	.0317543	5.89	0.000	.124		. 2492982
steel	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
				Root MSE		=	1.4887
				R-squared		=	0.0012
				Prob > F		=	0.0000
-				F(1, 24429	)	=	34.70
Linear regress	sion			Number of F(1, 24429		=	24,4 34.

#### . reg autos D1, robust

Linear regress	ion			Number of	ohe	=	24,431
Linear regress	1011			F(1, 24429		=	37.06
				Prob > F	,	=	0.0000
				R-squared		=	0.0013
				Root MSE		=	1.4684
							211001
		Robust					
autos	Coef.	Std. Err.	t	P> t	[95% Cor	ıf.	Interval]
D1	.1911917	.0314075	6.09	0.000	.1296312		. 2527523
_cons	.0609594	.0098857	6.17	0.000	.041583	3	.0803359
. reg aero D1,	robust						
. reg dero Di,	Tobust						
Linear regress	ion			Number of		=	24,431
				F(1, 24429	9)	=	19.11
				Prob > F		=	0.0000
				R-squared		=	0.0007
				Root MSE		=	1.6948
		Robust					
aero	Coef.	Std. Err.	t	P> t	[95% Cor	nf.	Interval]
D4	.1563953	.0357753	4.37	0.000	.0862735		.2265172
D1	. 1303333		4.37	0.000	.0002/33	,	
_cons	.0797626	.0114226	6.98	0.000	.0573736		.1021516
	.0797626						
_cons	.0797626 , robust				.0573736		
_cons	.0797626 , robust			0.000	. <b>0573736</b>	5	.1021516
_cons	.0797626 , robust			0.000 Number of	. <b>0573736</b>	=	.1021516
_cons	.0797626 , robust			0.000 Number of F(1, 24429	. <b>0573736</b>	= =	.1021516 24,431 20.04
_cons	.0797626 , robust			0.000 Number of F(1, 24429 Prob > F	. <b>0573736</b>	= = =	.1021516 24,431 20.04 0.0000
_cons	.0797626 , robust	.0114226		0.000 Number of F(1, 24429 Prob > F R-squared	. <b>0573736</b>	= = = =	.1021516 24,431 20.04 0.0000 0.0007
_cons	.0797626 , robust			0.000 Number of F(1, 24429 Prob > F R-squared	. <b>0573736</b> obs	= = = =	.1021516 24,431 20.04 0.0000 0.0007
_cons . reg ships D1 Linear regress	.0797626 , robust	. <b>0114226</b> Robust	6.98	Number of F(1, 24429 Prob > F R-squared Root MSE	. <b>0573736</b> obs	= = = = =	.1021516 24,431 20.04 0.0000 0.0007 1.7052

## . reg mines D1, robust

Linear regress	sion			Number of	obs	=	24,431
				F(1, 24429	)	=	47.08
				Prob > F		=	0.0000
				R-squared		=	0.0020
				Root MSE		=	1.6254
		Robust					
mines	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.2620335	.0381871	6.86	0.000	. 187	1844	.3368826
_cons	.0766196	.0108447	7.07	0.000	.055	3632	.0978759
. reg coal D1,	robust						
Linear regress	sion			Number of		=	24,431
				F(1, 24429	))	=	4.37
				Prob > F		=	0.0366
				R-squared		=	0.0001
				Root MSE		=	2.3918
		Robust					
coal	Coef.	Std. Err.	t	P> t	[95%	Conf.	<pre>Interval]</pre>
D1	.1044069	.0499539	2.09	0.037	.006	4941	.2023196
_cons	.1017995	.016135	6.31	0.000	.070	1739	.1334252
. reg oil D1,	robust						
Linear regress	ion			Number of	obs	=	24,431
				F(1, 24429		=	14.70
				Prob > F		=	0.0001
				R-squared		=	0.0005
				Root MSE		=	1.4646
		Robust					
oil	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.122165	.0318623	3.83	0.000	.059	7131	.184617
_cons	.0755045	.0098458	7.67	0.000	.056	2062	.0948028

## . reg util D1, robust

Linear regress	sion			Number of	obs	=	24,431
				F(1, 24429	)	=	11.79
				Prob > F		=	0.0006
				R-squared		=	0.0004
				Root MSE		=	1.1903
		Robust					
util	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.0836644	.024367	3.43	0.001	.035	9035	.1314253
_cons	.0547561	.0080425	6.81	0.000	.038	9923	.0705199
	•						
. reg telcm Di	l, robust						
Linear regress	sion			Number of		=	24,431
				F(1, 24429	)	=	25.81
				Prob > F		=	0.0000
				R-squared		=	0.0010
				Root MSE		=	1.1816
		Robust					
telcm	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.1351446	.0266025	5.08	0.000	. 08	3002	.1872872
_cons	.0536102	.0079174	6.77	0.000	.038	0916	.0691289
. reg bussv D	1, robust						
Linear regress	sion			Number of	ohe	=	24,431
Linear regress	31011			F(1, 24429		=	42.35
				Prob > F	,	=	0.0000
				R-squared		=	0.0017
				Root MSE		=	1.4817
				11001 1102			21.1027
		Robust					
bussv	Coef.	Std. Err.	t	P> t	[95%	Conf.	<pre>Interval]</pre>
D1	.21812	.0335175	6.51	0.000	. 152	4236	.2838163
_cons	.082505	.0099237	8.31	0.000	.063	0539	.1019561
	I.						

#### . reg hardw D1, robust

Linear regress	sion			Number of F(1, 24429 Prob > F R-squared Root MSE		= = = =	24,431 44.10 0.0000 0.0016 1.4069
hardw	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.2047722 .0557607	.0308344 .0094514	6.64 5.90	0.000 0.000	.14	4335 2355	.2652095 .074286
. reg chips Di	l, robust						
Linear regress	sion			Number of	obs	=	24,431
_				F(1, 24429	9)	=	39.31
				Prob > F		=	0.0000
				R-squared		=	0.0013
				Root MSE		=	1.6703
ahina	Coef.	Robust Std. Err.	_	D- I+I	[05%	Conf	Intervall
chips	coer.	Sta. Err.	t	P> t	[93%	coni.	Interval]
D1	.2207162	.0352042	6.27	0.000	.151	7137	.2897186
_cons	.0716918	.011259	6.37	0.000	.049	6235	.0937601
. reg labeq D:	l, robust						
Linear regress	sion			Number of	obs	=	24,431
J				F(1, 24429	9)	=	20.65
				Prob > F		=	0.0000
				R-squared		=	0.0007
				Root MSE		=	1.2835
1-1-	0	Robust		D. I.t.I	[050	Conf	Toda 11
labeq	Coef.	Std. Err.	t	P> t	[95%	cont.	Interval]
	I						
D1	.1244746	.0273885	4.54	0.000	.070	7915	.1781578

## . reg boxes D1, robust

D1 _cons	.1614724 .0961439	.0356996 .0123782	4.52 7.77	0.000 0.000	.0914989 .0718819	.2314459 .1204058
whlsl	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
				ROOL MSE	_	1.0257
				R-squared Root MSE	=	0.0006 1.8257
				Prob > F	=	0.0000
				F(1, 24429		20.46
Linear regress	sion			Number of		24,431
. reg whlsl D						
D1 _cons	.245917 .0779541	.0310654	7.92 8.47	0.000 0.000	.1850269 .0599176	.3068071 .0959907
trans	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
		Robust				
				Root MSE	=	1.3739
				R-squared	=	0.0025
				Prob > F	=	0.0000
				F(1, 24429	=	62.66
Linear regress				Number of	obs =	24,431
. reg trans Di	l. robust					
D1 _cons	.1362396 .0708776	.0295023 .008964	7.91	0.000	.0784133 .0533076	.1940659 .0884477
D1	1262206	0205022	4.62	0.000		
boxes	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
				Root MSE	=	1.3354
				R-squared	=	0.0008
				Prob > F	=	0.0000
				F(1, 24429	=	21.33
_	sion					

## . reg rtail D1, robust

Linear regress	ion			Number of obs F(1, 24429) Prob > F R-squared Root MSE		= = = =	24,431 33.36 0.0000 0.0012 1.0868
rtail	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.1377436 .0656963	.0238473 .0072999	5.78 9.00	0.000 0.000	.091 .051		.1844857 .0800046
. reg meals D1	., robust						
Linear regress	ion			Number of	obs	=	24,431
				F(1, 24429	)	=	50.98
				Prob > F		=	0.0000
				R-squared Root MSE		=	0.0022 1.3104
meals	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.2230893 .0592315	.0312455 .0087285	7.14 6.79	0.000 0.000	.161		.2843324
. reg banks D1	., robust						
Linear regress	ion			Number of	obs	=	24,431
-				F(1, 24429	)	=	30.35
				Prob > F		=	0.0000
				R-squared		=	0.0010
				Root MSE		=	1.1753
banks	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.1350398 .0646502	.0245131 .0079297	5.51 8.15	0.000 0.000	.086		.183087

## . reg insur D1, robust

Linear regress	sion			Number of F(1, 24429 Prob > F R-squared Root MSE		= = = =	24,431 5.17 0.0230 0.0002 1.3193
insur	Coef.	Robust Std. Err.	t	P> t	[95% Co	nf.	Interval]
D1 _cons	.0668081	.0293908	2.27 6.78	0.023 0.000	.009200 .042677		.1244159
. reg rlest D1	., robust						
Linear regress	ion			Number of	obs	=	24,431
				F(1, 24429	)	=	25.89
				Prob > F		=	0.0000
				R-squared		=	0.0010
				Root MSE		=	2.3216
rlest	Coef.	Robust Std. Err.		D>  +	[05% Co	n f	Interval]
D1	.2665452	.0523856	5.09 5.02	P> t  0.000 0.000	.163866	1	.3692243
_cons		.0133331	3.02	0.000	.04/519	_	
. reg fin D1,	robust						
Linear regress	sion			Number of		=	24,431
				F(1, 24429	)	=	35.57
				Prob > F		=	0.0000
				R-squared		=	0.0013
				Root MSE		=	1.3859
fin	Coef.	Robust Std. Err.	t	P> t	[95% Co	nf.	Interval]
D1 _cons	.1829611	.0306791	5.96 8.45	0.000	.122828	3	.2430939

# Table 3 (Pre):

# . reg agric D1, robust

Linear regress	sion			Number of		=	7,696
				F(1, 7694)		=	1.00
				Prob > F		=	0.3184
				R-squared		=	0.0001
				Root MSE		=	3.7071
		Robust					
agric	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.1323023	.1325829	1.00		. 127!		.3922009
_cons	.1280748	.0447183	2.86	0.004	.0404	4147	.2157349
. reg food D1,	, robust						
Linear regress	sion			Number of	obs	=	7,696
				F(1, 7694)		=	14.21
				Prob > F		=	0.0002
				R-squared		=	0.0014
				Root MSE		=	1.3172
food	Coef.	Robust Std. Err.		D>  +	[05%	Conf	Interval]
	Coer.	Stu. Ell.	t	P> t	[93%	COIII.	Intervati
D1	. 176527	.0468263	3.77	0.000	.0847	7347	.2683194
_cons	.0751472	.0158974	4.73	0.000	.0439	9839	.1063105
. reg beer D1,	, robust						
Linear regress	sion			Number of	obs	=	7,696
				F(1, 7694)		=	1.15
				Prob > F		=	0.2827
				R-squared		=	0.0001
						=	2.2335
				Root MSE			
		Robust		ROOT MSE			
beer	Coef.	Robust Std. Err.	t		[95%	Conf.	Interval]
beer D1	Coef. .0847156 .0880748		1.07 3.27	P> t  0.283		6985	Interval] .2392811 .140943

#### . reg smoke D1, robust

Linear regressi		Robust Std. Err.	t	Number of F(1, 7694 Prob > F R-squared Root MSE	i	= = = = = Conf.	7,696 4.28 0.0385 0.0004 2.4566
Linear regressi				F(1, 7694 Prob > F R-squared	1)	= = =	4.28 0.0385 0.0004
Linear regressi				F(1, 7694 Prob > F	1)	=	4.28 0.0385
Linear regressi				F(1, 7694		=	4.28
inear regressi.							
.inear rearessi				Number of	f obs	=	7.696
. reg fun D1, r	ohust						
D1 _cons	.100129 .0766885	.1258858 .0410236	0.80 1.87	0.426 0.062	1460 0037		.3468995 .157106
toys	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
				Root MSE		=	3.4096
				R-squared	t	=	0.0001
				Prob > F		=	0.4264
				F(1, 7694	1)	=	0.63
inear regressi				Number of	f obs	=	7,696
. reg toys D1,	robust						
D1 _cons	.1955216 .0563486	.0453871 .0156247	4.31 3.61	0.000 0.000	.106	5505 2572	.2844928 .0869773
				P> t			
smoke	Coef.	Robust Std. Err.	t	D>  +	[05%	Conf	Interval]
				Root MSE		=	1.2934
				R-squared	Ŀ	=	0.0018
				Prob > F		=	0.0000
Linear regressi	.on			Number of F(1, 7694		=	7,696 18.56

#### . reg books D1, robust

Linear regress	ion			Number of F(1, 7694) Prob > F R-squared Root MSE		= = =	7,696 3.54 0.0600 0.0003 2.2905
books	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.1522407 .0694185	.0809226 .0276568	1.88 2.51	0.060 0.012	006 .015		.3108709 .1236334
. reg hshld D1	, robust						
Linear regress	ion			Number of	obs	=	7,696
_				F(1, 7694)	)	=	17.99
				Prob > F		=	0.0000
				R-squared		=	0.0016
				Root MSE		=	1.6365
hshld	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.2331193 .0641959	.0549696 .0198332	4.24	0.000 0.001	.12	5364 3174	.3408746
. reg clths D1	, robust						
Linear regress	ion			Number of	obs	=	7,696
				F(1, 7694)	)	=	16.07
				Prob > F		=	0.0001
				R-squared		=	0.0025
				Root MSE		=	1.6571
		Robust					
clths	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.2927402	.0730328 .0195765	4.01 4.61	0.000 0.000	.149		.4359043

# . reg medeq D1, robust

Linear regress	ion			Number of	obs =	7,696
				F(1, 7694)	=	6.82
				Prob > F	=	0.0091
				R-squared	=	0.0008
				Root MSE	=	2.1903
		Robust				
medeq	Coef.	Std. Err.	t	P> t	[95% Conf.	<pre>Interval]</pre>
D1 _cons	.2261199 .0475302	.0866122 .0261886	2.61 1.81	0.009 0.070 -	.0563363 .0038066	.3959034 .098867
. reg drugs D1	, robust					
Linear regress	ion			Number of	obs =	7,696
				F(1, 7694)	=	2.56
				Prob > F	=	0.1094
				R-squared	=	0.0002
				Root MSE	=	1.4745
		Robust				
drugs	Coef.	Std. Err.	t	P> t	[95% Conf.	<pre>Interval]</pre>
D1 _cons	.0826416 .0470567	.0516095 .0178171	1.60 2.64	0.109 - 0.008	.0185271 .0121304	.1838103 .081983
. reg chems D1	, robust					
Linear regress	ion			Number of	obs =	7,696
				F(1, 7694)	=	3.90
				Prob > F	=	0.0483
				R-squared	=	0.0003
				Root MSE	=	1.5451
		Robust				
chems	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1 _cons	.0954406 .0783904	.0483207 .0188101	1.98 4.17	0.048 0.000	.0007189 .0415175	.1901624 .1152634

# . reg txtls D1, robust

D1 _cons	.4954862 .1391895	.1768065 .0465227	2.80 2.99	0.005 0.003	. 148		.842075 .2303867
cnstr	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
				Root MSE		=	3.9462
				R-squared		=	0.0012
				Prob > F		=	0.0051
				F(1, 7694)		=	7.85
Linear regress				Number of	obs	=	7,696
. reg cnstr D:	l, robust						
D1 _cons	.1587707 .0697512	.0523679 .0189921	3.03 3.67	0.002 0.000	.056		.2614261 .1069808
bldmt	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
		Robust					
				Root MSE		=	1.5666
				R-squared		=	0.0008
				Prob > F		=	0.0024
				F(1, 7694)		=	9.19
Linear regress	sion			Number of	obs	=	7,696
. reg bldmt D:	l, robust						
_cons	.0887217	.0204181	4.35	0.000	.048		.1287467
D1	.1739479	.0591935	2.94	0.003	. 057		. 2899834
txtls	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
				Root MSE		=	1.6899
				R-squared		=	0.0008
				Prob > F		=	0.0033

#### . reg steel D1, robust

Linear regress	sion			Number of F(1, 7694) Prob > F R-squared Root MSE		= = = =	7,696 4.47 0.0344 0.0004 1.9162
steel	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.1344092	.0635401 .0232421	2.12 3.90	0.034 0.000	.009		.2589652 .1361894
. reg mach D1,	, robust						
Linear regress	sion			Number of F(1, 7694) Prob > F R-squared Root MSE		= = = =	7,696 11.42 0.0007 0.0011 1.7013
mach	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.2037252 .0772402	.0602963	3.38 3.76	0.001 0.000	.085		.3219224 .1175002
. reg elceq Di	l, robust						
Linear regress	sion			Number of F(1, 7694) Prob > F R-squared Root MSE		= = = =	7,696 6.96 0.0084 0.0006 1.9595
elceq	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.170909 .069272	.0647822 .0237732	2.64 2.91	0.008 0.004	.043		.2978997 .1158739

# . reg autos D1, robust

Linear regress	sion			Number of F(1, 7694) Prob > F R-squared Root MSE		= = = =	7,696 7.32 0.0068 0.0007 1.9877
autos	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.1889787 .0835703	.0698247 .024011	2.71 3.48	0.007 0.001	.0521		.3258542
. reg aero D1,	robust						
Linear regress	sion			Number of F(1, 7694) Prob > F R-squared Root MSE		= = = =	7,696 2.93 0.0869 0.0003 2.4116
aero	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.1437392 .0954614	.0839539 .0291511	1.71 3.27	0.087 - 0.001	.0208		.3083116 .1526055
. reg ships D1	l, robust						
Linear regress	sion			Number of F(1, 7694) Prob > F R-squared Root MSE		= = = =	7,696 4.45 0.0350 0.0004 2.1336
ships	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.1587137 .0846197	.0752695 .0257651	2.11 3.28	0.035 0.001		1165 4113	.3062623 .1351263

# . reg mines D1, robust

	sion			Number of F(1, 7694)		7,696 10.37
				Prob > F	=	0.0013
				R-squared	=	0.0012
				Root MSE	=	1.8753
		Robust				
mines	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.2362862	.073388	3.22	0.001	.0924258	.3801467
_cons	.1085554	.0224453	4.84	0.000	.0645564	.1525543
. reg coal D1	, robust					
Linear regress	sion			Number of		7,696
				F(1, 7694)	=	3.01
				Prob > F	=	0.0826
				R-squared	=	0.0003
				Root MSE	=	2.8127
		Robust				
coal	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	Coef.		1.74		[95% Conf.	<pre>Interval] .3503196</pre>
		Std. Err.				
D1	.1645198 .2035646	Std. Err.	1.74	0.083 -	0212799	.3503196
D1 _cons	.1645198 .2035646 robust	Std. Err.	1.74	0.083 -	0212799 .1367607	.3503196 .2703686
D1 _cons	.1645198 .2035646 robust	Std. Err.	1.74	0.083 - 0.000	0212799 .1367607	.3503196
D1 _cons	.1645198 .2035646 robust	Std. Err.	1.74	0.083 - 0.000	0212799 .1367607	.3503196 .2703686
D1 _cons	.1645198 .2035646 robust	Std. Err.	1.74	0.083 - 0.000 Number of F(1, 7694)	0212799 .1367607	.3503196 .2703686 7,696 3.46
D1 _cons	.1645198 .2035646 robust	Std. Err.	1.74	0.083 - 0.000  Number of F(1, 7694) Prob > F	0212799 .1367607	.3503196 .2703686 7,696 3.46 0.0628
D1 _cons	.1645198 .2035646 robust	Std. Err0947826 .0340789	1.74	0.083 - 0.000  Number of F(1, 7694) Prob > F R-squared	0212799 .1367607	.3503196 .2703686 7,696 3.46 0.0628 0.0003
D1 _cons	.1645198 .2035646 robust	Std. Err.	1.74	0.083 - 0.000  Number of F(1, 7694) Prob > F R-squared	0212799 .1367607	.3503196 .2703686 7,696 3.46 0.0628 0.0003 1.6322
D1 _cons . reg oil D1, Linear regress	.1645198 .2035646 robust	Std. Err0947826 .0340789	1.74 5.97	0.083 0.000 Number of F(1, 7694) Prob > F R-squared Root MSE	obs = = = = = =	.3503196 .2703686 7,696 3.46 0.0628 0.0003 1.6322

#### . reg util D1, robust

3.03 4.23	0.002 0.000	.0940618 .0609875	.4391916 .1663323
t	P> t	[95% Conf.	Interval]
	NOOT FISE		2.2734
	Root MSE	=	2.2454
	R-squared	=	0.002
	F(1, 7694) Prob > F	) = =	9.17 0.002!
	Number of		7,696
1.58 2.24	0.115 0.025	0171321 .00435	.1585442 .065731
t	P> t	[95% Conf.	Interval]
		_	
	Root MSE	=	1.2946
	R-squared	=	0.0002
	Prob > F	=	0.1146
	F(1, 7694)	) =	2.49
	Number of	obs =	7,696
3.11 2.80	0.002 0.005	.0748113 .0189963	.3296093 .1077747
t	P> t	[95% Conf.	Interval]
	Root MSE	=	1.8729
	R-squared	=	0.0009
	Prob > F	=	0.0019
			7,696 9.68
		F(1, 7694	F(1, 7694) =

#### . reg hardw D1, robust

Linear regress	sion			Number of		=	7,696
				F(1, 7694)		=	3.89
				Prob > F		=	0.0486
				R-squared		=	0.0003
				Root MSE		=	1.6166
		Robust					
hardw	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.1057819	.0536367	1.97	0.049	.000		.2109245
_cons	.0530869	.0196083	2.71	0.007	.014	6493	.0915245
. reg chips Di	l, robust						
Linear regress	sion			Number of		=	7,696
				F(1, 7694)		=	4.40
				Prob > F		=	0.0360
				R-squared		=	0.0004
				Root MSE		=	2.3452
ahina	Conf	Robust Std. Err.		D. I.I.	[OE0.	Conf	Tntonus 11
chips	Coef.	Sta. Err.	t	P> t	[95%	Cont.	Interval]
D1	.1689061	.0805245	2.10	0.036	.011	0561	.3267561
DI		424274	2 60			5935	.1318507
_cons	.0762221	.028378	2.69	0.007	.020		
_cons		.028378	2.69	0.007	.020		
_cons . reg labeq Di	l, robust	.028378	2.69	Number of	obs	=	
_cons . reg labeq Di	l, robust	.028378	2.69	Number of F(1, 7694)	obs		7,696 0.48
_cons . reg labeq Di	l, robust	.028378	2.69	Number of F(1, 7694) Prob > F	obs	=	7,696 0.48 0.4863
_cons . reg labeq Di	l, robust	.028378	2.69	Number of F(1, 7694) Prob > F R-squared	obs	= =	7,696 0.48 0.4863 0.0000
_cons . reg labeq Di	l, robust	.028378	2.69	Number of F(1, 7694) Prob > F	obs	= = =	7,696 0.48 0.4863
_cons . reg labeq Di	l, robust	Robust	2.69	Number of F(1, 7694) Prob > F R-squared	obs	= = =	7,696 0.48 0.4863 0.0000
_cons	l, robust		t	Number of F(1, 7694) Prob > F R-squared	obs	= = = =	7,696 0.48 0.4863 0.0000
_cons . reg labeq D: Linear regress	l, robust	Robust		Number of F(1, 7694) Prob > F R-squared Root MSE	obs	= = = = = Conf.	7,696 0.48 0.4863 0.0000 1.5883

#### . reg boxes D1, robust

Linear regress	sion			Number of		=	7,696
				F(1, 7694)		=	6.02
				Prob > F		=	0.0141
				R-squared Root MSE		=	0.0006
				ROOT MSE		=	1.6889
		Robust					
boxes	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.1456552	.0593409	2.45	0.014	.029		.2619794
_cons	.0979497	.0204007	4.80	0.000	.057	9587	.1379406
. reg trans Di	l, robust						
Linear regress	sion			Number of	obs	=	7,696
				F(1, 7694)		=	23.40
				Prob > F		=	0.0000
				R-squared		=	0.0027
				Root MSE		=	1.8969
		Robust					
trans	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.3532632	.0730219	4.84	0.000	.210	1204	.496406
_cons	.137853	.0227386	6.06	0.000	.093	2791	. 1824269
. reg whlsl Di	l, robust						
				Number of	obs	=	7,696
				Number of F(1, 7694)		=	7,696 0.48
							•
. reg whlsl D:				F(1, 7694)		=	0.48
				F(1, 7694) Prob > F		=	0.48 0.4864
		Robust		F(1, 7694) Prob > F R-squared		= = =	0.48 0.4864 0.0000
		Robust Std. Err.	t	F(1, 7694) Prob > F R-squared		= = =	0.48 0.4864 0.0000
Linear regress	sion		t 0.70	F(1, 7694) Prob > F R-squared Root MSE		= = = = Conf.	0.48 0.4864 0.0000 2.9506

# . reg rtail D1, robust

Linear regress	sion			Number of F(1, 7694) Prob > F R-squared Root MSE		= = = =	7,696 10.99 0.0009 0.0011 1.3459
rtail	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.1614266 .0838675	.0487041 .0162198	3.31 5.17	0.001 0.000	.0659		.2568999 .1156627
. reg meals Di	l, robust						
Linear regress	sion			Number of F(1, 7694) Prob > F R-squared Root MSE		= = = =	7,696 10.94 0.0009 0.0015 1.7949
meals	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.2455767 .0630357	.0742607 .0213608	3.31 2.95	0.001 0.003	.1000		.3911479
. reg banks Di	l, robust						
Linear regress	sion			Number of F(1, 7694) Prob > F R-squared Root MSE		= = =	7,696 7.60 0.0059 0.0007 1.7719
banks	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.1670234 .0652239	.0605903 .0214473	2.76 3.04	0.006 0.002	.0482		.2857969 .1072664

# . reg insur D1, robust

	sion			Number of F(1, 7694) Prob > F R-squared Root MSE		= = =	7,696 2.38 0.1233 0.0003 1.8121
insur	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.1128438 .0422693	.0732118 .0216208	1.54 1.96		030 000		. 2563589 . 084652
. reg rlest Di	l, robust						
Linear regress	sion			Number of	obs	=	7,696
				F(1, 7694)		=	5.30
				Prob > F		=	0.0213
				R-squared		=	0.0006
				Root MSE		=	3.6659
	Conf	Robust		D. J. J.	[050	Caref	Tata
rlest	Coef.	Std. Err.	t	P> t	[95%	CONT.	Interval]
D1	.3299631	.1432742	2.30	0.021	.049	1067	.6108196
_cons	.11788	.0438823	2.69	0.007	.031		.2039012
. reg fin D1,	robust						
				Number of	obs	=	7.696
. reg fin D1,						=	7,696 11.29
				Number of F(1, 7694) Prob > F			11.29
				F(1, 7694) Prob > F		=	
				F(1, 7694)		=	11.29 0.0008
Linear regress	sion	Robust		F(1, 7694) Prob > F R-squared Root MSE		= = =	11.29 0.0008 0.0012 2.054
		Robust Std. Err.	t	F(1, 7694) Prob > F R-squared		= = =	11.29 0.0008 0.0012
Linear regress	sion		t 3.36	F(1, 7694) Prob > F R-squared Root MSE		= = = = Conf.	11.29 0.0008 0.0012 2.054

# Table 3 (Post):

# . reg agric D1, robust

Linear regress	sion			Number of F(1, 16733		=	16,735 25.33
				Prob > F		=	0.0000
				R-squared		=	0.0015
				Root MSE		=	1.413
		Robust					
agric	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.1980985 .0497959	.0393638 .011413	5.03 4.36	0.000 0.000	.120		.2752557 .0721665
. reg food D1,	, robust						
Linear regress	sion			Number of	obs	=	16,735
				F(1, 16733	3)	=	37.18
				Prob > F		=	0.0000
				R-squared		=	0.0021
				Root MSE		=	.73461
		Robust					
food	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.1216935 .0591059	.0199589 .005948	6.10 9.94	0.000 0.000	.082		.1608151 .0707646
. reg beer D1,	, robust						
Linear regress	sion			Number of	obs	=	16,735
				F(1, 16733	3)	=	14.17
				Prob > F		=	0.0002
				R-squared		=	0.0008
				Root MSE		=	.99936
		Robust					
beer	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.104731	.0278265	3.76	0.000	.050		.1592739
_cons	.0568893	.0080723	7.05	0.000	.041	0668	.0727117

# . reg smoke D1, robust

Number of obs	=	16,735
F(1, 16733)	=	3.29
Prob > F	=	0.0698
R-squared	=	0.0002
Root MSE	=	1.3542
	F(1, 16733) Prob > F R-squared	F(1, 16733) = Prob > F = R-squared =

smoke	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.0646275	.0356374	1.81		0052257	.1344806
_cons	.0769571	.0109972	7.00		.0554015	.0985127

# . reg toys D1, robust

Linear regression	Number of obs	=	16,735
	F(1, 16733)	=	46.23
	Prob > F	=	0.0000
	R-squared	=	0.0027
	Root MSE	=	1.192

toys	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.2240311	.0329503	6.80	0.000	.1594451	.2886172
_cons	.0570966	.0096357	5.93	0.000	.0382097	.0759836

# . reg fun D1, robust

Linear regression	Number of obs	=	16,735
	F(1, 16733)	=	54.71
	Prob > F	=	0.0000
	R-squared	=	0.0033
	Root MSE	=	1.1319

fun	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.2337932	.031607	7.40	0.000	.1718401	.2957463
_cons	.0679555	.0091404	7.43	0.000	.0500393	.0858717

# . reg books D1, robust

Linear regress	sion			Number of F(1, 16733 Prob > F		= = =	16,735 13.01 0.0003
				R-squared Root MSE		=	0.0008 1.1226
				Nooc 1132			212220
		Robust					
books	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.1121972 .0621925	.0311032 .0090719	3.61 6.86	0.000 0.000	.051		.1731627 .0799743
. reg hshld Di	l, robust						
Linear regress	sion			Number of		=	16,735
				F(1, 16733	3)	=	48.98
				Prob > F		=	0.0000
				R-squared Root MSE		=	0.0029 .93902
				ROOT HISE		_	. 33302
		Robust					
hshld	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.1837152	.0262504	7.00	0.000	.132	2617	.2351687
_cons	.0538366	.0075819	7.10	0.000	.038	9752	.0686979
. reg clths Di	l, robust						
Linear regress	sion			Number of	obs	=	16,735
				F(1, 16733	3)	=	50.10
				Prob > F		=	0.0000
				R-squared		=	0.0033
				Root MSE		=	1.0168
		Robust					
clths	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
clths D1	Coef.		t 7.08	P> t	[95% .151		Interval]

# . reg medeq D1, robust

\_cons

.0579184

.008241

	,						
Linear regress	ion			Number of		=	16,73
				F(1, 16733	3)	=	63.2
				Prob > F		=	0.000
				R-squared		=	0.0037
				Root MSE		=	1.0504
		Robust					
medeq	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	. 2298839	.0289127	7.95	0.000	. 173	2119	. 2865558
_cons	.0650554	.0084943	7.66	0.000	.048		.0817053
. reg drugs D1	, robust						
Linear regress	ion			Number of	obs	=	16,735
				F(1, 16733	3)	=	29.02
				Prob > F		=	0.000
				R-squared		=	0.001
				Root MSE		=	1.1608
		Robust					
drugs	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.1754328 .0744887	.0325667 .0093689	5.39 7.95	0.000 0.000	.111		.2392669 .0928527
. reg chems D1	, robust						
Linear regress	ion			Number of	obs	=	16,73
				F(1, 16733	3)	=	27.24
				Prob > F		=	0.000
				R-squared		=	0.0016
				Root MSE		=	1.0191
		Robust					
chems	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.1465213	.0280716	5.22	0.000	.09	1498	.2015447

7.03

0.000

.0417652

.0740715

#### . reg txtls D1, robust

1, 16733) = 54.14 bb > F = 0.0006 squared = 0.0034 bt MSE = .95186   t  [95% Conf. Interval]  000 .1465302 .2529506  000 .0440627 .0741295   mber of obs = 16,735  1, 16733) = 47.45 bb > F = 0.0006 squared = 0.0028 bt MSE = 1.357
b > F = 0.0006 squared = 0.0034 ot MSE = .95186   t  [95% Conf. Interval]  000 .1465302 .2529506 000 .0440627 .0741295  mber of obs = 16,735 1, 16733) = 47.45 ob > F = 0.0006 squared = 0.0028
bb > F = 0.0006 squared = 0.0034 ot MSE = .95186   t  [95% Conf. Interval] 000 .1465302 .2529506 000 .0440627 .0741295  mber of obs = 16,735 1, 16733) = 47.45 ob > F = 0.0006
bb > F = 0.0006 squared = 0.0034 ot MSE = .95186   t  [95% Conf. Interval] 000 .1465302 .2529506 000 .0440627 .0741295
bb > F = 0.0006 squared = 0.0034 ot MSE = .95186   t  [95% Conf. Interval] 000 .1465302 .2529506 000 .0440627 .0741295
bb > F = 0.0006 squared = 0.0034 ot MSE = .95186   t  [95% Conf. Interval]  000 .1465302 .2529506 000 .0440627 .0741295
bb > F = 0.0000 squared = 0.0034 ot MSE = .95186  t  [95% Conf. Interval]
bb > F = 0.0000 squared = 0.0034 ot MSE = .95186  t  [95% Conf. Interval]
ob > F = 0.0000 squared = 0.0034 ot MSE = .95186
ob > F = 0.0000 squared = 0.0034 ot MSE = .95186
ob > F = 0.0006 squared = 0.0034
ob > F = 0.0006 squared = 0.0034
•
mber of obs = <b>16,735</b>
000 .0263701 .0612913
000 .118864 .2408693
t  [95% Conf. Interval]
ot MSE = <b>1.1042</b>
squared = <b>0.002</b> 6
ob > F = 0.0006
1, 16733) = <b>33.4</b> 6

#### . reg steel D1, robust

Linear regress	sion			Number of		=	16,735
				F(1, 16733	()	=	34.75
				Prob > F		=	0.0000
				R-squared		=	0.0022
				Root MSE		=	1.2437
		Robust					
steel	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.2115099	.0358794	5.90	0.000	.141		.2818373
_cons	.0442931	.010009	4.43	0.000	.024	6744	.0639117
. reg mach D1,	, robust						
Linear regress	sion			Number of		=	16,735
				F(1, 16733	()	=	40.96
				Prob > F		=	0.0000
				R-squared		=	0.0026
				Root MSE		=	1.0363
	66	Robust		D. Lt.	[050	66	T-111
mach	Coef.	Std. Err.	t	P> t	[95%	Cont.	Interval]
	.1901363	.0297083	6.40	0.000	. 13	1905	.2483677
D1	. 1901303			0.000			
D1 _cons	.0585575	.0083453	7.02	0.000	.042	1997	.0749152
	.0585575					1997	.0749152
_cons . reg elceq Di	.0585575 1, robust				.042	1 <b>997</b> -	.0749152
_cons . reg elceq Di	.0585575 1, robust			0.000	.042		
_cons . reg elceq Di	.0585575 1, robust			0.000 Number of	.042	=	16,735
_cons . reg elceq Di	.0585575 1, robust			0.000 Number of F(1, 16733	.042	= =	16,735 45.44
_cons . reg elceq Di	.0585575 1, robust			0.000 Number of F(1, 16733 Prob > F	.042	= = =	16,735 45.44 0.0000
_cons	.0585575 1, robust			0.000 Number of F(1, 16733 Prob > F R-squared	.042	= = =	16,735 45.44 0.0000 0.0028
_cons	.0585575 1, robust	.0083453		0.000 Number of F(1, 16733 Prob > F R-squared	.042	= = =	16,735 45.44 0.0000 0.0028
_cons . reg elceq D3 Linear regress	.0585575 1, robust	.0083453	7.02	Number of F(1, 16733 Prob > F R-squared Root MSE	.042	= = = = = Conf.	16,735 45.44 0.0000 0.0028 1.0994

# . reg autos D1, robust

			F(1, 16733	3)	=	34.98
			Prob > F		=	0.0000
			R-squared		=	0.0021
			Root MSE		=	1.1536
	Robust					
Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
.1919093	.0324462	5.91	0.000	.128	3114	.2555073
.0505889	.0093086	5.43	0.000	.03	2343	.0688348
robust						
ion			Number of	obs	=	16,735
			F(1, 16733	3)	=	21.81
			Prob > F		=	0.0000
			R-squared		=	0.0013
			Root MSE		=	1.2325
	Robust					
Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
.1621558	.0347229	4.67	0.000	.094	0952	.2302164
.0725623	.0099433	7.30	0.000	.053	0723	.0920523
, robust						
ion			Number of	obs	=	16,735
			F(1, 16733	3)	=	16.78
			Prob > F		=	0.0000
			R-squared		=	0.0010
			Root MSE		=	1.4668
	Robust					
Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
.1658326 .051869	.0404834	4.10 4.37	0.000 0.000		4809 8625	.2451843 .0751131
	.1919093 .0505889  robust  ion  Coef.  .1621558 .0725623  , robust  ion  Coef.  .1658326	Coef. Std. Err.  .1919093 .0324462 .0505889 .0093086  robust ion  Coef. Std. Err.  .1621558 .0347229 .0725623 .0099433  , robust ion  Coef. Std. Err.  .1658326 .0404834	Coef. Std. Err. t  .1919093 .0324462 5.91 .0505889 .0093086 5.43  robust  ion  Coef. Std. Err. t  .1621558 .0347229 4.67 .0725623 .0099433 7.30  , robust  ion  Coef. Std. Err. t  .1658326 .0404834 4.10	Coef. Std. Err. t P> t   .1919093 .0324462 5.91 0.000 .0505889 .0093086 5.43 0.000  robust  ion	Robust Coef. Std. Err. t P> t  [95% .1919093 .0324462 5.91 0.000 .128 .0505889 .0093086 5.43 0.000 .03  robust  ion  Robust Coef. Std. Err. t P> t  [95% .1621558 .0347229 4.67 0.000 .094 .0725623 .0099433 7.30 0.000 .053  , robust  ion  Number of obs F(1, 16733) Prob > F R-squared Root MSE  Number of obs F(1, 16733) Prob > F R-squared Root MSE  Coef. Std. Err. t P> t  [95% .1658326 .0404834 4.10 0.000 .086	Robust Coef. Std. Err. t P> t  [95% Conf.  .1919093 .0324462 5.91 0.000 .1283114 .0505889 .0093086 5.43 0.000 .032343  robust  ion  Number of obs = F(1, 16733) = Prob > F = R-squared = Root MSE = Ro

#### . reg mines D1, robust

Linear regress	sion			Number of of f(1, 16733) Prob > F R-squared Root MSE		16,735 38.22 0.0000 0.0026 1.4965
mines	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1 _cons	.2737524 .0619721	.0442822 .0120097	6.18 5.16		.1869545 .0384318	.3605503 .0855123
. reg coal D1,	, robust					
Linear regress	sion			Number of of f(1, 16733) Prob > F R-squared Root MSE		16,735 1.63 0.2013 0.0001 2.1694
coal	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1 _cons	.0744757 .0551246	.0582733 .0175843	1.28		.0397461 .0206574	.1886976 .0895917
. reg oil D1,	robust					
Linear regress	sion			Number of of f(1, 16733) Prob > F R-squared Root MSE		16,735 11.29 0.0008 0.0007 1.3808
oil	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1 _cons	.131304 .0678538	.0390789 .0111349	3.36 6.09		.0547052 .0460283	.2079027 .0896793

#### . reg util D1, robust

Linear regress	sion			Number of		16,735
				F(1, 16733) Prob > F		2.22
					=	0.1362
				R-squared Root MSE	=	0.0001 .67422
				ROOL MSE	=	.07422
		Robust				
util	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.0274387	.018415	1.49		.0086565	.063534
_cons	.0507982	.0054562	9.31	0.000	.0401034	.0614931
. reg telcm Di	l, robust					
Linear regress	sion			Number of	obs =	16,735
				F(1, 16733	) =	25.40
				Prob > F	=	0.0000
				R-squared	=	0.0017
				Root MSE	=	1.1256
		Robust				
telcm	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.1659098	.032919	5.04	0.000	.1013852	.2304345
_cons	.0621273	.0090448	6.87	0.000	.0443986	.079856
. reg bussv Di	l, robust					
Linear regress	sion			Number of	obs =	16,735
				F(1, 16733	) =	53.74
				Prob > F	=	0.0000
				R-squared	=	0.0033
				Root MSE	=	.94119
		Robust				
bussv	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.1947108	.026562	7.33		.1426465	. 246775
_cons	.0682157	.007592	8.99	0.000	.0533345	.0830969

# . reg hardw D1, robust

Linear regress	sion			Number of F(1, 16733		=	16,735 44.74
				Prob > F		=	0.0000
				R-squared		=	0.0029
				Root MSE		=	1.299
hardw	Coef.	Robust Std. Err.	t	P> t	[95 <sub>%</sub>	Conf.	Interval]
D1 _cons	.2516567 .0569871	.0376256 .0104498	6.69 5.45	0.000 0.000	. 177		.325407 .0774698
. reg chips D1	l, robust						
Linear regress	sion			Number of	ohs	=	16,735
Linear regress	,1011			F(1, 16733		=	48.38
				Prob > F	,	=	0.0000
				R-squared		=	0.0030
				Root MSE		=	1.2425
		Robust					
chips	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.2451684 .0696139	.0352485 .010017	6.96 6.95	0.000 0.000	.176		.3142592 .0892482
. reg labeq Di	l, robust						
Linear regress	sion			Number of	obs	=	16,735
				F(1, 16733	3)	=	40.06
				Prob > F		=	0.0000
				R-squared		=	0.0025
				Root MSE		=	1.1147
		Robust					
labeq	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.2009019	.0317425	6.33	0.000	.138		.2631205
_cons	.0019003	.0089836	9.12	0.000	.064	2210	.0995691

# . reg boxes D1, robust

Linear regress	ion			Number of F(1, 16733 Prob > F R-squared Root MSE		= = = =	16,735 15.66 0.0001 0.0010 1.1364
boxes	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.1313892 .0584609	.0331994 .0091325	3.96 6.40	0.000 0.000	.0663		.1964635 .0763616
. reg trans D1	., robust						
Linear regress	ion			Number of	obs	=	16,735
				F(1, 16733	)	=	42.39
				Prob > F		=	0.0000
				R-squared		=	0.0026
				Root MSE		=	1.0475
		Robust					
trans	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.1942439 .0504813	.029833 .0084418	6.51 5.98	0.000 0.000	.135		.2527197 .067028
. reg whlsl D1	., robust						
Linear regress	ion			Number of	obs	=	16,735
3				F(1, 16733	)	=	61.99
				Prob > F		=	0.0000
				R-squared		=	0.0037
				Root MSE		=	.92674
		Robust					
whlsl	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.2048131 .0591626	.0260126	7.87 7.91	0.000	.1538		.2558005

# . reg rtail D1, robust

\_cons

.064387

.0060863

Linear regress	sion			Number of	obs	=	16,735
3				F(1, 16733		=	22.66
				Prob > F		=	0.0000
				R-squared		=	0.0014
				Root MSE		=	.944
		Robust					
rtail	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.126271	.0265255	4.76	0.000	.0742	2782	.1782639
_cons	.0573621	.0076181	7.53	0.000	.0424	1298	.0722944
. reg meals Di	l, robust						
_inear regress	sion			Number of		=	16,735
				F(1, 16733	3)	=	50.87
				Prob > F		=	0.0000
				R-squared		=	0.0034
				Root MSE		=	1.0126
		Robust					
meals	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.212392 .0574866	.0297789 .0081323	7.13 7.07	0.000 0.000	.1546		.2707619 .0734267
. reg banks Di	l, robust						
Linear regress	sion			Number of	obs	=	16,735
				F(1, 16733	3)	=	29.63
				Prob > F		=	0.0000
				R-squared		=	0.0019
				Root MSE		=	.75699
		Robust					
banks	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.1198957	.0220278	5.44	0.000	.0767	7188	.1630726

10.58

0.000

.0524572

.0763168

# . reg insur D1, robust

Linear regress	ion			Number of		=	16,735
				F(1, 16733	3)	=	3.03
				Prob > F		=	0.0819 0.0002
				R-squared Root MSE		=	1.0154
				ROOL MSE		_	1.0154
		Robust					
insur	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.0452814	.0260252	1.74		0057		.0962935
_cons	.0681662	.0082639	8.25	0.000	.05	1968	.0843643
. reg rlest D1	, robust						
Linear regress:	ion			Number of	obs	=	16,735
				F(1, 16733	3)	=	40.63
				Prob > F		=	0.0000
				R-squared		=	0.0025
				Root MSE		=	1.2991
		Robust			•		
rlest	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	. 2359524	.0370184	6.37	0.000	.1633	3925	.3085123
D1 _cons	.2359524 .059715	.0370184 .010469	6.37 5.70	0.000 0.000	.1633		.3085123 .0802353
	.059715						
_cons	.059715 robust				.039		
_cons	.059715 robust			0.000	.039	1948	.0802353
_cons	.059715 robust			0.000 Number of	.039	=	.0802353 16,735
_cons	.059715 robust			0.000 Number of F(1, 1673	.039	= =	.0802353 16,735 29.55
_cons	.059715 robust			0.000 Number of F(1, 16733 Prob > F	.039	= = = =	.0802353 16,735 29.55 0.0000
_cons	.059715 robust			0.000 Number of F(1, 16733 Prob > F R-squared	.039	= = = = =	16,735 29.55 0.000 0.0019
_cons	.059715 robust	.010469		0.000 Number of F(1, 16733 Prob > F R-squared	.039: obs 3)	= = = = = =	16,735 29.55 0.000 0.0019
_cons	.059715	.010469 Robust	5.70	Number of F(1, 1673; Prob > F R-squared Root MSE	.039: obs 3)	= = = = Conf.	.0802353 16,735 29.55 0.0000 0.0019 .92916

# Table 4 (Whole):

# . reg agric D1, robust

cons	Linear regress	sion			Number of F(1, 2415 Prob > F R-squared Root MSE	9)	= = =	24,161 11.70 0.0006 0.0005 1.4931
cons	agric	Coef.		t	P> t	[95%	Conf.	Interval]
Linear regression    Number of obs   24								.1033289
F(1, 24159) = Prob > F = 0. R-squared = 0. Root MSE = .9  Robust  D1 .0106554 .0118123 0.90 0.3670124974 .033 _cons .0385437 .0087838 4.39 0.000 .0213269 .055  . reg beer D1, robust  Linear regression  Number of obs = 24 F(1, 24159) = Prob > F = 0. R-squared = 0. Root MSE = 1.	. reg food D1	, robust						
Prob > F = 0. R-squared = 0. Root MSE = .9    Robust	Linear regress	sion			Number of	obs	=	24,161
R-squared = 0. Root MSE = .9    Robust					F(1, 2415	9)	=	0.81
Robust  food Coef. Std. Err. t P> t  [95% Conf. Inter D1 .0106554 .0118123 0.90 0.3670124974 .033 _cons .0385437 .0087838 4.39 0.000 .0213269 .055  . reg beer D1, robust  Linear regression					Prob > F		=	0.3670
Robust   P> t  [95% Conf. Inter					•	l	=	0.0000
food Coef. Std. Err. t P> t  [95% Conf. Inter D1 .0106554 .0118123 0.90 0.3670124974 .033 _cons .0385437 .0087838 4.39 0.000 .0213269 .055  . reg beer D1, robust  Linear regression					Root MSE		=	.91949
cons	food	Coef.		t	P> t	[95%	Conf.	Interval]
Linear regression $ \begin{array}{ccccccccccccccccccccccccccccccccccc$								.0338082
F(1, 24159) = Prob > F = 0. R-squared = 0. Root MSE = 1.	. reg beer D1	, robust						
F(1, 24159) = Prob > F = 0. R-squared = 0. Root MSE = 1.	linear regress	sion			Number of	: ohe	_	24,161
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Linear regress	31011						0.07
$\begin{array}{cccccccccccccccccccccccccccccccccccc$					-	, , ,		0.7987
Root MSE = 1.						I	=	0.0000
					•		=	1.4549
beer   Coef. Std. Err. t P> t  [95% Conf. Inter								
	beer	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D10047655 .0186866 -0.26 0.7990413925 .031	D1	0047655	.0186866	-0.26	0.799	0413	3925	.0318614
								.0842425

# . reg smoke D1, robust

-	sion			Number of		24,161
				F(1, 24159		0.01
				Prob > F	=	0.9156
				R-squared	=	0.0000
				Root MSE	=	1.1917
		Robust				
smoke	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.0016242	.0153247	0.11		.0284131	.0316615
_cons	.0520245	.0110303	4.72	0.000	.0304045	.0736445
. reg toys D1	, robust					
Linear regres	sion			Number of	obs =	24,161
				F(1, 24159		3.92
				Prob > F	=	0.0478
				R-squared	=	0.0002
				Root MSE	=	2.1413
		Robust				
toys	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.0545397	.0275518	1.98	0.048	.0005364	.1085429
_cons	.0202416	.0194197	1.04	0.297 -	.0178222	.0583054
. reg fun D1,	robust					
. reg fun D1,				Number of	obs =	24,161
				Number of 6		24,161 8.05
				F(1, 24159	) =	8.05
				F(1, 24159 Prob > F	) = =	8.05 0.0045
		Robust		F(1, 24159 Prob > F R-squared	) = = = =	8.05 0.0045 0.0003
		Robust Std. Err.	t	F(1, 24159 Prob > F R-squared Root MSE	) = = = =	8.05 0.0045 0.0003 1.7956
Linear regres	sion		t 2.84	F(1, 24159 Prob > F R-squared Root MSE	) = = = = =	8.05 0.0045 0.0003 1.7956

#### . reg books D1, robust

	sion			Number of obs	=	24,161
				F(1, 24159)	=	4.47
				Prob > F	=	0.0345
				R-squared	=	0.0002
				Root MSE	=	1.565
		Robust				
books	Coef.	Std. Err.	t	P> t  [95%	Conf.	Interval]
D1	.042515	.0201121	2.11		0941	.081936
_cons	.0229992	.0147697	1.56	0.119005	9504	.0519488
. reg hshld Di	l, robust					
Linear regress	sion			Number of obs	=	24,161
				F(1, 24159)	=	3.16
				Prob > F	=	0.0756
				R-squared	=	0.0001
				Root MSE	=	1.1587
hshld	Coef.	Robust Std. Err.	t	P> t  [95%	. Conf.	Interval]
5.4						
D1 _cons	.0264687 .0277829	.0148963 .0108147	1.78 2.57	0.076002 0.010 .006	7289 5854	.0556663 .0489803
_cons	.0277829					
_cons . reg clths D1	.0277829 1, robust			0.010 .006		
_cons . reg clths D1	.0277829 1, robust			0.010 .006	5854	.0489803
_cons . reg clths D1	.0277829 1, robust			0.010 .006  Number of obs F(1, 24159) Prob > F	=	.0489803
_cons . reg clths D1	.0277829 1, robust			0.010 .006  Number of obs F(1, 24159)	= =	.0489803 24,161 15.83
_cons . reg clths D1	.0277829 1, robust			0.010 .006  Number of obs F(1, 24159) Prob > F	= = = =	.0489803 24,161 15.83 0.0001
_cons . reg clths D1	.0277829 1, robust			0.010 .006  Number of obs F(1, 24159) Prob > F R-squared	= = = =	.0489803 24,161 15.83 0.0001 0.0007
	.0277829 1, robust	.0108147		Number of obs F(1, 24159) Prob > F R-squared Root MSE	= = = = = =	.0489803 24,161 15.83 0.0001 0.0007 1.1357
_cons . reg clths D1 Linear regress	.0277829 1, robust	.0108147	2.57	Number of obs F(1, 24159) Prob > F R-squared Root MSE	= = = = = =	.0489803 24,161 15.83 0.0001 0.0007

#### . reg medeq D1, robust

Linear r	regression Number of obs	=	24,161
	F(1, 24159)	=	2.93
	Prob > F	=	0.0868
	R-squared	=	0.0001
	Root MSE	=	1.5891

medeq	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.0351139	.0205019	1.71	0.087	0050711	.0752989
_cons	.0369371	.0129722	2.85	0.004	.0115108	.0623635

# . reg drugs D1, robust

Linear regression	Number of obs	=	24,161
	F(1, 24159)	=	3.73
	Prob > F	=	0.0536
	R-squared	=	0.0002
	Root MSE	=	1.138

drugs	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.0282167	.0146164	1.93	0.054	0004324	.0568658
_cons	.0353061	.0109464	3.23	0.001	.0138504	.0567618

# . reg chems D1, robust

Linear regression	Number of obs	=	24,161
	F(1, 24159)	=	8.78
	Prob > F	=	0.0030
	R-squared	=	0.0004
	Root MSE	=	1.2716

chems	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.048416	.0163389	2.96	0.003	.0163908	.0804413
_cons	.024022	.0120616	1.99	0.046	.0003805	.0476636

# . reg txtls D1, robust

D1 _cons	.0705728 .0135763	.0256937 .0187823	2.75 0.72		02115 32381	.120934 .0503908
cnstr	Coef.	Robust Std. Err.	t	P> t  [95	% Conf.	Interval]
				Root MSE	=	1.999
				R-squared	=	0.0003
				Prob > F	=	0.0060
				F(1, 24159)	=	7.54
Linear regress				Number of obs	=	24,161
. reg cnstr D1	rohust					
D1 _cons	.0635755 .0115869	.0160318 .0117606	3.97 0.99		21522 14646	.0949989 .0346385
bldmt	Coef.	Robust Std. Err.	t	P> t  [95	% Conf.	Interval]
				Root MSE	=	1.2474
				R-squared	=	0.0001
				Prob > F	=	0.0001
Linear regress	ion			Number of obs F(1, 24159)		24,161 15.73
. reg bldmt D1	., robust					
_cons	.0133102	.0121821	1.09		05675	.0371879
D1	.0569988	.0167921	3.39	0.001 .02	40853	.0899122
txtls	Coef.	Robust Std. Err.	t	P> t  [95	% Conf.	Interval]
				Root MSE	=	1.3062
				R-squared	=	0.0005
				Prob > F	=	0.0007
				F(1, 24159)	=	11.52

#### . reg steel D1, robust

elceq

\_cons

**D1** 

Coef.

.0578206

.0240727

Std. Err.

.0199889

.0146102

. reg steet DI	, 105030					
inear regress	ion			Number of obs	=	24,161
				F(1, 24159)	=	9.52
				Prob > F	=	0.0020
				R-squared	=	0.0004
				Root MSE	=	1.6665
		Robust				
steel	Coef.	Std. Err.	t	P> t  [95%	Conf.	Interval]
D1	.0660936	.0214188	3.09	0.002 .024	1114	.1080758
_cons	.0080261	.0156833	0.51	0.609022	7141	.0387663
. reg mach D1,	robust					
Linear regress	ion			Number of obs	=	24,161
				F(1, 24159)	=	16.36
				Prob > F	=	0.0001
				R-squared	=	0.0007
				Root MSE	=	1.3658
		Robust				
mach	Coef.	Std. Err.	t	P> t  [95%	Conf.	Interval]
D1	.0709819	.0175499	4.04	0.000 .03	6583	.1053809
_cons	.0112849	.0129557	0.87	0.384014	1091	.0366789
. reg elceq D1	, robust					
Linear regress	ion			Number of obs	=	24,161
				F(1, 24159)	=	8.37
				Prob > F	=	0.0038
				R-squared	=	0.0003
				Root MSE	=	1.5552
		Robust				
_		NODUS C		B 111 50-0		

P>|t|

0.004

0.099

t

2.89

1.65

[95% Conf. Interval]

.0969999

.0527096

.0186412

-.0045643

# . reg autos D1, robust

Linear regress	ion			Number of o	bs =	24,161
Linear regress	. 2011			F(1, 24159)		5.06
				Prob > F	=	0.0245
				R-squared	=	0.0002
				Root MSE	=	1.5682
		Robust				
autos	Coef.	Std. Err.	t	P> t  [	95% Conf.	Interval]
D1	.0453181	.0201543	2.25		0058143	.0848218
_cons	.0254376	.0147786	1.72	0.085	0035294	.0544045
. reg aero D1,	robust					
Linear regress	ion			Number of o		24,161
				F(1, 24159)	=	11.30
				Prob > F	=	0.0008
				R-squared	=	0.0005
				Root MSE	=	1.7778
		Robust				
aero	Coef.	Std. Err.	t	P> t  [	95% Conf.	Interval]
D1	.0768158	.022851	3.36		0320264	.1216052
_cons	.0244637	.0166883	1.47	0.143	0082464	.0571737
. reg ships D1	., robust					
Linear regress	ion			Number of o	bs =	24,161
				F(1, 24159)	=	7.44
				Prob > F	=	0.0064
				R-squared	=	0.0003
				Root MSE	=	1.5085
		Robust				
ships	Coef.	Robust Std. Err.	t	P> t  [	95% Conf.	Interval]

1.25 0.213

-.0099924

.044905

.0174563

\_cons

.014004

#### . reg mines D1, robust

Linear regression	Number of obs	=	24,161
	F(1, 24159)	=	13.31
	Prob > F	=	0.0003
	R-squared	=	0.0005

Root MSE

= 1.5241

mines	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.071477	.0195938	3.65	0.000	.0330719	.1098822
_cons	.00992	.0142061	0.70	0.485	0179249	.0377649

# . reg coal D1, robust

Linear regression	Number of obs	=	24,161
	F(1, 24159)	=	3.31
	Prob > F	=	0.0688
	R-squared	=	0.0001
	Root MSE	=	2.1133

coal	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.0494418	.0271664	1.82	0.069	003806	.1026896
_cons	.0213012	.0197695	1.08	0.281	0174482	.0600506

# . reg oil D1, robust

Linear regression	Number of obs	=	24,161
	F(1, 24159)	=	3.13
	Prob > F	=	0.0770
	R-squared	=	0.0001
	Root MSE	=	1.2798

oil	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.0290895	.0164472	1.77	0.077	0031481	.0613271
_cons	.0317853	.0120769	2.63	0.008	.0081139	.0554567

# . reg util D1, robust

Linear regress	sion			Number of F(1, 24159 Prob > F R-squared Root MSE		= = = =	24,161 0.09 0.7609 0.0000 1.0877
util	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.0042528 .0363273	.0139732 .0103835	0.30 3.50		.023		.0316411
. reg telcm Di	l, robust						
Linear regress	sion			Number of F(1, 24159 Prob > F R-squared Root MSE		= = = =	24,161 3.31 0.0689 0.0001 1.0242
telcm	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.0239495 .0274988	.013166 .0095849	1.82	0.069 - 0.004			.0497557 .0462858
. reg bussv Di	l, robust						
Linear regress	sion			Number of F(1, 24159 Prob > F R-squared Root MSE		= = = =	24,161 1.94 0.1640 0.0001 1.9601
bussv	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.035012 .0336506	.0251536 .0193401	1.39 1.74		.0142		.0843146 .0715584

#### . reg hardw D1, robust

D1	.0634259	.0182703 .0133167	3.47	0.001	.027615 00629	.0992369 .0459129
labeq	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
				Root MSE	=	1.4213
				R-squared	=	0.0005
				Prob > F	=	0.0005
				F(1, 24159)		12.05
Linear regress				Number of o	obs =	24,161
. reg labeq Di	l robust					
D1 _cons	.0634604 .0201984	.0224601 .0164889	2.83 1.22		.0194372 .0121208	.1074836 .0525176
chips	Coef.	Robust Std. Err.	t	P> t	[95% Conf	Interval]
				Root MSE	=	1.7477
				R-squared	=	0.0003
				Prob > F	=	0.0047
				F(1, 24159)	) =	7.98
Linear regress	sion			Number of o	obs =	24,161
. reg chips Di	l, robust					
_cons	.0335208	.0141494	2.37		.0057871	.0612546
D1	.0434467	.0196226	2.21	0.027	.0049851	.0819082
hardw	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
				Root MSE	=	1.5261
				R-squared	=	0.0002
				Prob > F	=	0.0268
Linear regression				F(1, 24159)		4.90
	510N			Number of o	obs =	24,161

# . reg boxes D1, robust

D1

\_cons

.0417864

.0188416

cg boxes ba	.,						
Linear regress	ion			Number of	obs	=	24,161
				F(1, 24159) =		8.30	
				Prob > F		=	0.0038
				R-squared		=	0.0003
				Root MSE		=	1.2503
		Robust					
boxes	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.0464646	.0160664 .0118273	2.89	0.004 0.033	.0149734		.0779558
		.0110175					10404020
. reg trans D1							
Linear regression				Number of		=	24,161
				F(1, 24159	)	=	6.44
				Prob > F		=	0.0112
				R-squared		=	0.0003
				Root MSE		=	1.3455
		Robust					
trans	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.0438552	.0172874	2.54	0.011	.0099		.0777396
_cons	.0187886	.0128076	1.47	0.142 -	0063	3151	.0438922
. reg whlsl D1	., robust						
inear regression					=	24,161	
				F(1, 24159	)	=	3.85
				Prob > F		=	0.0496
				R-squared		=	0.0002
				Root MSE		=	1.6545
		Robust					
whlsl	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]

1.96

1.25

0.050

0.213

.0000683

-.0107826

.0212841

.0151139

.0835044

.0484658

# . reg rtail D1, robust

Linear regress	sion			Number of o F(1, 24159) Prob > F R-squared Root MSE		24,161 3.99 0.0457 0.0002 1.1304
rtail	Coef.	Robust Std. Err.	t	P> t  [	95% Conf.	Interval]
D1 _cons	.0290248 .0313992	.0145283 .0106521	2.00 2.95		0005485 0105204	.0575011
. reg meals Di	l, robust					
Linear regress	sion			Number of o F(1, 24159) Prob > F R-squared Root MSE		24,161 13.56 0.0002 0.0006 1.3327
meals	Coef.	Robust Std. Err.	t	P> t  [	95% Conf.	Interval]
D1 _cons	.0630997 .0165494	.0171376 .0123333	3.68 1.34		0295089 0076246	.0966904
. reg banks Di	l, robust					
Linear regress	sion			Number of o F(1, 24159) Prob > F R-squared Root MSE		24,161 3.67 0.0554 0.0002 1.4727
banks	Coef.	Robust Std. Err.	t	P> t  [	95% Conf.	Interval]
D1 _cons	.0362695 .0343249	.0189347 .0137139	1.92 2.50		0008437 0074447	.0733828 .0612051

### . reg insur D1, robust

D1 _cons	.047346 .024418	.0201842 .0144251	2.35 1.69	0.019 0.091	.0077 .0038		.0869082 .0526921
fin	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
				Root MSE		=	1.5693
				R-squared		=	0.0002
				Prob > F		=	0.0190
				F(1, 24159		=	5.50
. <b>reg fin D1</b> , Linear regress				Number of	obs	=	24,161
D1 _cons	.0799477 001631	.0273815 .019918	2.92 -0.08	0.004 0.935	.0262 0406		.1336171 .0374096
rlest	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
				Root MSE		=	2.13
				R-squared		=	0.0004
				Prob > F		=	0.0035
				F(1, 24159	9)	=	8.53
Linear regress	sion			Number of	obs	=	24,161
. reg rlest Di	l, robust						
_cons	.0347184	.012894	2.69	0.229	.0094		.0555554 .0599914
D1	.0211199	.0175686	1.20		0133		
insur	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
				Root MSE		=	1.367
				R-squared		=	0.0001
				Prob > F		=	0.2293
,				F(1, 24159	9)	=	1.45
Linear regress	sion			Number of	obs	=	24,161

# Table 4 (Pre):

### . reg agric D1, robust

**D1** 

\_cons

-.0980827

.1080144

.0467966

.0357885

. reg agric bi	, Tobust					
Linear regress	ion			Number of ob	s =	7,696
_				F(1, 7694)	=	0.54
				Prob > F	=	0.4619
				R-squared	=	0.0001
				Root MSE	=	1.7089
		Robust				
agric	Coef.	Std. Err.	t	P> t  [9	5% Conf.	Interval]
D1	.0286549	.0389498	0.74		476974	.1050072
_cons	.0269727	.0278056	0.97	0.3320	275339	.0814793
. reg food D1,	robust					
Linear regress	ion			Number of ob	s =	7,696
				F(1, 7694)	=	0.02
				Prob > F	=	0.8950
				R-squared	=	0.0000
				Root MSE	=	1.08
		Robust				
food	Coef.	Std. Err.	t	P> t  [9	5% Conf.	Interval]
D1 _cons	.0032448 .0265792	.0245787 .0187719	0.13 1.42		449361 102188	.0514258 .0633773
. reg beer D1,	robust					
Linear regress	ion			Number of ob	s =	7,696
-				F(1, 7694)	=	4.39
				Prob > F	=	0.0361
				R-squared	=	0.0006
				Root MSE	=	2.0564
		Robust				

-2.10

3.02

0.036

0.003

-.1898168

.0378592

-.0063485

.1781697

### . reg smoke D1, robust

Linear regress	sion			Number of obs F(1, 7694) Prob > F R-squared Root MSE	= = = =	7,696 0.68 0.4094 0.0001 .95379
smoke	Coef.	Robust Std. Err.	t	P> t  [95	% Conf.	Interval]
D1 _cons	017924 .0334439	.0217263 .0159344	-0.82 2.10		05134 22081	.0246654 .0646798
. reg toys D1,	, robust					
Linear regress	sion			Number of obs F(1, 7694) Prob > F R-squared Root MSE	= = = =	7,696 0.10 0.7567 0.0000 3.1026
toys	Coef.	Robust Std. Err.	t	P> t  [95	% Conf.	Interval]
D1 _cons	0219198 .0632407	.0707466 .0494652	-0.31 1.28		06024 37245	.1167627 .160206
. reg fun D1,	robust					
Linear regress	sion			Number of obs F(1, 7694) Prob > F R-squared Root MSE	= = =	7,696 0.64 0.4221 0.0001 2.2584
fun	Coef.	Robust Std. Err.	t	P> t  [95	% Conf.	Interval]
D1 _cons	0412687 .0539841	.051403 .0390295	-0.80 1.38		20327 25243	.0594952

# . reg books D1, robust

Linear regress	sion			Number of		7,696
				F(1, 7694		0.12
				Prob > F	. =	0.7251
				R-squared		0.0000
				Root MSE	=	2.1731
		Robust				
books	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	0174003	.0494814	-0.35	0.725	1143973	.0795967
_cons	.0401209	.0369392	1.09	0.277	0322899	.1125317
. reg hshld Di	l. robust					
. reg named D	i, iobusc					
Linear regress	sion			Number of		7,696
				F(1, 7694	1) =	0.02
				Prob > F	=	0.8840
				R-squared		0.0000
				Root MSE	=	1.3992
		Robust				
hshld	Coef.	Std. Err.	t	P>   t	[95% Conf.	Interval]
D1	.0046494	.0318757	0.15	0.884	0578356	.0671345
_cons	.0240638	.0232292	1.04	0.300	0214717	.0695993
. reg clths D1	l, robust					
Linear regress	sion			Number of	obs =	7,696
				F(1, 7694		0.13
				Prob > F	=	0.7231
				R-squared	i =	0.0000
				Root MSE	=	1.1307
		Robust				
clths	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.0091244	.0257541	0.35	0.723	0413606	.0596094
_cons	.021947	.0189455	1.16	0.247	0151914	.0590854

# . reg medeq D1, robust

\_cons

.0624743 .0260836

chems	Coef.	Robust Std. Err.	t	P> t  [9	5% Conf.	Interval]
				Root MSE	=	1.5148
				R-squared	=	0.000
				Prob > F	=	0.520
				F(1, 7694)	=	0.4
_inear regres	sion			Number of ob	s =	7,69
. reg chems D	l, robust					
D1 _cons	.0166097 .0264969	.028743 .0223465	0.58 1.19		397345 173083	.072953
drugs	Coef.	Robust Std. Err.	t	P> t  [9	5% Conf.	Interval]
				Root MSE	=	1.263
				R-squared	=	0.000
				F(1, 7694) Prob > F	=	0.33 0.5634
inear regres	sion			Number of ob F(1, 7694)	s = =	7,69
. reg drugs D	l, robust					
_cons	.0440972	.028982	1.52		127154	.1009099
D1	.0105194	.0506848	0.21	0.8360	888367	.1098754
medeq	Coef.	Robust Std. Err.	t	P> t  [9	5% Conf.	Interval]
				Root MSE	=	2.2153
				R-squared	=	0.000
				Prob > F	=	0.835
				F(1, 7694)	=	0.04

2.40 0.017

.0113432

.1136053

# . reg txtls D1, robust

Linear regress	sion			Number of obs F(1, 7694) Prob > F R-squared Root MSE	s = = = = =	7,696 0.81 0.3693 0.0001 1.4532
txtls	Coef.	Robust Std. Err.	t	P> t  [9!	5% Conf.	Interval]
D1 _cons	0297067 .0465844	.0330838	-0.90 1.87		)45599 )21294	.0351465 .0952982
. reg bldmt Di	l, robust					
Linear regress	sion			Number of obs	; =	7,696
				F(1, 7694)	=	0.24
				Prob > F	=	0.6259
				R-squared	=	0.0000
				Root MSE	=	1.5004
bldmt	Coef.	Robust Std. Err.	+	D> +  [01	St Conf	Intervall
	Coet.	Sta. Err.	t	P> t  [9	o% Cont.	Interval]
D1 _cons	0166553 .0395833	.0341623 .0255692	-0.49 1.55		336227 105392	.0503121 .0897059
. reg cnstr Di	l, robust					
Linear regress	sion			Number of obs	s =	7,696
J				F(1, 7694)	=	0.05
				Prob > F	=	0.8218
				R-squared	=	0.0000
				Root MSE	=	2.8164
		Robust				
cnstr	Coef.	Std. Err.	t	P> t  [95	% Conf.	Interval]
D1	0144468	.0641399	-0.23	0.82214	101784	.1112849
_cons	.0578344	.0475387	1.22	0.22403	353545	.1510232

# . reg steel D1, robust

Linear regress	sion			Number F(1, 76 Prob > R-squar Root MS	94) F ed	= = = =	7,696 0.91 0.3401 0.0001 1.9985
steel	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	0433842 .0666641	.0454792 .0347497	-0.95 1.92	0.340 0.055	132 001		.0457675 .1347829
. reg mach D1,	, robust						
Linear regress	sion			Number	of obs	=	7,696
				F(1, 76	94)	=	0.00
				Prob >		=	0.9883
				R-squar		=	0.0000
				Root MS	E	=	1.687
mach	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.000562 .042374	.0384001 .0290935	0.01 1.46	0.988 0.145	074 014		.0758367 .0994051
. reg elceq Di	l, robust						
Linear regress	sion			Number	of obs	=	7,696
				F(1, 76		=	0.00
				Prob >		=	0.9939
				R-squar	ed	=	0.0000
				Root MS	E	=	1.9956
		Robust					
elceq	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	000348	.0454467	-0.01	0.994	08	9436	.08874

# . reg autos D1, robust

Linear regres	sion			Number o F(1, 769 Prob > F R-square Root MSE	4) d	= = = =	7,696 0.33 0.5668 0.0000 1.954
autos	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	025477 .0687937	.0444789 .0336415	-0.57 2.04	0.567 0.041	112		.0617138
. reg aero D1	, robust						
Linear regres	sion			Number o	f obs	=	7,696
_				F(1, 769	4)	=	1.35
				Prob > F		=	0.2446
				R-square		=	0.0002
				Root MSE		=	2.4957
	Coof	Robust		D- I+I	[050	Conf	Intervall
aero	Coef.	Std. Err.	t	P> t	[95%	CONT.	Interval]
D1	.0661572	.0568537	1.16	0.245	045	2915	.1776059
_cons	.0367078	.041543	0.88	0.377	044	7278	.1181435
. reg ships D	1, robust						
Linear regres	sion			Number o	f obs	=	7,696
_				F(1, 769	4)	=	0.24
				Prob > F		=	0.6224
				R-square	d	=	0.0000
				Root MSE		=	1.7536
ships	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
211143	20211	5.0. 2.11		17 [6]	[ ] ] %		
D1 _cons	0196657 .041286	.0399301 .0297583	-0.49 1.39	0.622 0.165	0979 017		.0586081 .0996204
	l						

# . reg mines D1, robust

. reg oil D1,	sion			Number of obs F(1, 7694) Prob > F R-squared Root MSE	= = = =	7,696 0.02 0.8827 0.0000 1.3769
	sion			F(1, 7694)	=	0.02
	sion					
	ion			Number of obs	_	7 606
	robust					
D1 _cons	0814163 .0680864	.0473445 .0364918	-1.72 1.87	0.086174 0.062003		.0113918 .1396202
coal	Coef.	Robust Std. Err.	t	P> t  [95%	Conf.	Interval]
				Root MSE	=	2.0809
				R-squared	=	0.0004
				Prob > F	=	0.0855
Linear regress	sion			Number of obs F(1, 7694)	=	7,696 2.96
. reg coal D1						
_cons	.044555	.0276155	1.61	0.107009		.098689
D1	0068686	.0369124	-0.19	0.85207	9227	.0654898
mines	Coef.	Robust Std. Err.	t	P> t  [95%	conf.	Interval]
				•		1.6212
						0.8524 0.0000
					=	0.03
mines	Coef		+	Number of obs F(1, 7694) Prob > F R-squared Root MSE	= =	0. 0. 1.

# . reg util D1, robust

Linear regress	sion			Number F(1, 76 Prob > R-squar Root MS	94) F	= = =	7,696 0.27 0.6030 0.0000 1.5507
util	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	0183704 .0400669	.0353169 .0260865	-0.52 1.54	0.603 0.125	087 011		.0508603 .0912036
. reg telcm Di	l, robust						
. reg telcm Di				Number F(1, 76 Prob > R-squar Root MS	94) F ed	= = = =	7,696 1.03 0.3099 0.0001 1.0065
		Robust Std. Err.	t	F(1, 76 Prob > R-squar	94) F ed E	= = =	1.03 0.3099 0.0001

Linear regression	Number of obs	=	7,696
	F(1, 7694)	=	0.10
	Prob > F	=	0.7518
	R-squared	=	0.0000
	Root MSE	=	3.1294

bussv	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1	0225105	.0711798		0.752	1620422	.1170212
_cons	.0721245	.055542		0.194	036753	.1810019

#### . reg hardw D1, robust

D1

\_cons

-.014224

.0468133

.0352644

.0265964

. reg naruw D.	i, lobust						
Linear regress	sion			Number of	obs	=	7,69
				F(1, 7694	1)	=	0.0
				Prob > F		=	0.847
				R-squared	i	=	0.000
				Root MSE		=	1.506
		Robust					
hardw	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval
D1	0065834	.0342902	-0.19	0.848	073	8016	.060634
_cons	.0522531	.0261861	2.00	0.046	.000	9211	.10358
. reg chips Di	l, robust						
_inear regress	sion			Number of	obs	=	7,69
				F(1, 7694	1)	=	0.1
				Prob > F		=	0.745
				R-squared	i	=	0.000
				Root MSE		=	2.169
		Robust					
chips	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval
D1	.0160302	.0493826	0.32	0.745	080		.112833
_cons	.0417876	.0374067	1.12	0.264	031	5398	.1151149
. reg labeq Di	l, robust						
Linear regress	sion			Number of	obs	=	7,69
				F(1, 7694	1)	=	0.1
				Prob > F		=	0.686
				R-squared	i	=	0.000
				Root MSE		=	1.549
		Robust					
labeq	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval
D.1		0252644	0 40	0 607	000		054000

-0.40

1.76

0.687

0.078

-.0833517

-.0053229

.0549038

.0989494

# . reg boxes D1, robust

Linear regress	sion			Number of F(1, 7694		=	7,696 0.12
				Prob > F		=	0.7272
				R-squared		=	0.0000
				Root MSE		=	1.4025
		Robust					
boxes	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	0111429	.0319344	-0.35		073		.0514572
_cons	.0497248	.0238151	2.09	0.037	.003	0408	.0964088
. reg trans Di	l, robust						
Linear regress	sion			Number of	obs	=	7,696
				F(1, 7694	.)	=	0.22
				Prob > F	•	=	0.6379
				R-squared		=	0.0000
				Root MSE		=	1.6865
		Robust					
trans	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	0180681	.0383892	-0.47	0.638	093	3214	.0571851
_cons	.0369573	.0290345	1.27	0.203	019	9583	.0938729
. reg whlsl D:	l, robust						
Linear regress	sion			Number of	obs	=	7,696
				F(1, 7694	.)	=	0.56
				Prob > F		=	0.4525
				R-squared		=	0.0001
				Root MSE		=	2.5283
		Robust					
whlsl	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	0432999	.0576399	-0.75	0.453	156	2899	. 06969
_cons	.0480478	.0406652	1.18	0.237	03	1667	.1277627

### . reg rtail D1, robust

Linear regress	sion			Number of		7,696
				F(1, 7694	) =	1.00
				Prob > F	=	0.3182
				R-squared	=	0.0001
				Root MSE	=	1.2835
		Robust				
rtail	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	029182	.0292339	-1.00	0.318	0864884	.0281245
_cons	.0480633	.0214937	2.24	0.025	.0059299	.0901967
. reg meals D1	l, robust					
				North and a fe	- 6 -	7 606
Linear regress	sion			Number of		7,696
				F(1, 7694		0.53
				Prob > F	=	0.4655
				R-squared		0.0001
				Root MSE	=	1.5843
		Robust				
meals	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.0263569	.0361103	0.73	0.465	0444291	.0971429
_cons	.0175874	.0257962	0.68	0.495	0329802	.0681551
. reg banks D1	l, robust					
Linear regress	sion			Number of	obs =	7,696
				F(1, 7694		0.13
				Prob > F	=	0.7216
				R-squared	=	0.0000
				Root MSE	=	1.8071
		Robust				
banks	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.0146599	.0411407	0.36	0.722	065987	.0953068
_cons	.0516872	.0308989	1.67	0.094	0088829	.1122574

# . reg insur D1, robust

Linear regress	sion			Number of obs F(1, 7694) Prob > F R-squared Root MSE	= = = =	7,696 1.10 0.2945 0.0001 1.7429
insur	Coef.	Robust Std. Err.	t	P> t  [95%	Conf.	Interval]
D1 _cons	0416089 .0615406	.0396892 .0295374	-1.05 2.08	0.295119 0.037 .003	4106 6393	.0361928
. reg rlest Di	l, robust					
Linear regress	sion			Number of obs	=	7,696
				F(1, 7694)	=	0.04
				Prob > F R-squared	=	0.8351 0.0000
				Root MSE	=	3.1252
rlest	Coef.	Robust Std. Err.	t	P> t  [95%	Conf.	Interval]
D1 _cons	.0148135 .0384954	.0711721 .0526989	0.21 0.73	0.835124 0.465064	7033	.1543302
. reg fin D1,	robust					
Linear regress	sion			Number of obs	=	7,696
•				F(1, 7694)	=	0.11
				Prob > F	=	0.7408
				R-squared Root MSE	=	0.0000 2.0015
fin	Coef.	Robust Std. Err.	t	D> +  [050	Conf	Interval]
1111	coer.	Stu. Eff.	ι .	P> t  [95%	CONT.	Intervat]
D1 _cons	.0150873 .0285288	.0455988 .0332046	0.33 0.86	0.741074 0.390036		.1044733 .0936189

# Table 4 (Post):

# . reg agric D1, robust

Linear regress	Number of obs F(1, 16463) Prob > F R-squared Root MSE		= = = = =	16,465 14.89 0.0001 0.0009 1.3807		
agric	Coef.	Robust Std. Err.	t	P> t  [9	5% Conf.	Interval]
D1 _cons	.0830053 .0030567	.0215138 .0152927	3.86 0.20		408359 269187	.1251747 .0330321
. reg food D1	, robust					
Linear regress	sion			Number of ob	s =	16,465
				F(1, 16463)	=	1.20
				Prob > F	=	0.2742
				R-squared	=	0.0001
				Root MSE	=	.83389
food	Coef.	Robust Std. Err.	t	P> t  [9	5% Conf.	Interval]
D1 _cons	.0141977 .0441067	.0129835 .0094555	1.09 4.66	0.2740	112514 255728	.0396467
. reg beer D1	, robust					
Linear regress	sion			Number of ob	s =	16,465
				F(1, 16463)	=	5.51
				Prob > F	=	0.0189
				R-squared	=	0.0003
				Root MSE	=	1.0622
		Robust				
beer	Coef.	Std. Err.	t	P> t  [9	5% Conf.	Interval]
D1	.0388335 .0330423	.016544 .0119365	2.35		064055 096454	.0712615
_cons	.0330423	. 0119303	2.77	0.000 .0	030434	.0304392

# . reg smoke D1, robust

Prob > F	Linear regress	sion			Number of ob	os =	16,465
R-squared = 0.000 Root MSE = 1.2876  smoke						=	0.30
Root MSE						=	0.5868
Smoke   Coef. Std. Err.   t   P> t    [95% Conf. Interval]					R-squared	=	0.0000
Smoke   Coef. Std. Err.   t   P   t   [95% Conf. Interval]					Root MSE	=	1.2878
D1 .0109036 .0200619 0.54 0.5870284198 .05022; _cons .0606637 .0143599 4.22 0.000 .0325167 .0888108  . reg toys D1, robust  Linear regression			Robust				
cons	smoke	Coef.	Std. Err.	t	P> t  [9	95% Conf.	Interval]
. reg toys D1, robust  Linear regression  Number of obs = 16,463 F(1, 16463) = 15.07 Prob > F = 0.000 R-squared = 0.0009 Root MSE = 1.4929  toys  Coef. Std. Err. t P> t  [95% Conf. Interval] D1 .0902572 .0232531 3.88 0.000 .0446787 .1358358 _cons .0002487 .0167432 0.01 0.9880325696 .0330673  . reg fun D1, robust  Linear regression  Number of obs = 16,463 F(1, 16463) = 23.44 Prob > F = 0.0006 R-squared = 0.0014 Root MSE = 1.5315  fun Coef. Std. Err. t P> t  [95% Conf. Interval] D1 .115467 .0238468 4.84 0.000 .0687247 .1622093	D1	.0109036	.0200619			2284198	.050227
Number of obs	_cons	.0606637	.0143599	4.22	0.000 .6	3325167	.0888108
F(1, 16463)	. reg toys D1	, robust					
F(1, 16463)	linear regress	sion			Number of o	ns –	16 465
Prob > F = 0.000000000000000000000000000000000	Linear regress	31011					
R-squared = 0.0009 Root MSE = 1.4929  toys							
Root MSE = 1.4929  toys							
toys					•		
toys					11000 1101		211525
D1 .0902572 .0232531 3.88 0.000 .0446787 .1358358 _cons .0002487 .0167432 0.01 0.9880325696 .0330673  . reg fun D1, robust  Linear regression			Robust				
cons	toys	Coef.	Std. Err.	t	P> t  [9	95% Conf.	Interval]
Linear regression $ \begin{array}{ccccccccccccccccccccccccccccccccccc$							.1358358 .0330671
F(1, 16463) = 23.49 Prob > F = 0.0006 R-squared = 0.0014 Root MSE = 1.5319  Robust fun Coef. Std. Err. t P> t  [95% Conf. Interval]  D1 .115467 .0238468 4.84 0.000 .0687247 .1622093	. reg fun D1,	robust					
Prob > F = 0.0006 R-squared = 0.0014 Root MSE = 1.5315  Robust fun Coef. Std. Err. t P> t  [95% Conf. Interval]  D1 .115467 .0238468 4.84 0.000 .0687247 .1622093	Linear regress	sion			Number of ob	os =	16,465
R-squared = 0.0014 Root MSE = 1.5319  Robust fun Coef. Std. Err. t P> t  [95% Conf. Interval]  D1 .115467 .0238468 4.84 0.000 .0687247 .1622093					F(1, 16463)	=	23.45
Root MSE = 1.5319  Robust  fun Coef. Std. Err. t P> t  [95% Conf. Interval]  D1 .115467 .0238468 4.84 0.000 .0687247 .1622093					Prob > F	=	0.0000
Robust fun Coef. Std. Err. t P> t  [95% Conf. Interval] D1 .115467 .0238468 4.84 0.000 .0687247 .1622093					R-squared	=	0.0014
fun Coef. Std. Err. t P> t  [95% Conf. Interval] D1 .115467 .0238468 4.84 0.000 .0687247 .1622093					Root MSE	=	1.5315
fun Coef. Std. Err. t P> t  [95% Conf. Interval] D1 .115467 .0238468 4.84 0.000 .0687247 .1622093			Robust				
	fun	Coef.		t	P> t  [9	95% Conf.	Interval]
_cons   .0066754 .017342 0.38 0.7000273168 .0406677	D1	.115467		4.84	0.000 .0	0687247	.1622093
1	_cons	.0066754	.017342	0.38	0.7006	273168	.0406677

#### . reg books D1, robust

Linear regress	sion			Number of of F(1, 16463) Prob > F R-squared Root MSE		16,465 14.81 0.0001 0.0009 1.1774
books	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1 _cons	.0705868 .0150383	.0183406 .0131609	3.85 1.14		.0346373 .0107585	.1065363
. reg hshld Di	l, robust					
Linear regress	sion			Number of o	obs =	16,465
				F(1, 16463)	) =	5.28
				Prob > F	=	0.0216
				R-squared	=	0.0003
				Root MSE	=	1.0272
hshld	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Intervall
D1 _cons	.0367412	.0159958	2.30	0.022	.0053877	.0680947
. reg clths Di	l, robust					
Linear regress	sion			Number of o	obs =	16,465
				F(1, 16463)		20.91
				Prob > F	=	0.0000
				R-squared	=	0.0013
				Root MSE	=	1.1379
		Robust				
clths	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1 _cons	.0810516 .0061062	.0177243 .0127423	4.57 0.48		.0463101 .0188701	.1157932 .0310825

### . reg medeq D1, robust

Linear regression				Number of F(1, 16463 Prob > F R-squared Root MSE		= = = =	16,465 6.35 0.0117 0.0004 1.1883
medeq	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.0466364 .033608	.0185042 .0134011	2.52 2.51	0.012 0.012	.0103		.0829065 .0598757
. reg drugs Di	l, robust						
Linear regress	sion			Number of F(1, 16463 Prob > F R-squared Root MSE		= = =	16,465 4.06 0.0438 0.0002 1.0743
drugs	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.0337153 .0394021	.0167254 .0122155	2.02	0.044 0.001	.0009		.0664988
. reg chems D:	l, robust						
Linear regress	sion			Number of F(1, 16463 Prob > F R-squared Root MSE		= = = =	16,465 21.03 0.0000 0.0013 1.1399
chems	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
D1 _cons	.0814021 .0061433	.0177524 .0128472	4.59 0.48	0.000 0.633 -	.046		.1161987 .0313251

# . reg txtls D1, robust

Linear regress	sion			Number		=	16,465
				F(1, 16		=	25.88
				Prob > 1		=	0.0000
				R-square		=	0.0016
				Root MSI	E	=	1.231
		Robust					
txtls	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.0975799	.0191826	5.09	0.000	.059		. 13518
_cons	002161	.0135987	-0.16	0.874	028	8159	.0244939
. reg bldmt D:	l, robust						
Linear regress	sion			Number	of obs	=	16,465
				F(1, 16	463)	=	34.28
				Prob > I	F	=	0.0000
				R-square	ed	=	0.0021
				Root MSI	E	=	1.1091
		Robust					
bldmt	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.1011403	.0172739	5.86	0.000	.067	2815	.1349991
_cons	0014303	.0124683	-0.11	0.909	025	8696	.023009
. reg cnstr Di	l, robust						
Linear regress	sion			Number	of obs	=	16,465
				F(1, 16	463)	=	23.26
				Prob > I	F	=	0.0000
				R-square	ed	=	0.0014
				Root MSI	E	=	1.4682
		Robust					
cnstr	Coef.	Std. Err.	t	P> t	[95%	Conf.	<pre>Interval]</pre>
D1	.1103069	.0228722	4.82	0.000	. 065		.1551388
_cons	0070019	.0163847	-0.43	0.669	039	11/7	.0251139

### . reg steel D1, robust

Linear regres	sion			Number of ol F(1, 16463) Prob > F R-squared Root MSE	bs = = = = = =	16,465 25.64 0.0000 0.0016 1.4856
steel	Coef.	Robust Std. Err.	t	P> t  [9	95% Conf.	Interval]
D1 _cons	.1172501 0192382	.023154 .0163276	5.06 -1.18		0718657 .051242	.1626344 .0127655
. reg mach D1	, robust					
Linear regres	sion			Number of ol	bs =	16,465
				F(1, 16463)	=	31.65
				Prob > F	=	0.0000
				R-squared	=	0.0019
				Root MSE	=	1.186
		Robust				
mach	Coef.	Std. Err.	t	P> t  [	95% Cont.	Interval]
D1 _cons	.1039206 0031703	.0184715 .0133116	5.63 -0.24		0677144 0292624	.1401269 .0229218
. reg elceq D	1, robust					
Linear regress	sion			Number of ol	bs =	16,465
Linear regres	sion				bs = =	16,465 17.67
Linear regress	sion			Number of ol F(1, 16463) Prob > F		
Linear regres	sion			F(1, 16463)	=	17.67
Linear regres	sion			F(1, 16463) Prob > F	=	17.67 0.0000
Linear regres	sion	Robust		F(1, 16463) Prob > F R-squared	= =	17.67 0.0000 0.0011
Linear regress	coef.	Robust Std. Err.	t	F(1, 16463) Prob > F R-squared Root MSE	= = =	17.67 0.0000 0.0011
			t 4.20	F(1, 16463) Prob > F R-squared Root MSE	= = =	17.67 0.0000 0.0011 1.299

# . reg autos D1, robust

\_cons

Linear regres:	sion			Number of	obs	=	16,465
				F(1, 16463	3)	=	13.87
				Prob > F		=	0.0002
				R-squared		=	0.0008
				Root MSE		=	1.3504
		Robust					
autos	Coef.	Std. Err.	t	P> t	[95%	Cont.	Interval]
D1	.0783719	.0210409	3.72	0.000	.0371	.295	.1196142
_cons	.0052786	.014965	0.35	0.724 -	0240	543	.0346116
. reg aero D1	, robust						
_inear regres:	sion			Number of	obs	=	16,465
				F(1, 16463	3)	=	15.97
				Prob > F		=	0.0001
				R-squared		=	0.0010
				Root MSE		=	1.3142
		Robust					
aero	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.0817637	.0204574	4.00	0.000	.041	.665	.1218625
_cons	.0187706	.0149883	1.25	0.210	010	608	.0481493
. reg ships D	l, robust						
_inear regres:	sion			Number of	obs	=	16,465
				F(1, 16463	3)	=	16.34
				Prob > F		=	0.0001
				R-squared		=	0.0010
				Root MSE		=	1.3789
		Robust					
ships	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
D1	.0868742	.0214914	4.04	0.000	. 0447	486	.1289997
	0062765	0151460	0 42	0 674	022	212	026066

0.42

0.674

-.023313

.036066

.0151469

.0063765

### . reg mines D1, robust

D1 _cons	.044891 .0278438	.019184 .0138534	2.34 2.01		72883 06897	.0824937 .054998
oil	Coef.	Robust Std. Err.	t	P> t  [95	% Conf.	Interval]
				Root MSE	=	1.2318
				R-squared	=	0.0003
				Prob > F	=	0.0193
Linear regres	2 TOII			F(1, 16463)	=	16,465 5.48
. reg oil D1,				Number of obs	_	16 <i>4</i> 65
cons	000452	.0234686	-0.02	0.9850	46453	.0455489
D1	.110705	.0331581	3.34		57116	. 1756985
coal	Coef.	Robust Std. Err.	t	P> t  [95	% Conf.	Interval]
				NOOT HISE		2.122,7
				R-squared Root MSE	=	2.1277
				Prob > F	=	0.0008 0.0007
				F(1, 16463)	=	11.15
Linear regres	sion			Number of obs	=	16,465
. reg coal D1	, robust					
_cons	0061839	.0163765	-0.38		82836	.0259157
D1	.1081227	.0230011	4.70	0.000 .06	30381	.1532073
mines	Coef.	Robust Std. Err.	t	P> t  [95	% Conf.	Interval]
				Root MSE	=	1.4762
				R-squared	=	0.0013
				Prob > F	=	0.0000
_				F(1, 16463)	=	22.10
Linear regres	510N			Number of obs	=	16,465

# . reg util D1, robust

Linear regression			Number F(1, 16 Prob > R-squar Root MS			16,465 1.49 0.2218 0.0001 .78242
		Robust				
util	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1 _cons	.0148659 .0345886	.0121672 .0091814	1.22 3.77	0.222 0.000	008983 .0165921	.0387148
. reg telcm Di	l, robust					
Linear regress	sion			Number of		16,465
				F(1, 16463	3) =	8.21
				Prob > F	=	0.0042
				R-squared	=	0.0005
				Root MSE	=	1.0322
		Robust				
telcm	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1 _cons	.0460764 .0216109	.0160787 .0115525	2.87 1.87	0.004 0.061 -	.0145605 0010333	.0775924 .044255
. reg bussv Di	l, robust					
Linear regress	sion			Number of	obs =	16,465
				F(1, 16463	3) =	14.88
				Prob > F	=	0.0001
				R-squared	=	0.0009
				Root MSE	=	1.0298
		Robust				
bussv	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1	.0618527	.0160349	3.86	0.000	.0304225	.0932829
_cons	.0157618	.0116538	1.35	0.176	007081	.0386045

# . reg hardw D1, robust

D1

\_cons

.0997827

.0072566

Linear regress	sion			Number of obs	=	16,465
				F(1, 16463)	=	7.8
				Prob > F =		0.0052
				R-squared	=	0.000
				Root MSE	=	1.5349
		Robust				
hardw	Coef.	Std. Err.	t	P> t  [95	% Conf.	Interval
D1	.0668649	.0239276	2.79	0.005 .01	99641	.1137656
_cons	.024811	.0167759	1.48	0.13900	80715	.0576936
. reg chips Di	1, robust					
_inear regres:	sion			Number of obs	=	16,46
				F(1, 16463) =		13.2
				Prob > F	=	0.000
				R-squared	=	0.000
				Root MSE	=	1.510
		Robust				
chips	Coef.	Std. Err.	t	P> t  [95	% Conf.	Interval
D1	.0856425	.023537	3.64	0.000 .03	95074	. 131777
_cons	.0101602	.0167634	0.61	0.54402	26979	.0430184
. reg labeq Di	1, robust					
_inear regres	sion			Number of obs	=	16,46
				F(1, 16463)	=	22.2
				Prob > F	=	0.000
				R-squared	=	0.0013
				Root MSE	=	1.357
		Robust				
labeq	Coef.	Std. Err.	t	P> t  [95	% Conf.	Interval
	*****	*****				

4.72

0.48

.021145

.0150874

0.000

0.631

.0583362

-.0223162

.1412292

.0368295

#### . reg boxes D1, robust

Linear regress	sion			Number of F(1, 16463 Prob > F	) = =	16,465 16.18 0.0001
				R-squared Root MSE	=	0.0010 1.1722
		Robust				
boxes	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1 _cons	.0734149 .0138268	.0182493 .0133257	4.02 1.04		.0376444 012293	.1091855 .0399467
. reg trans D1	l, robust					
Linear regress	sion			Number of	obs =	16,465
				F(1, 16463) =		16.50
				Prob > F	=	0.0000
				R-squared Root MSE	=	0.0010
				KOUL MSE	=	1.1519
		Robust				
trans	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1 _cons	.0728654 .0103408	.0179355 .0130307	4.06 0.79		.0377098 .0152007	.1080209 .0358824
. reg whlsl D1	l, robust					
Linear regress	sion			Number of	obs =	16,465
				F(1, 16463	) =	26.73
				Prob > F	=	0.0000
				R-squared	=	0.0016
				Root MSE	=	1.0141
		Robust				
whlsl	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
D1 _cons	.0816269 .0052619	.0157881 .011521	5.17 0.46		.0506806 .0173206	.1125732 .0278444

### . reg rtail D1, robust

egression Number of obs	=	16,465
F(1, 16463)	=	11.84
Prob > F	=	0.0006
R-squared	=	0.0007
Root MSE	=	1.051
Robust		
tail Coef. Std. Err. t P> t  [95% C	conf.	Interval]
D1 .0562959 .0163613 3.44 0.001 .02422 cons .023651 .011985 1.97 0.048 .00015		.0883659 .0471429
als D1, robust		
egression Number of obs	=	16,465
F(1, 16463)	=	18.59
Prob > F	=	0.0000
R-squared	=	0.0011
Root MSE	=	1.197
Robust		
eals Coef. Std. Err. t P> t  [95% C	onf	<pre>Interval]</pre>
	.0111.	2111011101
D1 .0803618 .0186402 4.31 0.000 .04382		.1168986
D1 .0803618 .0186402 4.31 0.000 .04382 cons .0160667 .0135135 1.19 0.23401042	249	
	249	.1168986
cons .0160667 .0135135 1.19 0.23401042	249	.1168986
nks D1, robust	249	.1168986 .0425546
cons .0160667 .0135135 1.19 0.23401042  nks D1, robust  egression Number of obs	249 211 =	.1168986 .0425546
cons .0160667 .0135135 1.19 0.23401042  nks D1, robust  egression Number of obs F(1, 16463)	249 211 = = =	.1168986 .0425546 16,465 5.33
cons .0160667 .0135135 1.19 0.23401042  nks D1, robust  egression	249 211 = = = =	.1168986 .0425546 16,465 5.33 0.0209
nks D1, robust  egression  Number of obs F(1, 16463) Prob > F R-squared Root MSE	249 211 = = = = =	.1168986 .0425546 16,465 5.33 0.0209 0.0003
nks D1, robust  egression  Number of obs F(1, 16463) Prob > F R-squared Root MSE	= = = = = = =	.1168986 .0425546 16,465 5.33 0.0209 0.0003
nks D1, robust  egression  Number of obs F(1, 16463) Prob > F R-squared Root MSE	= = = = = = = = = = = = = = = = = = =	.1168986 .0425546 16,465 5.33 0.0209 0.0003 1.2871

### . reg insur D1, robust

inear regression				Number of F(1, 1646; Prob > F R-squared Root MSE		16,465 7.94 0.0048 0.0005 1.1497
insur	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1 _cons	.0504655 .0222471	.0179045 .0129679	2.82 1.72	0.005 0.086	.0153708 0031715	.0855602 .0476657
. reg rlest Di	l, robust					
Linear regress	sion			Number of	obs =	16,465
				F(1, 1646	3) =	23.95
				Prob > F	=	0.0000
				R-squared	=	0.0015
				Root MSE	=	1.4466
rlest	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
D1 _cons	.1103573 0202882	.0225492	4.89	0.000	.0661584 051343	.1545562
	0202882	.0156454	-1.28	0.200	-1031343	.0107666
. reg fin D1,		. 0130434	-1.26	0.200	-1032343	.010/666
	robust	. 0130434	-1.26			
. reg fin D1,	robust	. 0130434	-1.26	Number of	obs =	16,465 9.23
	robust	. 0130434	-1.26		obs =	16,465
	robust	. 0130434	-1.26	Number of F(1, 1646:	obs = 3) =	16,465 9.23
	robust	.0130434	-1.26	Number of F(1, 1646; Prob > F	obs = 3) = =	16,465 9.23 0.0024
Linear regress	robust	Robust	-1.26	Number of F(1, 1646; Prob > F R-squared	obs = 3) = = = = =	16,465 9.23 0.0024 0.0006 1.3197
	robust		-1.28	Number of F(1, 1646; Prob > F R-squared	obs = 3) = = = =	16,465 9.23 0.0024 0.0006 1.3197
Linear regress	<b>robust</b> sion	Robust		Number of F(1, 1646 Prob > F R-squared Root MSE	obs = 3) = = = = =	16,465 9.23 0.0024 0.0006 1.3197

# Table 5 (Whole):

### . reg agric d1 TOM Jan Hal, robust

Linear regression	Number of obs	=	24,161
	F(4, 24156)	=	19.32
	Prob > F	=	0.0000
	R-squared	=	0.0030
	Root MSE	=	2.3946

agric	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2826242	.0386594	-7.31	0.000	358399	2068494
TOM	.1260796	.0397728	3.17	0.002	.0481223	.2040368
Jan	.1491407	.053782	2.77	0.006	.0437247	.2545567
Hal	.040138	.0327779	1.22	0.221	0241087	.1043847
_cons	.0869168	.023449	3.71	0.000	.0409552	.1328783

# . reg food d1 TOM Jan Hal, robust

Linear regression	Number of obs	=	24,161
	F(4, 24156)	=	57.01
	Prob > F	=	0.0000
	R-squared	=	0.0095
	Root MSF	=	. 95223

food	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	1841051	.0160017	-11.51	0.000	2154695	1527407
TOM	.1190735	.015965	7.46	0.000	.0877812	.1503659
Jan	.1234387	.0213331	5.79	0.000	.0816244	.1652529
Hal	.0205976	.0128825	1.60	0.110	0046528	.045848
_cons	.0680238	.0096271	7.07	0.000	.0491541	.0868935

#### . reg beer d1 TOM Jan Hal, robust

Linear regression	Number of obs	=	24,161
	E(A 24156)	_	27 18

F(4, 24156) = 27.18 Prob > F = 0.0000 R-squared = 0.0046 Root MSE = 1.5033

beer	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1 TOM	2145861 .1393328	.0250102 .0234291	-8.58 5.95	0.000 0.000	2636076 .0934104	1655647 .1852553
Jan	.0925286	.0234291	2.78	0.005	.0272341	.1578232
Hal	.0026219	.0203088	0.13	0.897	0371846	.0424283
_cons	.080604	.0159846	5.04	0.000	.0492732	.1119348

#### . reg smoke d1 TOM Jan Hal, robust

Linear regression Number of obs = 24,161

Number of obs = 24,161 F(4, 24156) = 15.82 Prob > F = 0.0000 R-squared = 0.0025 Root MSE = 1.3316

smoke	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	1171699	.0227467	-5.15	0.000	1617549	0725849
TOM	.1025717	.021402	4.79	0.000	.0606224	.144521
Jan	.093978	.0299589	3.14	0.002	.0352568	.1526993
Hal	.0107874	.0181896	0.59	0.553	0248654	.0464401
_cons	.0693583	.013227	5.24	0.000	.0434326	.095284

#### . reg toys d1 TOM Jan Hal, robust

Linear regression Number of obs = 24,161F(4, 24156) = 22.78

Prob > F = 0.0000 R-squared = 0.0035

Root MSE = 2.157

toys	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	2561772	.0341247	-7.51	0.000	3230636	1892907
TOM	.14885	.0349838	4.25	0.000	.0802796	.2174204
Jan	.1528156	.0495497	3.08	0.002	.0556952	.249936
Hal	.0503336	.029646	1.70	0.090	0077744	.1084416
_cons	.0607652	.0211579	2.87	0.004	.0192945	.1022359

#### . reg fun d1 TOM Jan Hal, robust

Linear regression Number of obs = 24,161

F(4, 24156) = 48.58 Prob > F = 0.0000 R-squared = 0.0085 Root MSE = 1.6658

Robust fun Std. Err. [95% Conf. Interval] Coef. t P>|t| **d1** -.3119208 .0277409 -11.24 0.000 -.257547 -.3662946 TOM .1874021 .0286344 6.54 0.000 .1312768 .2435274 Jan .184473 .0374747 4.92 0.000 .1110203 .2579258 0.036 Hal .0474791 .0226204 2.10 .0031418 .0918165 \_cons .0757755 .0168965 4.48 0.000 .0426572 .1088937

#### . reg books d1 TOM Jan Hal, robust

Linear regression Number of obs = 24,161

F(4, 24156) = 30.00 Prob > F = 0.0000 R-squared = 0.0048

Root MSE = 1.5877

books	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2518503	.0261005	-9.65	0.000	3030089	2006917
TOM	.0889433	.0252563	3.52	0.000	.0394395	.1384472
Jan	.1005684	.0353976	2.84	0.004	.0311869	.16995
Hal	.0322414	.0214662	1.50	0.133	0098337	.0743166
_cons	.0817349	.0167349	4.88	0.000	.0489334	.1145364

### . reg hshld d1 TOM Jan Hal, robust

Linear regression Number of obs = 24,161

F(4, 24156) = 55.83 Prob > F = 0.0000 R-squared = 0.0094 Root MSE = 1.2003

hshld	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2178469	.0205991	-10.58	0.000	2582224	1774713
TOM	.1433456	.0195052	7.35	0.000	.1051142	.1815769
Jan	.167846	.0263863	6.36	0.000	.1161272	.2195648
Hal	.0460746	.0162287	2.84	0.005	.0142653	.0778839
_cons	.0516906	.012515	4.13	0.000	.0271605	.0762207

#### . reg clths d1 TOM Jan Hal, robust

Linear regression Number of obs = 24,161

Number of obs = 24,161 F(4, 24156) = 48.49 Prob > F = 0.0000 R-squared = 0.0088 Root MSE = 1.2458

clths	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	1990382	.0221085	-9.00	0.000	2423723	1557041
TOM	.1432409	.020733	6.91	0.000	.1026029	.183879
Jan	.2086952	.0322475	6.47	0.000	.145488	.2719023
Hal	.0462675	.0166363	2.78	0.005	.0136594	.0788757
_cons	.0560951	.0125414	4.47	0.000	.0315132	.080677

#### . reg medeq d1 TOM Jan Hal, robust

Linear regression Number of obs = 24,161

Number of obs = 24,161 F(4, 24156) = 42.63 Prob > F = 0.0000 R-squared = 0.0064 Root MSE = 1.5052

medeq	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	230645	.0237957	-9.69	0.000	2772861	1840039
TOM	.1347109	.0229574	5.87	0.000	.0897129	.1797089
Jan	.2083205	.036258	5.75	0.000	.1372526	.2793884
Hal	.0231177	.0205708	1.12	0.261	0172024	.0634378
_cons	.0680815	.0146755	4.64	0.000	.0393166	.0968464

#### . reg drugs d1 TOM Jan Hal, robust

F(4, 24156) = 24,161 Prob > F Linear regression

R-squared Root MSE = 0.0092

= 1.2595

drugs	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	2548456	.0221769	-11.49	0.000	2983137	2113776
TOM	.1420204	.0202541	7.01	0.000	.1023211	.1817198
Jan	.110236	.0287696	3.83	0.000	.0538458	.1666261
Hal	.0452587	.017022	2.66	0.008	.0118945	.0786229
_cons	.0686124	.0128558	5.34	0.000	.0434142	.0938107

#### . reg chems d1 TOM Jan Hal, robust

Linear regression Number of obs = 24,161

F(4, 24156) 50.82 Prob > F 0.0000 R-squared = 0.0089

Root MSE = 1.2036

chems	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2268625	.0210474	-10.78	0.000	2681167	1856083
TOM	.1538465	.0196061	7.85	0.000	.1154174	.1922756
Jan	.0918135	.025751	3.57	0.000	.0413399	.1422872
Hal	. 0525239	.0163304	3.22	0.001	.0205153	.0845324
_cons	.0562133	.0123822	4.54	0.000	.0319433	.0804832

#### . reg txtls d1 TOM Jan Hal, robust

txtls	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2270384	.0227671	-9.97	0.000	2716634	1824134
TOM	.1550435	.0220622	7.03	0.000	.1118003	.1982868
Jan	.1481731	.0297567	4.98	0.000	.0898481	.206498
Hal	.0433157	.0177809	2.44	0.015	.008464	.0781674
_cons	.0547412	.0132679	4.13	0.000	.0287353	.080747

#### . reg bldmt d1 TOM Jan Hal, robust

Robust bldmt Coef. Std. Err. t P>|t| [95% Conf. Interval] -.2224177 -10.75 -.2629631 **d1** .0206858 0.000 -.1818722 TOM .1356021 .0187764 7.22 0.000 .0987993 .1724049 Jan .1477048 .0261411 5.65 0.000 .0964665 .198943 Hal .0577003 .0158989 3.63 0.000 .0265376 .0888631 \_cons .0543545 .0121183 4.49 0.000 .0306019 .0781071

#### . reg cnstr d1 TOM Jan Hal, robust

Linear regression Number of obs = 24,161

F(4, 24156) = 23.81 Prob > F = 0.0000 R-squared = 0.0048

2.4887

.4242531

.1205983

.1246755

Root MSE

0.000

0.098

0.002

Robust Coef. Std. Err. [95% Conf. Interval] cnstr t P>|t| **d1** -.3090074 .0412611 -7.49 0.000 -.3898818 -.2281331 TOM .2055405 .0418201 4.91 0.000 .1235704 .2875105

4.54

1.66

3.05

.0652962

.0333431

.0248771

# . reg steel d1 TOM Jan Hal, robust

.2962685

.0552438

.0759149

Jan

Hal

\_cons

Linear regression Number of obs = 24,161

F(4, 24156) = 52.97 Prob > F = 0.0000 R-squared = 0.0094 Root MSE = 1.4828

.1682839

.0271543

-.0101108

Robust [95% Conf. Interval] steel Coef. Std. Err. t P>|t| d1 -.2721661 .0261805 -10.40 0.000 -.3234816 -.2208507 0.000 TOM .2082241 8.46 .0246162 .1599749 .2564734 0.000 Jan .1480344 .0333945 4.43 .0825791 .2134898 Hal .0586663 .0201569 2.91 0.004 .0191576 .0981751 \_cons .0147166 0.002 .0457923 3.11 .0169469 .0746377

### . reg mach d1 TOM Jan Hal, robust

Linear regression Number of obs = 24,161F(4, 24156) = 51.99Prob > F = 0.0000

Prob > F = 0.0000 R-squared = 0.0093 Root MSE = 1.2785

mach	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2260104	.0227752	-9.92	0.000	2706512	1813696
TOM	.1682732	.0210204	8.01	0.000	.127072	.2094744
Jan	.1544459	.0291211	5.30	0.000	.0973667	.2115251
Hal	.0582319	.0172187	3.38	0.001	.0244821	.0919817
_cons	.0511447	.0131633	3.89	0.000	.0253438	.0769455

### . reg elceq d1 TOM Jan Hal, robust

Linear regression Number of obs = 24,161

F(4, 24156) = 57.56 Prob > F = 0.0000 R-squared = 0.0099 Root MSE = 1.4234

elceq	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2884436	.0245952	-11.73	0.000	3366517	2402356
TOM	.1715275	.022813	7.52	0.000	.1268127	.2162424
Jan	.1595294	.0309969	5.15	0.000	.0987735	.2202854
Hal	.0495382	.0192225	2.58	0.010	.0118609	.0872154
_cons	.0676077	.0148299	4.56	0.000	.0385402	.0966752

### . reg autos d1 TOM Jan Hal, robust

Linear regression Number of obs = 24,161F(4, 24156) = 49.49

Prob > F = 0.0000 R-squared = 0.0088

Root MSE = 1.4639

autos	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1 TOM Jan Hal _cons	2514882 .2080728 .1560777 .0441172 .0521129	.0258213 .0237524 .0327951 .019774 .0150292	-9.74 8.76 4.76 2.23 3.47	0.000 0.000 0.000 0.026 0.001	3020995 .1615166 .0917974 .005359 .0226547	2008769 .2546291 .2203581 .0828754

#### . reg aero d1 TOM Jan Hal, robust

Linear regression Number of obs = 24,161

Number of obs = 24,161 F(4, 24156) = 34.37 Prob > F = 0.0000 R-squared = 0.0059 Root MSE = 1.6943

aero	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2636448	.0285905	-9.22	0.000	3196839	2076056
TOM	.1646208	.0281171	5.85	0.000	.1095095	.2197321
Jan	.1142582	.0378987	3.01	0.003	.0399745	.1885419
Hal	.0616153	.0230203	2.68	0.007	.0164941	.1067366
_cons	.072096	.0172973	4.17	0.000	.0381922	.1059997

### . reg ships d1 TOM Jan Hal, robust

Number of obs = 24,161 F(4, 24156) = 39.79 Prob > F = 0.0000 R-squared = 0.0068 Root MSE = 1.7029 Linear regression

ships	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	292296	.0287079	-10.18	0.000	3485654	2360267
TOM	.1669335	.0278587	5.99	0.000	.1123287	.2215383
Jan	.1261641	.0387452	3.26	0.001	.0502212	.2021071
Hal	.0589359	.0231938	2.54	0.011	.0134746	.1043971
_cons	.0601448	.0170029	3.54	0.000	.0268179	.0934716

#### . reg mines d1 TOM Jan Hal, robust

Number of obs = 24,161 F(4, 24156) = 48.15 Prob > F = 0.0000 R-squared = 0.0084 Root MSE = 1.6202 Linear regression

mines	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2770358	.0274489	-10.09	0.000	3308372	2232343
TOM	.1832587	.0277985	6.59	0.000	.1287719	.2377454
Jan	.2248336	.0398913	5.64	0.000	.1466441	.303023
Hal	.0511817	.0217939	2.35	0.019	.0084644	.0938991
_cons	.0745249	.0161114	4.63	0.000	.0429456	.1061042

#### . reg coal d1 TOM Jan Hal, robust

Linear regression Number of obs = 24,161F(4, 24156) = 18.92

Number of obs = 24,161 F(4, 24156) = 18.92 Prob > F = 0.0000 R-squared = 0.0034 Root MSE = 2.3916

coal	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2896092	.0408371	-7.09	0.000	3696524	2095661
TOM	.1999153	.0413021	4.84	0.000	.1189606	.28087
Jan	.0827786	.0535764	1.55	0.122	0222344	.1877916
Hal	.022097	.0328908	0.67	0.502	042371	.086565
_cons	.1123052	.0226523	4.96	0.000	.0679053	.1567051

### . reg oil d1 TOM Jan Hal, robust

Linear regression Number of obs = 24,161

Number of obs = 24,161 F(4, 24156) = 55.95 Prob > F = 0.0000 R-squared = 0.0106 Root MSE = 1.4486

oil	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	3327246	.0260124	-12.79	0.000	3837104	2817387
TOM	.1680715	.0245864	6.84	0.000	.1198807	.2162623
Jan	.0814514	.0332166	2.45	0.014	.0163449	.1465579
Hal	.0524055	.0196007	2.67	0.008	.0139869	.0908242
_cons	.0854777	.0145135	5.89	0.000	.0570304	.113925

#### . reg util d1 TOM Jan Hal, robust

R-squared = 0.0039 Root MSE = 1.1913

util	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	1412107	.0201257	-7.02	0.000	1806584	101763
TOM	.1162867	.0189797	6.13	0.000	.0790853	.153488
Jan	.0880898	.0257553	3.42	0.001	.0376078	.1385718
Hal	011819	.0161308	-0.73	0.464	0434364	.0197984
_cons	.0649443	.0124003	5.24	0.000	.0406389	.0892496

### . reg telcm d1 TOM Jan Hal, robust

Linear regression Number of obs = 24,161F(4, 24156) = 43.50

Prob > F = 0.0000 R-squared = 0.0083 Root MSE = 1.1772

telcm	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1 TOM Jan Hal cons	2194492 .132761 .1042211 .0437272	.0209032 .0200357 .0278688 .0159073	-10.50 6.63 3.74 2.75 4.36	0.000 0.000 0.000 0.006 0.000	2604209 .0934899 .0495966 .012548	1784776 .1720321 .1588456 .0749064

### . reg bussv d1 TOM Jan Hal, robust

bussv	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	2331534	.024063	-9.69	0.000	2803183	1859884
TOM	.1422751	.0241946	5.88	0.000	.0948522	.1896981
Jan	.1912352	.0350277	5.46	0.000	.1225787	.2598916
Hal	.0382203	.0198462	1.93	0.054	0006795	.0771201
_cons	.0834559	.0154576	5.40	0.000	.0531581	.1137538

#### . reg hardw d1 TOM Jan Hal, robust

Linear regression Number of obs = 24,161

Number of obs = 24,161 F(4, 24156) = 52.70 Prob > F = 0.0000 R-squared = 0.0097 Root MSE = 1.4018

hardw	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2693399	.0246543	-10.92	0.000	3176638	221016
TOM	.1770192	.0236885	7.47	0.000	.1305882	.2234502
Jan	.1688124	.0322338	5.24	0.000	.1056323	.2319926
Hal	.0531688	.0188765	2.82	0.005	.0161698	.0901678
_cons	.0496875	.0143607	3.46	0.001	.0215396	.0778354

#### . reg chips d1 TOM Jan Hal, robust

Linear regression Number of obs = 24,161

F(4, 24156) = 46.88 Prob > F = 0.0000 R-squared = 0.0079 Root MSE = 1.669

Robust chips Std. Err. [95% Conf. Interval] Coef. t P>|t| .0277489 0.000 **d1** -.2783274 -10.03 -.332717 -.2239377 TOM .2014547 .0268661 7.50 0.000 .1487954 .254114 Jan .1808419 .03673 4.92 0.000 .1088488 .2528351 .0590488 .0224189 2.63 0.008 .0151064 .1029912 Hal .0610356 3.42 0.001 .0260289 .0960423 .01786 \_cons

#### . reg labeq d1 TOM Jan Hal, robust

Linear regression Number of obs = 24,161

F(4, 24156) = 36.18 Prob > F = 0.0000 R-squared = 0.0068 Root MSE = 1.2804

Robust [95% Conf. Interval] labeq Coef. Std. Err. t P>|t| **d1** -.2081542 .0227974 -9.13 0.000 -.2528386 -.1634699 TOM 0.000 .1336057 .0212332 6.29 .0919873 .1752242 Jan .081006 .0287873 2.81 0.005 .024581 .1374309 .0648855 .0173227 3.75 0.000 .0988391 Hal .0309318 .0130482 4.26 0.000 \_cons .0555371 .0299619 .0811124

#### . reg boxes d1 TOM Jan Hal, robust

boxes	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2038879	.0227276	-8.97	0.000	2484354	1593404
TOM	.146294	.0216484	6.76	0.000	.1038617	.1887262
Jan	.1016106	.031232	3.25	0.001	.0403939	.1628272
Hal	.0485021	.0180637	2.69	0.007	.0130961	.083908
_cons	.0619889	.0131927	4.70	0.000	.0361305	.0878474

#### . reg trans d1 TOM Jan Hal, robust

Robust trans Coef. Std. Err. t P>|t| [95% Conf. Interval] .0235271 -13.54 0.000 **d1** -.3184571 -.3645717 -.2723425 TOM 8.58 0.000 .2337555 .1902942 .0221734 .1468329 Jan .2195417 .0323366 6.79 0.000 .15616 .2829235 .0183621 .0705529 Hal .034562 1.88 0.060 -.001429 .0884006 .0140641 6.29 0.000 .060834 .1159672 \_cons

#### . reg whisi di TOM Jan Hal, robust

Root MSE = 1.8279

whlsl	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2780072	.0296873	-9.36	0.000	3361962	2198182
TOM	.1755838	.0294667	5.96	0.000	.1178273	.2333403
Jan	.1322498	.0383671	3.45	0.001	.0570479	.2074517
Hal	.0404034	.0250582	1.61	0.107	0087122	.089519
_cons	.0990932	.0184783	5.36	0.000	.0628745	.1353119

### . reg rtail d1 TOM Jan Hal, robust

Linear regression Number of obs = 24,161

F(4, 24156) = 47.62 Prob > F = 0.0000 R-squared = 0.0088 Root MSE = 1.0811

rtail	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1 TOM Jan Hal cons	1947507 .140075 .1077311 .0420599 .0583993	.0191854 .0177529 .0249706 .0146066 .0108887	-10.15 7.89 4.31 2.88 5.36	0.000 0.000 0.000 0.004 0.000	2323552 .1052782 .0587871 .01343 .0370569	1571462 .1748718 .156675 .0706898

#### . reg meals d1 TOM Jan Hal, robust

Linear regression Number of obs = 24,161

F(4, 24156) = 46.45 Prob > F = 0.0000 R-squared = 0.0082

Root MSE = 1.3103

meals	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2231568	.022494	-9.92	0.000	2672464	1790673
TOM	.1219042	.0209775	5.81	0.000	.0807871	.1630213
Jan	.1869148	.0328736	5.69	0.000	.1224804	.2513491
Hal	.0589634	.0177373	3.32	0.001	.0241972	.0937295
_cons	.0526464	.0129079	4.08	0.000	.0273461	.0779467

#### . reg banks d1 TOM Jan Hal, robust

Linear regression Number of obs = 24,161

F(4, 24156) = 36.39 Prob > F = 0.0000 R-squared = 0.0065 Root MSE = 1.1751

Robust [95% Conf. Interval] banks Coef. Std. Err. P>|t| t **d1** -.1838027 .0197456 -9.31 0.000 -.2225053 -.1451 TOM .1271667 0.000 .0202071 6.29 .0875594 .1667739 .1164455 .0257563 4.52 0.000 .0659616 .1669294 Jan Hal .0260783 .0157978 1.65 0.099 -.0048864 .057043 5.29 0.000 .0887177 .0647457 .0122302 .0407737 \_cons

### . reg insur d1 TOM Jan Hal, robust

24,161 Linear regression Number of obs = F(4, 24156) = 23.37 Prob > F = 0.0000 R-squared Root MSE = 0.0039

insur	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	1707561	.0218441	-7.82	0.000	2135719	1279403
TOM	.1147632	.0214107	5.36	0.000	.0727968	.1567296
Jan	.0486751	.0309103	1.57	0.115	011911	.1092611
Hal	.0259408	.0177573	1.46	0.144	0088647	.0607462
_cons	.059471	.0136663	4.35	0.000	.0326842	.0862578

#### . reg rlest d1 TOM Jan Hal, robust

Number of obs = Linear regression 24,161

= F(4, 24156) 28.78 0.0000 Prob > F = R-squared = 0.0048 Root MSE = 2.3271

1.3209

rlest	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	3086538	.0383759	-8.04	0.000	3838729	2334346
TOM	.1991734	.0376791	5.29	0.000	.12532	.2730268
Jan	.2386943	.0553213	4.31	0.000	.1302611	.3471274
Hal	.0392652	.0315084	1.25	0.213	0224933	.1010237
_cons	.0825151	.0236055	3.50	0.000	.0362468	.1287833

#### . reg fin d1 TOM Jan Hal, robust

Linear regression Number of obs = 24,161 F(4, 24156) 53.78 =

Prob > F 0.0000 = R-squared = 0.0092 Root MSE 1.3842 =

fin	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2829065	.0234313	-12.07	0.000	3288333	2369798
TOM	.1460331	.0225078	6.49	0.000	.1019165	.1901497
Jan	.1600917	.0321567	4.98	0.000	.0970626	.2231208
Hal	.0298781	.0186306	1.60	0.109	0066389	.0663952
_cons	.0922261	.0144337	6.39	0.000	.0639351	.1205171

## *Table 5.1:*

#### . reg agric d1 TOM Jan Hal, robust

Number of obs = 7,696 F(4, 7691) = 5.80 Linear regression 0.0001 Prob > F = 0.0030

R-squared Root MSE = 3.7024

agric	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	477022	.1109428	-4.30	0.000	6945002	2595438
TOM	.2304574	.1182322	1.95	0.051	00131	.4622248
Jan	.1587504	.1418656	1.12	0.263	1193448	.4368455
Hal	0479382	.0902044	-0.53	0.595	2247634	.1288871
_cons	.1911196	.0627898	3.04	0.002	.0680344	.3142048

#### . reg food d1 TOM Jan Hal, robust

Linear regression 7,696

Number of obs = F(4, 7691) = 18.87 Prob > F 0.0000 Prob > F =
R-squared =
Root MSE = 0.0092

1.3123

food	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	2453047	.0386427	-6.35	0.000	321055	1695544
TOM	.1905263	.0421682	4.52	0.000	.107865	.2731875
Jan	.1925333	.0492478	3.91	0.000	.0959942	.2890724
Hal	0280996	.0315989	-0.89	0.374	090042	.0338428
_cons	.0973132	.023266	4.18	0.000	.0517054	.1429209

### . reg beer d1 TOM Jan Hal, robust

beer	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	3443287	.0683696	-5.04	0.000	4783517	2103056
TOM	.2763992	.0644663	4.29	0.000	.1500276	.4027708
Jan	.1396603	.0826328	1.69	0.091	0223226	.3016432
Hal	0980781	.0533952	-1.84	0.066	2027474	.0065911
_cons	.1439412	.0425097	3.39	0.001	.0606106	.2272718

#### . reg smoke d1 TOM Jan Hal, robust

Linear regression Number of obs = 7,696F(4, 7691) = 13.22

Prob > F = 0.0000 R-squared = 0.0063 Root MSE = 1.2907

smoke	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	1643462	.0415167	-3.96	0.000	2457302	0829621
TOM	.1568609	.0396928	3.95	0.000	.0790523	.2346696
Jan	.218011	.047663	4.57	0.000	.1245786	.3114435
Hal	0397423	.0309352	-1.28	0.199	1003836	.0208991
_cons	.0757672	.0236207	3.21	0.001	.0294642	.1220702

### . reg toys d1 TOM Jan Hal, robust

Linear regression	Number of obs	=	7,696
	F(4, 7691)	=	4.11
	Prob > F	=	0.0025
	R-squared	=	0.0020
	Root MSE	=	3.407

toys	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	3367579	.097805	-3.44	0.001	5284825	1450334
TOM	.2125254	.1040802	2.04	0.041	.0084997	.416551
Jan	.11005	.1353661	0.81	0.416	1553043	.3754044
Hal	0173888	.0834612	-0.21	0.835	1809955	.1462179
_cons	.1056754	.0580516	1.82	0.069	0081216	.2194724

### . reg fun d1 TOM Jan Hal, robust

Linear regression	Number of obs	=	7,696
	F(4, 7691)	=	13.66
	Prob > F	=	0.0000

R-squared = **0.0072** Root MSE = **2.4488** 

fun	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	4407367	.0744711	-5.92	0.000	5867203	294753
TOM	.3025525	.0809978	3.74	0.000	.1437747	.4613303
Jan	.2196943	.092829	2.37	0.018	.0377241	.4016645
Hal	068261	.0591714	-1.15	0.249	1842531	.047731
_cons	.1375775	.0438445	3.14	0.002	.0516303	.2235247

### . reg books d1 TOM Jan Hal, robust

Number of obs	=	7,696
F(4, 7691)	=	10.77
Prob > F	=	0.0000
R-squared	=	0.0050
Root MSE	=	2.2856
	F(4, 7691) Prob > F R-squared	F(4, 7691) = Prob > F = R-squared =

books	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	4003484	.0681923	-5.87	0.000	534024	2666728
TOM	.0829924	.0668051	1.24	0.214	0479638	.2139486
Jan	.1918345	.0851679	2.25	0.024	.0248821	.3587868
Hal	0730875	.0548469	-1.33	0.183	1806024	.0344275
_cons	.1551088	.0432451	3.59	0.000	.0703367	.239881

### . reg hshld d1 TOM Jan Hal, robust

Linear regression	Number of obs	=	7,696
	F(4, 7691)	=	19.64
	Prob > F	=	0.0000
	R-squared	=	0.0093
	Root MSE	=	1.6305

hshld	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	3079094	.0500501	-6.15	0.000	4060212	2097975
TOM	.2274428	.0487261	4.67	0.000	.1319263	.3229592
Jan	.2571242	.0577943	4.45	0.000	.1438316	.3704168
Hal	0424972	.0391702	-1.08	0.278	1192815	.0342871
_cons	.0971682	.0307497	3.16	0.002	.0368903	.157446

### . reg clths d1 TOM Jan Hal, robust

Linear regression	Number of obs	=	7,696
	F(4, 7691)	=	13.91
	Prob > F	=	0.0000
	R-squared	=	0.0076
	Root MSE	=	1.6531

clths	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	. Interval]
<b>d1</b>	2611346	.0553445	-4.72	0.000	3696249	1526442
TOM	.1772091	.0515532	3.44	0.001	.0761508	.2782673
Jan	.316914	.0757867	4.18	0.000	.1683514	.4654767
Hal	0431402	.0390233	-1.11	0.269	1196365	.0333561
_cons	.1239981	.029317	4.23	0.000	.0665288	.1814673

### . reg medeq d1 TOM Jan Hal, robust

Linear regression	Number of obs	=	7,696
	F(4, 7691)	=	6.59
	Prob > F	=	0.0000
	R-squared	=	0.0029
	Root MSE	=	2.1884

medeq	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	2091779	.0602018	-3.47	0.001	3271898	091166
TOM	.1576118	.059148	2.66	0.008	.0416656	.2735581
Jan	.2479168	.0925681	2.68	0.007	.066458	.4293756
Hal	0387611	.0533531	-0.73	0.468	1433476	.0658255
_cons	.0738451	.0367318	2.01	0.044	.0018408	.1458495
_cons	.0/30451	.030/310	2.01	0.044	.0018408	.1456495

### . reg drugs d1 TOM Jan Hal, robust

Linear regression

Number of obs	=	7,696
F(4, 7691)	=	8.00
Prob > F	=	0.0000
R-squared	=	0.0041
Root MSE	=	1.472

drugs	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2128342	.0455726	-4.67	0.000	3021689	1234995
TOM	.1219956	.0419865	2.91	0.004	.0396906	.2043005
Jan	.0832465	.0543035	1.53	0.125	0232031	.1896962
Hal	0008966	.0352968	-0.03	0.980	0700879	.0682947
_cons	.0628817	.0274978	2.29	0.022	.0089785	.1167849

## . reg chems d1 TOM Jan Hal, robust

Linear regression

Number of obs	=	7,696
F(4, 7691)	=	17.07
Prob > F	=	0.0000
R-squared	=	0.0085
Root MSE	=	1.539

chems	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	3148744	.0478484	-6.58	0.000	4086704	2210784
TOM	.2007148	.045902	4.37	0.000	.1107344	.2906952
Jan	.1141875	.0513461	2.22	0.026	.0135352	.2148399
Hal	033365	.0372123	-0.90	0.370	1063112	.0395811
_cons	.1128157	.028453	3.96	0.000	.05704	.1685913

#### . reg txtls d1 TOM Jan Hal, robust

Number of obs = F(4, 7691) = Linear regression 7,696 F(4, 7691) 14.77 Prob > F = 0.0000 R-squared Root MSE = 0.0074

txtls	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	3098811	.0533546	-5.81	0.000	4144706	2052916
TOM	.1745449	.0520086	3.36	0.001	.0725938	.2764959
Jan	.2151694	.0624218	3.45	0.001	.0928056	.3375332
Hal	0743163	.0406382	-1.83	0.067	1539782	.0053455
_cons	.1449154	.0303599	4.77	0.000	.0854018	.204429

### . reg bldmt d1 TOM Jan Hal, robust

7,696 Linear regression Number of obs F(4, 7691) 18.01 Prob > F 0.0000 =

0.0093 R-squared = Root MSE 1.5603

=

1.6846

bldmt	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	3291021	.0497215	-6.62	0.000	4265698	2316344
TOM	.1987153	.0450768	4.41	0.000	.1103525	.2870782
Jan	.1763575	.0552875	3.19	0.001	.0679789	.284736
Hal	0313807	.0375961	-0.83	0.404	1050792	.0423178
_cons	.1059834	.0287236	3.69	0.000	.0496773	.1622896

### . reg cnstr d1 TOM Jan Hal, robust

Number of obs	=	7,696
F(4, 7691)	=	5.87
Prob > F	=	0.0001
R-squared	=	0.0041
Root MSE	=	3.9413
	F(4, 7691) Prob > F R-squared	F(4, 7691) = Prob > F = R-squared =

cnstr	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	4416724	.123459	-3.58	0.000	6836857	1996591
TOM	.3461587	.1273508	2.72	0.007	.0965163	.595801
Jan	.5334781	.1836415	2.90	0.004	.1734908	.8934653
Hal	0671466	.0932773	-0.72	0.472	2499955	.1157024
_cons	.1859915	.0695876	2.67	0.008	.0495808	.3224021

### . reg steel d1 TOM Jan Hal, robust

Linear regression	Number of obs	=	7,696
-	F(4, 7691)	=	17.22
	Prob > F	=	0.0000
	D. cauprod	_	0 0000

R-squared = **0.0093** Root MSE = **1.908** 

steel	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1 TOM	3755033 .2995765	.0604424	-6.21 5.13	0.000	493987 .1850314	2570197 .4141215
Jan Hal _cons	.1624581 0493307 .1260859	.0676409 .0463067 .0334832	2.40 -1.07 3.77	0.016 0.287 0.000	.0298635 1401044 .0604496	.2950527 .041443 .1917221

### . reg mach d1 TOM Jan Hal, robust

Linear regression Number of obs = 7,696

F(4, 7691) = 14.68 Prob > F = 0.0000R-squared = 0.0076

1.6961

Root MSE

Robust mach Coef. Std. Err. t P>|t| [95% Conf. Interval] .0552998 -.1514449 **d1** -.2598476 -4.70 0.000 -.3682503 TOM .2600066 .0514804 5.05 0.000 .3609222 .159091 .2155935 .0631564 3.41 0.001 Jan .0917898 .3393972 Hal -.0198338 .0406192 -0.490.625 -.0994586 .059791 .0867484 .031225 2.78 0.005 .0255388 .1479579 \_cons

#### . reg elceq d1 TOM Jan Hal, robust

Linear regression Number of obs = 7,696

F(4, 7691) = 17.57 Prob > F = 0.0000 R-squared = 0.0088 Root MSE = 1.9518

elceq	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	4141235	.061152	-6.77	0.000	5339981	2942489
TOM	.2330713	.0567632	4.11	0.000	.1218001	.3443426
Jan	.1876834	.0682211	2.75	0.006	.0539514	.3214154
Hal	0300126	.0469224	-0.64	0.522	1219933	.0619681
_cons	.1134091	.0365474	3.10	0.002	.0417662	.1850519

#### . reg autos d1 TOM Jan Hal, robust

Linear regression Number of obs = 7,696F(4, 7691) = 17.79

Prob > F = 0.0000 R-squared = 0.0098 Root MSE = 1.9791

autos	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	3981284	.0646768	-6.16	0.000	5249126	2713442
TOM	.3113267	.0581116	5.36	0.000	.1974121	.4252413
Jan	.2086478	.0728715	2.86	0.004	.0657999	.3514958
Hal	0341668	.0474141	-0.72	0.471	1271115	.0587778
_cons	.114086	.0362824	3.14	0.002	.0429626	.1852093

### . reg aero d1 TOM Jan Hal, robust

Linear regression Number of obs = 7,696F(4, 7691) = 7.76

Prob > F = 0.0000 R-squared = 0.0041 Root MSE = 2.4075

aero	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	3202547	.0735685	-4.35	0.000	4644691	1760404
TOM	.2300245	.0752671	3.06	0.002	.0824805	.3775684
Jan	.1227742	.0895176	1.37	0.170	0527047	.2982531
Hal	.0388038	.0583796	0.66	0.506	075636	.1532437
_cons	.0937085	.043276	2.17	0.030	.0088757	.1785412

### . reg ships d1 TOM Jan Hal, robust

ships	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1 TOM Jan Hal	46563 .2820228 .1744605 0278623	.0641424 .0635887 .0796732 .0514174	-7.26 4.44 2.19 -0.54	0.000 0.000 0.029 0.588	5913665 .1573717 .0182793 1286544	3398934 .4066739 .3306417 .0729298
_cons	.1283455	.0379499	3.38	0.001	.0539533	.2027377

#### . reg mines d1 TOM Jan Hal, robust

R-squared = 0.0000 Root MSE = 1.8694

mines	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	3081189	.0554417	-5.56	0.000	4167997	199438
TOM	.2708997	.0608423	4.45	0.000	.1516322	.3901672
Jan	.2514315	.0768072	3.27	0.001	.1008684	.4019946
Hal	0259271	.0447954	-0.58	0.563	1137383	.0618841
_cons	.1270345	.0322968	3.93	0.000	.0637239	.190345

### . reg coal d1 TOM Jan Hal, robust

Linear regression Number of obs = 7,696 F(4, 7691) = 7.22

Prob > F 0.0000 =

R-squared 0.0039 Root MSE 2.8082

coal	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	3494243	.0838581	-4.17	0.000	5138089	1850396
TOM	.2772263	.0916671	3.02	0.003	.0975337	.4569188
Jan	.197006	.1042155	1.89	0.059	0072848	.4012969
Hal	0574744	.0697338	-0.82	0.410	1941717	.0792229
_cons	.2419862	.0426624	5.67	0.000	.1583562	.3256162

### . reg oil d1 TOM Jan Hal, robust

Linear regression Number of obs 7,696 =

F(4, 7691) 16.31 = Prob > F 0.0000 R-squared = 0.0096 Root MSE 1.625

oil	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1 TOM Jan Hal cons	3464012 .2385907 .0919937 .0195385	.0520722 .0512455 .0578565 .0390701	-6.65 4.66 1.59 0.50 3.46	0.000 0.000 0.112 0.617 0.001	4484768 .1381355 0214207 0570497 .0441307	2443255 .3390459 .2054081 .0961266 .1598575

### . reg util d1 TOM Jan Hal, robust

Linear regression Number of obs = 7,696F(4, 7691) = 16.38

Prob > F = 0.0000 R-squared = 0.0085 Root MSE = 1.8661

util	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	3600041	.0583587	-6.17	0.000	4744031	2456051
TOM	.2247737	.0561895	4.00	0.000	.114627	.3349205
Jan	.2478707	.0684894	3.62	0.000	.1136129	.3821285
Hal	0820297	.0450107	-1.82	0.068	1702629	.0062036
_cons	.1231393	.033987	3.62	0.000	.0565155	.1897631

### . reg telcm d1 TOM Jan Hal, robust

Linear regression Number of obs = 7,696

F(4, 7691) = 8.41 Prob > F = 0.0000 R-squared = 0.0048 Root MSE = 1.2919

telcm	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	1947817	.0423013	-4.60	0.000	2777037	1118597
TOM	.120871	.0406937	2.97	0.003	.0411003	.2006417
Jan	.0920316	.0475253	1.94	0.053	0011311	.1851942
Hal	0382791	.031229	-1.23	0.220	0994963	.0229382
_cons	.0647631	.0232447	2.79	0.005	.0191972	.110329

#### . reg bussv d1 TOM Jan Hal, robust

Linear regression Number of obs = 7,696F(4, 7691) = 8.29

Prob > F = 0.0000 R-squared = 0.0039

Root MSE = 2.2427

bussv	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	2494708	.0652878	-3.82	0.000	3774528	1214889
TOM	.1945179	.0685983	2.84	0.005	.0600465	.3289894
Jan	.2869166	.0915323	3.13	0.002	.1074884	.4663448
Hal	0358242	.0532376	-0.67	0.501	1401845	.068536
_cons	.1393194	.0414908	3.36	0.001	.0579862	.2206527

### . reg hardw d1 TOM Jan Hal, robust

Linear regression Number of obs = 7,696

F(4, 7691) = 11.20 Prob > F = 0.0000 R-squared = 0.0060 Root MSE = 1.6124

hardw	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2597894	.0514038	-5.05	0.000	3605549	159024
ТОМ	.1909285	.0502588	3.80	0.000	.0924076	.2894495
Jan	.1247493	.0563478	2.21	0.027	.0142922	.2352064
Hal	0335417	.0386435	-0.87	0.385	1092935	.0422101
_cons	.0800302	.0301339	2.66	0.008	.0209595	.139101

#### . reg chips d1 TOM Jan Hal, robust

Number of obs = 7,696 F(4, 7691) = 10.52 Prob > F = 0.0000 R-squared = 0.0052 Root MSE = 2.34 Linear regression

chips	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	3117956	.0705036	-4.42	0.000	4500018	1735894
TOM	.3061723	.0686381	4.46	0.000	.171623	.4407216
Jan	.1772476	.0835688	2.12	0.034	.0134299	.3410652
Hal	0132002	.0556936	-0.24	0.813	1223749	.0959746
_cons	.083844	.0454816	1.84	0.065	0053124	.1730004

### . reg labeq d1 TOM Jan Hal, robust

Linear regression

Number of obs = 7,696 F(4, 7691) = 4.72 Prob > F = 0.0008 R-squared = 0.0027 Root MSE = 1.5864 R-squared Root MSE

labeq	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	1972601	.0521329	-3.78	0.000	2994548	0950654
TOM	.0998731	.0479217	2.08	0.037	.0059336	.1938127
Jan	0405789	.0553718	-0.73	0.464	1491228	.0679649
Hal	.0079643	.0383729	0.21	0.836	0672571	.0831857
_cons	.0550992	.029007	1.90	0.058	0017624	.1119608

#### . reg boxes d1 TOM Jan Hal, robust

Linear regression	Number of obs	=	7,696
	F(4, 7691)	=	13.38
	Prob > F	=	0.0000
	R-squared	=	0.0068

R-squared = **0.0068** Root MSE = **1.684** 

boxes	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2897631	.0521145	-5.56	0.000	3919217	1876045
TOM	.2031608	.0508885	3.99	0.000	.1034056	.302916
Jan	.1643553	.0634087	2.59	0.010	.0400568	.2886537
Hal	0330924	.0409458	-0.81	0.419	1133574	.0471726
_cons	.1276748	.0289639	4.41	0.000	.0708978	.1844519

### . reg trans d1 TOM Jan Hal, robust

Linear regression Number of obs = 7,696F(4, 7691) = 27.76

Number of obs = 7,696 F(4, 7691) = 27.76 Prob > F = 0.0000 R-squared = 0.0144 Root MSE = 1.8861

trans	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1 TOM Jan Hal _cons	4654731 .2866703 .3801181 0478964 .1897503	.0594535 .0559462 .0759367 .0449751 .034331	-7.83 5.12 5.01 -1.06 5.53	0.000 0.000 0.000 0.287 0.000	5820183 .1770005 .2312615 1360598 .1224521	348928 .3963401 .5289747 .040267

### . reg whlsl d1 TOM Jan Hal, robust

Linear regression	Number of obs	=	7,696
	F(4, 7691)	=	9.25
	Prob > F	=	0.0000
	R-squared	=	0.0046
	Root MSE	=	2.9445

whlsl	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	4389948	.0883226	-4.97	0.000	6121311	2658585
TOM	.2946914	.0895836	3.29	0.001	.1190831	.4702998
Jan	.0945747	.1043292	0.91	0.365	109939	.2990883
Hal	0482007	.071886	-0.67	0.503	1891168	.0927154
_cons	.2230884	.0520512	4.29	0.000	.1210539	.3251229

### . reg rtail d1 TOM Jan Hal, robust

Linear regression	Number of obs	=	7.696
Elifedi Tegression	F(4, 7691)	=	17.77
	Prob > F	=	0.0000
	R-squared	=	0.0094
	Root MSE	=	1.3405

rtail	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2599532	.0434573	-5.98	0.000	3451413	1747652
TOM	.1930568	.0403392	4.79	0.000	.1139809	.2721327
Jan	.1867723	.051144	3.65	0.000	.0865161	.2870284
Hal	0450536	.0322406	-1.40	0.162	108254	.0181468
_cons	.1156373	.02391	4.84	0.000	.0687672	.1625075

### . reg meals d1 TOM Jan Hal, robust

Linear regression Number of obs = 7,696F(4, 7691) = 10.23

Prob > F = 0.0000 R-squared = 0.0055

Root MSE = 1.7916

meals	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1 TOM Jan Hal cons	2560694 .1649749 .2497549 0070918 .0817836	.056141 .0524707 .0780976 .0432293	-4.56 3.14 3.20 -0.16 2.66	0.000 0.002 0.001 0.870 0.008	3661212 .0621179 .0966623 091833 .0214199	1460177 .2678318 .4028474 .0776494

### . reg banks d1 TOM Jan Hal, robust

Linear regression Number of obs = 7,696

F(4, 7691) = 10.02 Prob > F = 0.0000 R-squared = 0.0057 Root MSE = 1.7679

banks	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2620596	. 0546687	-4.79	0.000	3692252	1548941
TOM	.2070958	.0590249	3.51	0.000	.091391	.3228006
Jan	.1823028	.0634732	2.87	0.004	.0578781	.3067275
Hal	0266818	.0422137	-0.63	0.527	1094322	.0560686
_cons	.0868292	.0326515	2.66	0.008	.0228234	.1508349

#### . reg insur d1 TOM Jan Hal, robust

Linear regression	Number of obs	=	7,696
	F(4, 7691)	=	7.47
	Prob > F	=	0.0000
	D. anunnad	_	0 0020

R-squared = **0.0038** Root MSE = **1.8093** 

insur	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1 TOM Jan Hal cons	2330277 .1530545 .1459846 0594875	.0547342 .0563814 .0762964 .0430365	-4.26 2.71 1.91 -1.38 2.57	0.000 0.007 0.056 0.167 0.010	3403217 .0425317 0035772 1438507	1257337 .2635774 .2955464 .0248757

### . reg rlest d1 TOM Jan Hal, robust

Linear regression Number of obs = 7,696F(4, 7691) = 9.87

Prob > F = 0.0000 R-squared = 0.0052 Root MSE = 3.6583

rlest	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	4886805	.1125469	-4.34	0.000	7093031	2680579
TOM	.4382448	.1117408	3.92	0.000	.2192025	.6572871
Jan	.3699116	.1494559	2.48	0.013	.0769373	.6628859
Hal	0698248	.0877059	-0.80	0.426	2417522	.1021026
_cons	.1586161	.065815	2.41	0.016	.0296008	.2876315

#### . reg fin d1 TOM Jan Hal, robust

Linear regression Number of obs = 7,696F(4, 7691) = 20.81

Prob > F = 0.0000 R-squared = 0.0107 Root MSE = 2.0446

Robust fin [95% Conf. Interval] Coef. Std. Err. t P>|t| **d1** -.4722043 .0632563 -7.46 0.000 -.5962039 -.3482046 TOM .2469965 .0627667 3.94 0.000 .1239566 .3700363 .0795284 Jan .2865769 3.60 0.000 .1306795 .4424743 Hal -.0547079 .0489164 -1.12 0.263 -.1505975 .0411816 \_cons .1661105 .0380553 4.36 0.000 .0915119 .2407092

# *Table 5.2:*

#### . reg agric d1 TOM Jan Hal, robust

Linear regression Number of obs = 16,465

F(4, 16460) = 22.41 Prob > F = 0.0000 R-squared = 0.0057

Root MSE = 1.4151

agric	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	1978555	.0290267	-6.82	0.000	254751	1409599
TOM	.085855	.0278061	3.09	0.002	.0313522	.1403579
Jan	.1456404	.0414899	3.51	0.000	.0643156	.2269652
Hal	.0806382	.0231591	3.48	0.000	.0352438	.1260326
_cons	.0371155	.0172928	2.15	0.032	.0032197	.0710113

#### . reg food d1 TOM Jan Hal, robust

Linear regression Number of obs = 16,465

F(4, 16460) = 43.56 Prob > F = 0.0000 R-squared = 0.0124 Root MSE = .7243

Robust food Coef. Std. Err. t P>|t| [95% Conf. Interval] .0158533 -9.94 d1 -.1576324 0.000 -.1887066 -.1265583 TOM .0903263 .0143193 6.31 0.000 .0622588 .1183937 .0909253 .0209182 Jan 4.35 0.000 .0499232 .1319273 Hal .0432141 .0117989 3.66 0.000 .020087 .0663413 \_cons .0541195 .0088611 6.11 0.000 .0367507 .0714883

#### . reg beer d1 TOM Jan Hal, robust

Linear regression

Number of obs = 16,465 F(4, 16460) = 23.04 Prob > F = 0.0000 Prob > F = 0.0000 R-squared = 0.0063 Root MSE = .99678

beer	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	1589972	.0209664	-7.58	0.000	2000936	1179007
TOM	.0834787	.0194506	4.29	0.000	.0453535	.1216039
Jan	.0712633	.02935	2.43	0.015	.0137341	.1287925
Hal	.0493723	.0163281	3.02	0.003	.0173674	.0813772
_cons	.0507839	.0120535	4.21	0.000	.0271577	.0744101

#### . reg smoke d1 TOM Jan Hal, robust

Linear regression

Number of obs = 16,465 F(4, 16460) = 7.08 Prob > F = 0.0000 R-squared = 0.0016 Root MSE = 1.35

smoke	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0982062	.0272163	-3.61	0.000	1515532	0448592
TOM	.0794272	.0254558	3.12	0.002	.029531	.1293233
Jan	.0352567	.0379046	0.93	0.352	0390404	.1095538
Hal	.0343654	.0224385	1.53	0.126	0096164	.0783473
_cons	.0666744	.015967	4.18	0.000	.0353773	.0979715

#### . reg toys d1 TOM Jan Hal, robust

Linear regression Number of obs = 16,465F(4, 16460) = 38.05

Prob > F = 0.0000 R-squared = 0.0107 Root MSE = 1.1841

toys	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2221461	.0255512	-8.69	0.000	2722292	172063
TOM	.1223242	.0242621	5.04	0.000	.0747679	.1698805
Jan	.1741895	.0343439	5.07	0.000	.1068717	.2415073
Hal	.0817612	.0193142	4.23	0.000	.0439033	.1196192
_cons	.0398371	.0144195	2.76	0.006	.0115733	.0681009

### . reg fun d1 TOM Jan Hal, robust

Linear regression Number of obs = 16,465

F(4, 16460) = 54.60 Prob > F = 0.0000R-squared = 0.0152

Root MSE = 1.125

fun	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	2578636	.0238912	-10.79	0.000	304693	2110342
TOM	.1394141	.0228414	6.10	0.000	.0946425	.1841858
Jan	.169099	.0331342	5.10	0.000	.1041524	.2340455
Hal	.1012652	.0183666	5.51	0.000	.0652647	.1372658
_cons	.0470679	.0135937	3.46	0.001	.0204228	.0737129

### . reg books d1 TOM Jan Hal, robust

books	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	1900874	.0234708	-8.10	0.000	2360927	1440821
TOM	.0910029	.0225311	4.04	0.000	.0468396	.1351663
Jan	.0580263	.0328291	1.77	0.077	0063222	.1223749
Hal	.0809425	.0183344	4.41	0.000	.0450051	.1168799
_cons	.0474785	.0135759	3.50	0.000	.0208683	.0740887

#### . reg hshld d1 TOM Jan Hal, robust

Linear regression Number of obs = 16,465F(4, 16460) = 44.81

Number of obs = 16,465 F(4, 16460) = 44.81 Prob > F = 0.0000 R-squared = 0.0124 Root MSE = .93246

hshld	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	1798119	.0203093	-8.85	0.000	2196202	1400035
TOM	.1087839	.0187386	5.81	0.000	.0720541	.1455136
Jan	.126111	.0275103	4.58	0.000	.0721879	.1800342
Hal	.087251	.0152366	5.73	0.000	.0573855	.1171164
_cons	.0304377	.0112259	2.71	0.007	.0084338	.0524417

#### . reg clths d1 TOM Jan Hal, robust

Linear regression

Number of obs = 16,465 F(4, 16460) = 44.06 Prob > F = 0.0000 0.0121

R-squared Root MSE .99916

clths	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1 TOM Jan Hal _cons	1713269 .1312063 .1574097 .0877575	.0212016 .0201067 .0308718 .0162295 .0121301	-8.08 6.53 5.10 5.41 1.96	0.000 0.000 0.000 0.000 0.050	2128843 .0917949 .0968976 .0559459 -4.47e-06	1297695 .1706176 .2179219 .1195692 .0475481

### . reg medeq d1 TOM Jan Hal, robust

Linear regression Number of obs = 16,465

F(4, 16460) = 52.45 Prob > F 0.0000 R-squared Root MSE = 0.0143

Root MSE 1.0422

medeq	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2409498	.0222469	-10.83	0.000	2845562	1973433
TOM	.1239519	.021076	5.88	0.000	.0826406	.1652632
Jan	.1898655	.0302479	6.28	0.000	.1305763	.2491547
Hal	.0521473	.0170087	3.07	0.002	.0188084	.0854862
_cons	.0659771	.0127017	5.19	0.000	.0410804	.0908737

#### . reg drugs d1 TOM Jan Hal, robust

Root MSE = **1.1465** 

drugs	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1 TOM Jan Hal _cons	2747103 .1479299 .1235464 .0669827 .0721908	.0249826 .0227056 .0336498 .0187637	-11.00 6.52 3.67 3.57 5.26	0.000 0.000 0.000 0.000 0.000	3236789 .1034245 .0575892 .0302039 .0452987	2257417 .1924353 .1895036 .1037616 .0990829

### . reg chems d1 TOM Jan Hal, robust

Linear regression Number of obs = 16,465F(4, 16460) = 40.36

Prob > F = 0.0000 R-squared = 0.0114 Root MSE = 1.0085

chems	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	1896126	.0221002	-8.58	0.000	2329314	1462939
TOM	.1346585	.0201355	6.69	0.000	.0951908	.1741262
Jan	.0820117	.0291111	2.82	0.005	.0249508	.1390726
Hal	.0923755	.0164826	5.60	0.000	.0600678	.1246833
_cons	.0297088	.0122271	2.43	0.015	.0057423	.0536753

### . reg txtls d1 TOM Jan Hal, robust

Linear regression Number of obs = 16,465F(4, 16460) = 39.95

Prob > F = 0.0000 R-squared = 0.0112 Root MSE = 1.0945

txtls	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	1908321	.0233251	-8.18	0.000	2365519	1451124
TOM	.1486576	.0225406	6.60	0.000	.1044756	.1928395
Jan	.1168819	.0322781	3.62	0.000	.0536133	.1801506
Hal	.0978825	.0178847	5.47	0.000	.0628266	.1329385
_cons	.0120936	.0131614	0.92	0.358	0137043	.0378914

### . reg bldmt d1 TOM Jan Hal, robust

Linear regression Number of obs = 16,465F(4, 16460) = 45.93

F(4, 16460) = 45.93 Prob > F = 0.0000 R-squared = 0.0130Root MSE = .9433

bldmt	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	1778337	.0206535	-8.61	0.000	2183168	1373505
TOM	.1090984	.0187913	5.81	0.000	.0722654	.1459315
Jan	.1351057	.0281918	4.79	0.000	.0798467	.1903647
Hal	.0990408	.0153399	6.46	0.000	.0689728	.1291087
_cons	.0303623	.011483	2.64	0.008	.0078544	.0528702

### . reg cnstr d1 TOM Jan Hal, robust

Prob > F = 0.0000 R-squared = 0.0112 Root MSE = 1.3494

cnstr	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2485132	.0276452	-8.99	0.000	3027008	1943257
TOM	.1528474	.0270293	5.65	0.000	.0998672	.2058277
Jan	. 1834557	.03965	4.63	0.000	.1057375	.2611739
Hal	.1119403	.0223086	5.02	0.000	.0682131	.1556675
_cons	.0228022	.0157228	1.45	0.147	0080162	.0536206

#### . reg steel d1 TOM Jan Hal, robust

Linear regression Number of obs = 16,465F(4, 16460) = 42.22

F(4, 16460) = 42.22 Prob > F = 0.0000 R-squared = 0.0120 Root MSE = 1.2335

steel	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2271594	.0271509	-8.37	0.000	2803781	1739406
TOM	.1718914	.0249321	6.89	0.000	.1230217	.2207611
Jan	.1421785	.0373292	3.81	0.000	.0690093	.2153476
Hal	.1087859	.020142	5.40	0.000	.0693054	.1482664
_cons	.0078435	.0146968	0.53	0.594	0209638	.0366509

### . reg mach d1 TOM Jan Hal, robust

mach	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1 TOM	2111024 .131003	.022564 .020676	-9.36 6.34	0.000 0.000	2553303 .0904757	1668746 .1715303
Jan	.1258846	.030669	4.10	0.000	.0657701	.1859992
Hal	.094661	.0166776	5.68	0.000	.0619711	.1273508
_cons	.0344421	.0124753	2.76	0.006	.0099891	.0588951

#### . reg elceq d1 TOM Jan Hal, robust

Linear regression Number of obs = 16,465F(4, 16460) = 48.52

Prob > F = 0.0000 R-squared = 0.0137 Root MSE = 1.0911

elceq	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1 TOM Jan Hal cons	2362364 .1452713 .1472328 .0863944 .0464235	.0236658 .0219754 .032189 .0177509	-9.98 6.61 4.57 4.87 3.51	0.000 0.000 0.000 0.000	2826238 .1021971 .0841388 .0516008	189849 .1883456 .2103268 .121188

### . reg autos d1 TOM Jan Hal, robust

Linear regression	Number of obs	=	16,465
	F(4, 16460)	=	37.97
	Prob > F	=	0.0000
	R-squared	=	0.0103
	Root MSE	=	1.1449

autos	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	1887108	.0246872	-7.64	0.000	2371004	1403213
TOM	.1664069	.0232978	7.14	0.000	.1207407	.2120731
Jan	.132018	.033663	3.92	0.000	.0660349	.1980012
Hal	.0803029	.0187283	4.29	0.000	.0435934	.1170123
_cons	.0227687	.0138587	1.64	0.100	0043959	.0499334

### . reg aero d1 TOM Jan Hal, robust

Linear regression	Number of obs	=	16,465
	F(4, 16460)	=	34.37
	Prob > F	=	0.0000
	R-squared	=	0.0097
	Root MSE	=	1.2264

aero	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	2389373	.0263656	-9.06	0.000	2906168	1872578
TOM	.1383552	.0247346	5.59	0.000	.0898728	.1868376
Jan	.1105889	.0361819	3.06	0.002	.0396684	.1815094
Hal	.0721474	.0199522	3.62	0.000	.0330388	.111256
_cons	.0617321	.0150336	4.11	0.000	.0322646	.0911997

#### . reg ships d1 TOM Jan Hal, robust

Linear regression Number of obs = 16,465F(4, 16460) = 24.51

Prob > F = 0.0000 R-squared = 0.0064

Root MSE = **1.4635** 

ships	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2184182	.0305102	-7.16	0.000	2782214	158615
TOM	.1201799	.0292299	4.11	0.000	.0628861	.1774737
Jan	.1043564	.0427321	2.44	0.015	.020597	.1881159
Hal	.0990371	.0240879	4.11	0.000	.0518222	.146252
_cons	.0279281	.0173707	1.61	0.108	0061204	.0619766

### . reg mines d1 TOM Jan Hal, robust

Linear regression Number of obs = 16,465

F(4, 16460) = 35.12 Prob > F = 0.0000 R-squared = 0.0094

Root MSE = 1.4892

mines	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	2621417	.0312095	-8.40	0.000	3233157	2009676
TOM	.1488156	.0301722	4.93	0.000	.0896747	.2079564
Jan	.2126463	.0461452	4.61	0.000	.1221967	.3030958
Hal	.0870993	.0241672	3.60	0.000	.039729	.1344697
_cons	.0495315	.018117	2.73	0.006	.0140202	.0850428

#### . reg coal d1 TOM Jan Hal, robust

coal	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2569375	.0459562	-5.59	0.000	3470167	1668583
TOM	.1762392	.0443781	3.97	0.000	.0892533	.2632251
Jan	.0278221	.0614945	0.45	0.651	0927138	.148358
Hal	.0587695	.0355363	1.65	0.098	0108855	.1284245
_cons	.0490541	.0264921	1.85	0.064	0028732	.1009814

#### . reg oil d1 TOM Jan Hal, robust

Linear regression Number of obs = 16,465F(4, 16460) = 40.56

Prob > F = 0.0000 R-squared = 0.0115 Root MSE = 1.3583

oil	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	3261416	.0297628	-10.96	0.000	38448	2678033
TOM	.1396218	.0275444	5.07	0.000	.0856319	.1936118
Jan	.0767371	.0405771	1.89	0.059	0027984	.1562727
Hal	.0677686	.0222292	3.05	0.002	.024197	.1113402
_cons	.0776157	.0161533	4.80	0.000	.0459535	.1092778

#### . reg util d1 TOM Jan Hal, robust

R-squared = 0.0029 Root MSE = .66954

util	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0485128	.0146389	-3.31	0.001	0772066	0198191
TOM	.0723251	.0131512	5.50	0.000	.0465473	.0981028
Jan	.0129101	.0190255	0.68	0.497	0243819	.0502021
Hal	.0204338	.0108312	1.89	0.059	0007965	.0416641
_cons	.0373093	.0084556	4.41	0.000	.0207355	.0538831

### . reg telcm d1 TOM Jan Hal, robust

Linear regression Number of obs = 16,465

F(4, 16460) = 40.38 Prob > F = 0.0000 R-squared = 0.0115 Root MSE = 1.1189

telcm	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2321254	.0237943	-9.76	0.000	2787649	1854859
TOM	.1352282	.0227711	5.94	0.000	.0905944	.179862
Jan	.1107436	.0343264	3.23	0.001	.0434602	.1780271
Hal	.0821361	.0182117	4.51	0.000	.0464392	.117833
_cons	.0461459	.0134378	3.43	0.001	.0198064	.0724854

### . reg bussv d1 TOM Jan Hal, robust

Linear regression	Number of obs	=	16,465
	F(4, 16460)	=	55.19
	Prob > F	=	0.0000
	R-squared	=	0.0158
	Root MSE	=	.93319

bussv	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2240518	.0203289	-11.02	0.000	2638987	1842049
TOM	.1232798	.0190358	6.48	0.000	.0859675	.160592
Jan	.1456716	.0275597	5.29	0.000	.0916515	.1996916
Hal	.0726814	.0151764	4.79	0.000	.0429339	.1024288
_cons	.0566363	.011321	5.00	0.000	.034446	.0788267

### . reg hardw d1 TOM Jan Hal, robust

Linear regression	Number of obs	=	16,465
	F(4, 16460)	=	47.16
	Prob > F	=	0.0000
	R-squared	=	0.0134
	Poot MSE	_	1 2012

hardw	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2745394	.0275684	-9.96	0.000	3285765	2205022
TOM	.1698322	.0262488	6.47	0.000	.1183818	.2212826
Jan	.1906222	.0392535	4.86	0.000	.1136812	.2675632
Hal	.0937056	.021006	4.46	0.000	.0525316	.1348796
_cons	.0361202	.015587	2.32	0.020	.0055679	.0666725

### . reg chips d1 TOM Jan Hal, robust

chips	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1 TOM Jan Hal cons	2644403 .1576097 .1834626 .092825	.0259917 .025095 .0367538 .0201688	-10.17 6.28 4.99 4.60 3.38	0.000 0.000 0.000 0.000 0.001	3153869 .1084208 .1114211 .053292	2134936 .2067986 .2555041 .1323579

### . reg labeq d1 TOM Jan Hal, robust

R-squared = **0.0122** Root MSE = **1.1077** 

labeq	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2161562	.0238753	-9.05	0.000	2629545	169358
TOM	.1435774	.0224776	6.39	0.000	.0995189	.1876359
Jan	.1399927	.0330699	4.23	0.000	.0751722	.2048132
Hal	.0915604	.0180193	5.08	0.000	.0562406	.1268803
_cons	.0570896	.013403	4.26	0.000	.0308182	.0833609

#### . reg boxes d1 TOM Jan Hal, robust

Linear regression Number of obs = 16,465F(4, 16460) = 27.57

Prob > F = 0.0000 R-squared = 0.0074 Root MSE = 1.1297

boxes	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	1662588	.0236928	-7.02	0.000	2126993	1198183
TOM	.1244584	.0221734	5.61	0.000	.0809961	.1679208
Jan	.0722609	.0348169	2.08	0.038	.0040161	.1405057
Hal	.0863141	.018324	4.71	0.000	.0503971	.1222311
_cons	.0307657	.0137101	2.24	0.025	.0038924	.057639

### . reg trans d1 TOM Jan Hal, robust

Linear regression Number of obs = 16,465

F(4, 16460) = 56.83 Prob > F = 0.0000 R-squared = 0.0159 Root MSE = 1.037

trans	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1 TOM Jan Hal cons	2522198 .1554431 .1432063 .072523	.0222028 .0209493 .0308101 .0168344	-11.36 7.42 4.65 4.31 3.10	0.000 0.000 0.000 0.000 0.002	2957397 .1143802 .0828153 .0395257	2086998 .196506 .2035974 .1055203

#### . reg whlsl d1 TOM Jan Hal, robust

whlsl	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2052868	.0200101	-10.26	0.000	2445086	1660649
TOM	.1312341	.0187719	6.99	0.000	.0944391	.168029
Jan	.1510621	.0270147	5.59	0.000	.0981103	.2040139
Hal	.0811621	.0149272	5.44	0.000	.0519032	.1104211
_cons	.0394471	.0111838	3.53	0.000	.0175256	.0613686

#### . reg rtail d1 TOM Jan Hal, robust

Linear regression Number of obs = 16,465F(4. 16460) = 36.77

Number of obs = 16,465 F(4, 16460) = 36.77 Prob > F = 0.0000 R-squared = 0.0103 Root MSE = .93456

rtail	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	1663595	.0202457	-8.22	0.000	2060432	1266757
TOM	.1193338	.0187163	6.38	0.000	.0826478	.1560198
Jan	.0705888	.0276189	2.56	0.011	.0164528	.1247247
Hal	.0825324	.0152348	5.42	0.000	.0526705	.1123943
_cons	.0313414	.0113125	2.77	0.006	.0091678	.0535151

#### . reg meals d1 TOM Jan Hal, robust

Linear regression Number of obs = 16,465F(4, 16460) = 46.52

F(4, 16460) = 46.52 Prob > F = 0.0000R-squared = 0.0132

Root MSE = **1.0093** 

meals	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1 TOM Jan Hal _cons	2093659 .1041323 .1574208 .0897496 .0391116	.0216084 .020148 .0310864 .0164205 .0121392	-9.69 5.17 5.06 5.47 3.22	0.000 0.000 0.000 0.000 0.001	2517208 .0646401 .0964881 .0575637	167011 .1436245 .2183536 .1219355 .0629057

### . reg banks d1 TOM Jan Hal, robust

Linear regression Number of obs = 16,465

F(4, 16460) = 40.93 Prob > F = 0.0000 R-squared = 0.0114 Root MSE = .75125

banks	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	1510293	.0161335	-9.36	0.000	1826527	1194059
TOM	.093927	.0149627	6.28	0.000	.0645985	.1232554
Jan	.0857245	.0230224	3.72	0.000	.0405981	.1308509
Hal	.0505982	.0121969	4.15	0.000	.026691	.0745054
_cons	.0545198	.0091238	5.98	0.000	.0366361	.0724035

#### . reg insur d1 TOM Jan Hal, robust

Linear	regression	Number of obs	=	16,465
		F(4, 16460)	=	22.14

Prob > F = 0.0000 R-squared = 0.0057 Root MSE = 1.0145

insur	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	1462488	.0208234	-7.02	0.000	1870649	1054326
TOM	.0973375	.0193235	5.04	0.000	.0594613	.1352137
Jan	.003091	.0274762	0.11	0.910	0507652	.0569472
Hal	.0657549	.0165619	3.97	0.000	.0332917	.098218
_cons	.0492828	.0131031	3.76	0.000	.0235994	.0749662

#### . reg rlest d1 TOM Jan Hal, robust

Linear regression Number of obs = 16,465

F(4, 16460) = 34.68 Prob > F = 0.0000 R-squared = 0.0092 Root MSE = 1.2973

rlest	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	2300345	.0271745	-8.47	0.000	2832995	1767694
TOM	.1031137	.0262686	3.93	0.000	.0516244	.1546031
Jan	.1773856	.0392713	4.52	0.000	.1004096	.2543615
Hal	.0898669	.0214186	4.20	0.000	.0478841	.1318496
_cons	.046122	.0150946	3.06	0.002	.016535	.075709

#### . reg fin d1 TOM Jan Hal, robust

Linear regression Number of obs = 16,465

F(4, 16460) = 43.34 Prob > F = 0.0000 R-squared = 0.0123 Root MSE = .92323

fin	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1 TOM Jan Hal _cons	2018467 .1059384 .1007186 .068863 .0570616	.0199903 .0182887 .0283376 .014993 .0111364	-10.10 5.79 3.55 4.59 5.12	0.000 0.000 0.000 0.000	2410299 .0700907 .0451738 .0394752 .035233	1626634 .1417862 .1562634 .0982509 .0788902

# Chapter 3: Table 1:

#### . reg Agric d1 d2 d3 d4, robust

Linear regression Number of obs = 1,125

Number of obs = 1,125 F(4, 1120) = 3.64 Prob > F = 0.0060 R-squared = 0.0171 Root MSE = .01181

Agric	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0035804	.0012897	-2.78	0.006	0061108	00105
d2	0035359	.0012483	-2.83	0.005	0059852	0010867
d3	004365	.0013406	-3.26	0.001	0069953	0017347
d4	001929	.0012903	-1.50	0.135	0044607	.0006026
_cons	.0033211	.0010912	3.04	0.002	.00118	.0054622

### . reg BanksFin d1 d2 d3 d4, robust

Linear regression Number of obs = 1,125

Number of obs = 1,125 F(4, 1120) = 4.15 Prob > F = 0.0024 R-squared = 0.0181 Root MSE = .01167

BanksFin	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0038931	.0012434	-3.13	0.002	0063327	0014534
d2	0030297	.0012777	-2.37	0.018	0055366	0005228
d3	0043893	.0013581	-3.23	0.001	007054	0017247
d4	0017321	.0012734	-1.36	0.174	0042307	.0007665
_cons	.0027775	.0010962	2.53	0.011	.0006267	.0049284

### . reg BuildingCnstr d1 d2 d3 d4, robust

Linear regression	Number of obs	=	1,125
	F(4, 1120)	=	3.31
	Prob > F	=	0.0105
	R-squared	=	0.0180
	Root MSE	=	.01376

BuildingCn~r	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	0041121	.0015347	-2.68	0.007	0071233	0011008
d2	0033246	.0014684	-2.26	0.024	0062057	0004436
d3	0055129	.0015918	-3.46	0.001	0086361	0023897
d4	0043101	.0014435	-2.99	0.003	0071424	0014777
_cons	.0032889	.0012791	2.57	0.010	.0007793	.0057986

### . reg Cement d1 d2 d3 d4, robust

Linear regression	Number of obs	=	1,125
	F(4, 1120)	=	0.98
	Prob > F	=	0.4177
	R-squared	=	0.0034
	Root MSE	=	.01078

Cement	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	000322	.0011612	-0.28	0.782	0026003	.0019563
d2	0014422	.001116	-1.29	0.197	0036319	.0007476
d3	0015526	.0011594	-1.34	0.181	0038274	.0007223
d4	000395	.0011246	-0.35	0.725	0026016	.0018115
_cons	.001464	.0009334	1.57	0.117	0003674	.0032955

### . reg Energy d1 d2 d3 d4, robust

Linear regression

Number of obs = 1,125 F(4, 1120) = 5.39 = Prob > F 0.0003 R-squared Root MSE = 0.0261

= .01071

Energy	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0027008	.0009979	-2.71	0.007	0046587	0007428
d2	0016925	.0010053	-1.68	0.093	0036649	.00028
d3	0053682	.0012238	-4.39	0.000	0077694	002967
d4	0028786	.0010156	-2.83	0.005	0048713	0008859
_cons	.0028117	.0008131	3.46	0.001	.0012163	.0044071

### . reg Hotel d1 d2 d3 d4, robust

Linear regression 1,125

Number of obs = F(4, 1120) = 3.04 = Prob > F 0.0165 R-squared Root MSE = 0.0139 = .01604

Hotel	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0036302	.001632	-2.22	0.026	0068323	0004281
d2	0040117	.0015818	-2.54	0.011	0071153	0009081
d3	0050951	.0017198	-2.96	0.003	0084695	0017208
d4	005283	.0016341	-3.23	0.001	0084893	0020768
_cons	.0045477	.0012997	3.50	0.000	.0019976	.0070979

### . reg Retail d1 d2 d3 d4, robust

Linear regression Number of obs = 1,125

F(4, 1120) = 2.96 Prob > F = 0.0191 R-squared = 0.0166 Root MSE = .01062

Retail	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	003448	.0011279	-3.06	0.002	0056611	0012348
d2	0031929	.0010864	-2.94	0.003	0053245	0010613
d3	0038395	.0012328	-3.11	0.002	0062583	0014206
d4	0030712	.0011154	-2.75	0.006	0052596	0008828
_cons	.0035528	.0009487	3.74	0.000	.0016913	.0054143

### . reg Telecomm d1 d2 d3 d4, robust

Linear regression Number of obs = 1,125

F(4, 1120) = 2.20 Prob > F = 0.0674 R-squared = 0.0111 Root MSE = .01105

Telecomm	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0020643	.0012165	-1.70	0.090	0044512	.0003226
d2	0027683	.001156	-2.39	0.017	0050364	0005002
d3	0035034	.0012727	-2.75	0.006	0060005	0010063
d4	0019457	.0011654	-1.67	0.095	0042322	.0003409
_cons	.0023874	.0010114	2.36	0.018	.0004029	.0043718

### . reg Transport d1 d2 d3 d4, robust

Linear regression	Number of obs	=	1,125
	F(4, 1120)	=	2.35
	Prob > F	=	0.0522
	R-squared	=	0.0116
	Root MSE	=	.014

Transport	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	0033566	.0014468	-2.32	0.021	0061955	0005178
d2	0029012	.0014503	-2.00	0.046	0057467	0000557
d3	0045974	.0015674	-2.93	0.003	0076728	001522
d4	0023617	.0014415	-1.64	0.102	00519	.0004666
_cons	.0030868	.0012059	2.56	0.011	.0007207	.0054529

### . reg Insurance d1 d2 d3 d4, robust

Linear regression	Number of obs	=	1,125
	F(4, 1120)	=	6.60
	Prob > F	=	0.0000
	R-squared	=	0.0287
	Root MSE	=	.0191

Insurance	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1 d2 d3 d4 cons	0047659 0061173 0085322 0092081 .0063177	.0019651 .0019485 .0020997 .001976	-2.43 -3.14 -4.06 -4.66 3.91	0.015 0.002 0.000 0.000 0.000	0086215 0099403 012652 0130852 .0031445	0009103 0022943 0044124 005331

#### . reg Indstrlinv d1 d2 d3 d4, robust

Linear regression Number of obs = 1,125F(4, 1120) = 4.04

F(4, 1120) = 4.04 Prob > F = 0.0029R-squared = 0.0211

Root MSE = .01371

Indstrlinv	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	004823	.0015204	-3.17	0.002	0078063	0018398
d2	0031717	.0015057	-2.11	0.035	006126	0002173
d3 d4	00597 0037423	.0016145 .0014766	-3.70 -2.53	0.000 0.011	0091377 0066395	0028022 0008451
_cons	.0041468	.0013131	3.16	0.002	.0015704	.0067232

### . reg Mediapblsh d1 d2 d3 d4, robust

Linear regression Number of obs = 1,125

F(4, 1120) = 2.09 Prob > F = 0.0802 R-squared = 0.0090

Root MSE = .01799

Mediapblsh	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0043488	.0018102	-2.40	0.016	0079005	0007971
d2	0025947	.0018692	-1.39	0.165	0062623	.0010729
d3	0043329	.0018995	-2.28	0.023	0080599	000606
d4	0044558	.0017747	-2.51	0.012	007938	0009737
_cons	.0035627	.0014518	2.45	0.014	.0007142	.0064113

#### . reg multiinv d1 d2 d3 d4, robust

Linear regression Number of obs = 1,125F(4, 1120) = 4.78

F(4, 1120) = 4.78 Prob > F = 0.0008R-squared = 0.0231

Root MSE = .01673

multiinv	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	0058386	.0017801	-3.28	0.001	0093313	0023459
d2	0036521	.0017662	-2.07	0.039	0071175	0001867
d3	0075851	.0018983	-4.00	0.000	0113098	0038604
d4	0053965	.0018003	-3.00	0.003	0089289	0018641
_cons	.0049824	.0015158	3.29	0.001	.0020083	.0079566

#### . reg multiinv d1 d2 d3 d4, robust

Linear regression Number of obs = 1,125

Number of obs = 1,125 F(4, 1120) = 4.78 Prob > F = 0.0008 R-squared = 0.0231 Root MSE = .01673

multiinv	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0058386	.0017801	-3.28	0.001	0093313	0023459
d2	0036521	.0017662	-2.07	0.039	0071175	0001867
d3	0075851	.0018983	-4.00	0.000	0113098	0038604
d4	0053965	.0018003	-3.00	0.003	0089289	0018641
_cons	.0049824	.0015158	3.29	0.001	.0020083	.0079566

### . reg Petroindst d1 d2 d3 d4, robust

Linear regression

				F(4, 11 Prob > R-squar Root MS	F = = =	3.60 0.0064 0.0187 .01686
Petroindst	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0058254	.0018549	-3.14	0.002	0094648	002186
d2	0036147	.0018919	-1.91	0.056	0073267	.0000974
d3	0067649	.0020564	-3.29	0.001	0107997	00273
d4	0042497	.0018256	-2.33	0.020	0078316	0006678
_cons	.004671	.0016567	2.82	0.005	.0014204	.0079215
_	I					

Number of obs =

1,125

### . reg Realestateinv d1 d2 d3 d4, robust

Linear regression	Number of obs	=	1,125
	F(4, 1120)	=	2.48
	Prob > F	=	0.0423
	R-squared	=	0.0123
	Root MSE	=	.01252

Realestate~v	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	. Interval]
d1	0023745	.001357	-1.75	0.080	005037	.000288
d2	002743	.0013511	-2.03	0.043	005394	0000919
d3	004361	.0014158	-3.08	0.002	0071389	0015831
d4	0023911	.0013531	-1.77	0.077	0050459	.0002638
_cons	.0027045	.0011556	2.34	0.019	.0004371	.004972

# *Table 1.1:*

### . reg Agric d2 d3 d4 d5, robust

Linear regression

Number of obs = 876 F(4, 871) = 1.18 Prob > F = 0.3190 R-squared = 0.0047 Root MSE = .01514

Agric	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	0020771	.0017042	-1.22	0.223	005422	.0012677
d3	000855	.0018105	-0.47	0.637	0044083	.0026984
d4	0009397	.0017026	-0.55	0.581	0042814	.0024019
d5	.0010167	.0017126	0.59	0.553	0023446	.0043779
_cons	.000681	.0013493	0.50	0.614	0019673	.0033293

#### . reg BanksFin d2 d3 d4 d5, robust

Linear regression

Number of obs = 876 F(4, 871) = 1.25 Prob > F = 0.2886 R-squared = 0.0051 Root MSE = .0129

BanksFin	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	0003392	.0013925	-0.24	0.808	0030723	.0023939
d3	.000098	.0015442	0.06	0.949	0029328	.0031288
d4	.0003132	.0014466	0.22	0.829	002526	.0031525
d5	.0022559	.0014563	1.55	0.122	0006023	.0051142
_cons	0005152	.0011224	-0.46	0.646	0027182	.0016877

#### . reg BuildingCnstr d2 d3 d4 d5, robust

Linear regression Number of obs = 876F(4, 871) = 0.23

Prob > F = 0.9222 R-squared = 0.0009 Root MSE = .01681

Robust BuildingCn~r Coef. Std. Err. [95% Conf. Interval] t P>|t| d2 -.0003384 .0018902 -0.18 0.858 -.0040483 .0033715 d3 .0004991 .0020701 0.24 0.810 -.0035638 .004562 d4 .0019318 -0.27 0.787 -.0005219 -.0043135 .0032696 .0045005 d5 .0007879 .0018916 0.42 0.677 -.0029246 -.0005904 .0015371 -0.38 0.701 -.0036074 .0024265 \_cons

#### . reg Cement d2 d3 d4 d5, robust

Linear regression Number of obs = 876

F(4, 871) = 1.33 Prob > F = 0.2574 R-squared = 0.0044 Root MSE = .0125

Cement	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	0006088	.0013793	-0.44	0.659	003316	.0020984
d3	0002243	.0016202	-0.14	0.890	0034043	.0029557
d4	.0001575	.0014225	0.11	0.912	0026344	.0029495
d5	.0018039	.0014208	1.27	0.205	0009846	.0045924
_cons	0007477	.0011689	-0.64	0.523	003042	.0015466

### . reg Energy d2 d3 d4 d5, robust

Linear regression	Number of obs	=	876
	F(4, 871)	=	0.62
	Prob > F	=	0.6456
	R-squared	=	0.0028
	Root MSE	=	.01632

Energy	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.0000195	.0019204	0.01	0.992	0037496	.0037887
d3	0016171	.0019956	-0.81	0.418	0055339	.0022997
d4	0008088	.00174	-0.46	0.642	0042238	.0026063
d5	.0009197	.0018959	0.49	0.628	0028014	.0046409
_cons	.0009566	.0014906	0.64	0.521	0019689	.0038821

### . reg Hotel d2 d3 d4 d5, robust

Linear regression	Number of obs	=	876
	F(4, 871)	=	0.26
	Prob > F	=	0.9016
	R-squared	=	0.0009
	Root MSE	=	.02259

Hotel	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	0012779	.0024728	-0.52	0.605	0061311	.0035754
d3	.0001915	.0027011	0.07	0.943	0051099	.005493
d4	.0006093	.0026854	0.23	0.821	0046614	.0058799
d5	.0003454	.0026382	0.13	0.896	0048326	.0055234
_cons	0001554	.002082	-0.07	0.941	0042416	.0039309

### . reg Retail d2 d3 d4 d5, robust

Linear regression	Number of obs	=	876
	F(4, 871)	=	1.73
	Prob > F	=	0.1421
	R-squared	=	0.0078
	Root MSE	=	.01436

Retail	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	002584	.0016053	-1.61	0.108	0057346	.0005667
d3	0023801	.0017163	-1.39	0.166	0057487	.0009885
d4	0030035	.0016049	-1.87	0.062	0061534	.0001464
d5	0002128	.0016111	-0.13	0.895	0033749	.0029493
_cons	.0017261	.0012648	1.36	0.173	0007563	.0042085

### . reg Telecomm d2 d3 d4 d5, robust

Linear regression	Number of obs	=	876
	F(4, 871)	=	0.51
	Prob > F	=	0.7315
	R-squared	=	0.0026
	Root MSE	=	.01528

Telecomm	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2 d3 d4 d5 cons	0014844 002255 0006931 0006448	.0016183 .0018209 .0017747 .0017057	-0.92 -1.24 -0.39 -0.38 0.42	0.359 0.216 0.696 0.705 0.675	0046606 0058289 0041763 0039925 0020565	.0016918 .001319 .00279 .0027028

### . reg Transport d2 d3 d4 d5, robust

Linear regression	Number of obs	=	876
	F(4, 871)	=	0.81
	Prob > F	=	0.5205
	R-squared	=	0.0038
	Root MSE	=	.01943

Transport	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	0005454	.0019936	-0.27	0.784	0044583	.0033676
d3	001575	.002265	-0.70	0.487	0060205	.0028705
d4	0017566	.0020677	-0.85	0.396	0058148	.0023016
d5	.001557	.0021837	0.71	0.476	002729	.005843
_cons	.0010367	.0015665	0.66	0.508	0020378	.0041112

### . reg Insurance d2 d3 d4 d5, robust

Linear regression	Number of obs	=	876
	F(4, 871)	=	0.66
	Prob > F	=	0.6199
	R-squared	=	0.0034
	Root MSE	=	.01912

Insurance	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	0027064	.0022321	-1.21	0.226	0070874	.0016746
d3	0008302	.0023277	-0.36	0.721	0053987	.0037384
d4	0021008	.0020884	-1.01	0.315	0061998	.0019981
d5	0028666	.0021135	-1.36	0.175	0070147	.0012816
_cons	.0018934	.0017097	1.11	0.268	0014622	.005249

# . reg Indstrlinv d2 d3 d4 d5, robust

Number of obs	=	876
F(4, 871)	=	1.31
Prob > F	=	0.2636
R-squared	=	0.0051
Root MSE	=	.01815
	F(4, 871) Prob > F R-squared	F(4, 871) = Prob > F = R-squared =

Indstrlinv	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	0010047	.0020692	-0.49	0.627	0050659	.0030564
d3	.0014171	.0021871	0.65	0.517	0028756	.0057097
d4	0010247	.002043	-0.50	0.616	0050344	.0029851
d5	.0021758	.0020087	1.08	0.279	0017667	.0061182
_cons	000296	.0016186	-0.18	0.855	0034729	.0028809

### . reg Mediapblsh d2 d3 d4 d5, robust

Linear regression	Number of obs	=	876
	F(4, 871)	=	0.14
	Prob > F	=	0.9655
	R-squared	=	0.0007
	Root MSE	=	.02772

Mediapblsh	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.0001453	.0030916	0.05	0.963	0059226	.0062132
d3	.0017995	.0030713	0.59	0.558	0042286	.0078276
d4	0002611	.0028852	-0.09	0.928	0059238	.0054016
d5	.0000319	.002822	0.01	0.991	0055068	.0055707
_cons	0004483	.0021088	-0.21	0.832	0045873	.0036907

#### . reg multiinv d2 d3 d4 d5, robust

Linear	regression	Number of	obs	=	876
		F(4, 871)		=	0.95

Prob > F = 0.4326 R-squared = 0.0042 Root MSE = .0169

multiinv	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.0010495	.001843	0.57	0.569	0025677	.0046668
d3	.0010313	.0019398	0.53	0.595	0027759	.0048385
d4	.000174	.0019167	0.09	0.928	0035878	.0039359
d5	.0030854	.001879	1.64	0.101	0006026	.0067734
_cons	00131	.0014386	-0.91	0.363	0041334	.0015135

#### . reg Petroindst d2 d3 d4 d5, robust

Linear regression Number of obs = 876

F(4, 871) = 2.77 Prob > F = 0.0263 R-squared = 0.0101 Root MSE = .01632

Petroindst	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	0022706	.0018404	-1.23	0.218	0058828	.0013415
d3	0016161	.0020065	-0.81	0.421	0055542	.0023219
d4	.0004058	.0019006	0.21	0.831	0033246	.0041361
d5	.0024123	.001879	1.28	0.200	0012757	.0061002
_cons	.0000709	.0015213	0.05	0.963	0029149	.0030568

### . reg Realestateinv d2 d3 d4 d5, robust

F(4, 871) = 0.92 Prob > F = 0.4498 R-squared = 0.0034 Root MSE = .01753

Realestate~v	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	0015502	.0019863	-0.78	0.435	0054486	.0023482
d3	0006544	.0021465	-0.30	0.761	0048673	.0035585
d4	0013215	.0019797	-0.67	0.505	0052071	.002564
d5	.0012889	.0019783	0.65	0.515	0025938	.0051717
_cons	.0009578	.0015913	0.60	0.547	0021655	.004081

# <u>Table 2:</u>

### . reg Agric Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

Agric	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0033539	.0011438	2.93	0.003	.0011098	.0055981
_cons	0000328	.0003472	-0.09	0.925	0007142	.0006485

#### . reg BanksFin Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

BanksFin	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.003262	.0011464		0.005	.0010127	.0055114
_cons	0004845	.0003403		0.155	0011521	.0001831

#### . reg BuildingCnstr Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

BuildingCn∼r	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0043151	.0013392	3.22	0.001	.0016875	.0069428
_cons	0010262	.0004023	-2.55	0.011	0018156	0002368

#### . reg Cement Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

Cement	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0009292	.0009881		0.347	0010095	.002868
_cons	.0005348	.0003277		0.103	0001082	.0011779

#### . reg Energy Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

Energy	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0031608	.0008828	3.58	0.000	.0014286	.0048931
_cons	0003491	.0003465	-1.01	0.314	0010289	.0003307

### . reg Hotel Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

Hotel	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0045051	.0013917	3.24	0.001	.0017744	.0072358
_cons	.0000426	.0005022	0.08	0.932	0009427	.0010279

#### . reg Retail Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

Retail	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0033882	.0009993	3.39	0.001	.0014275	.0053488
_cons	.0001647	.0003176	0.52	0.604	0004585	.0007878

#### . reg Telecomm Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

Telecomm	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0025717	.0010615	2.42	0.016	.0004889	.0046544
_cons	0001843	.0003264	-0.56	0.572	0008248	

#### . reg Transport Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

Transport	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0033052	.0012778	2.59	0.010	.000798	.0058124
_cons	0002184	.0004272	-0.51	0.609	0010567	.0006198

#### . reg Insurance Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

Insurance	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0071562	.0017192	4.16		.0037831	.0105294
_cons	0008386	.0005892	-1.42		0019946	.0003174

#### . reg Indstrlinv Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

Indstrlinv	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0044271	.0013693		0.001	.0017404	.0071137
_cons	0002803	.000394		0.477	0010534	.0004929

#### . reg Mediapblsh Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

Mediapblsh	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.003932	.0015559	2.53	0.012	.0008793	.0069848
_cons	0003693	.0005644	-0.65	0.513	0014768	

#### . reg multiinv Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

multiinv	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0056181	.0015936	3.53	0.000	.0024913	.0087448
_cons	0006357	.000498	-1.28	0.202	0016128	.0003415

#### . reg Petroindst Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

Petroindst	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0051138	.0017216		0.003	.0017359	.0084917
_cons	0004429	.000476		0.352	0013769	.0004911

#### . reg Realestateinv Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

Realestate~v	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0029687	.0012114		0.014	.0005919	.0053454
_cons	0002642	.000368		0.473	0009863	.0004579

#### . reg Agric d1 d2 d3 d4, robust

Linear regression Number of obs = 1,125F(4, 1120) = 3.64

Prob > F = 0.0060 R-squared = 0.0171

Root MSE = .01181

Agric	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0035804	.0012897	-2.78	0.006	0061108	00105
d2	0035359	.0012483	-2.83	0.005	0059852	0010867
d3	004365	.0013406	-3.26	0.001	0069953	0017347
d4	001929	.0012903	-1.50	0.135	0044607	.0006026
_cons	.0033211	.0010912	3.04	0.002	.00118	.0054622

### . reg BanksFin d1 d2 d3 d4, robust

Linear regression Number of obs = 1,125

F(4, 1120) = 4.15 Prob > F = 0.0024 R-squared = 0.0181

Root MSE = .01167

BanksFin	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0038931	.0012434	-3.13	0.002	0063327	0014534
d2	0030297	.0012777	-2.37	0.018	0055366	0005228
d3	0043893	.0013581	-3.23	0.001	007054	0017247
d4	0017321	.0012734	-1.36	0.174	0042307	.0007665
_cons	.0027775	.0010962	2.53	0.011	.0006267	.0049284

#### . reg BuildingCnstr d1 d2 d3 d4, robust

Linear regression Number of obs = 1,125F(4, 1120) = 3.31

Prob > F = 0.0105 R-squared = 0.0180 Root MSE = .01376

BuildingCn~r	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	0041121	.0015347	-2.68	0.007	0071233	0011008
d2	0033246	.0014684	-2.26	0.024	0062057	0004436
d3	0055129	.0015918	-3.46	0.001	0086361	0023897
d4	0043101	.0014435	-2.99	0.003	0071424	0014777
_cons	.0032889	.0012791	2.57	0.010	.0007793	.0057986

#### . reg Cement d1 d2 d3 d4, robust

Linear regression Number of obs = 1,125

F(4, 1120) = 0.98 Prob > F = 0.4177 R-squared = 0.0034 Root MSE = .01078

Interval]	[95% Conf.	P> t	t	Robust Std. Err.	Coef.	Cement
.0019563	0026003	0.782	-0.28	.0011612	000322	d1
.0007476	0036319	0.197	-1.29	.001116	0014422	d2
.0007223	0038274	0.181	-1.34	.0011594	0015526	d3
.0018115	0026016	0.725	-0.35	.0011246	000395	d4
.0032955	0003674	0.117	1.57	.0009334	.001464	_cons

#### . reg Energy d1 d2 d3 d4, robust

Linear regression

Number of obs = 1,125 F(4, 1120) = 5.39 Prob > F = 0.0003 R-squared = 0.0261 Root MSE = .01071

Energy	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0027008	.0009979	-2.71	0.007	0046587	0007428
d2	0016925	.0010053	-1.68	0.093	0036649	.00028
d3	0053682	.0012238	-4.39	0.000	0077694	002967
d4	0028786	.0010156	-2.83	0.005	0048713	0008859
_cons	.0028117	.0008131	3.46	0.001	.0012163	.0044071

#### . reg Hotel d1 d2 d3 d4, robust

Linear regression

Number of obs = 1,125 F(4, 1120) = 3.04 Prob > F = 0.0165 R-squared = 0.0139 Root MSE = .01604

Hotel	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	0036302	.001632	-2.22	0.026	0068323	0004281
d2	0040117	.0015818	-2.54	0.011	0071153	0009081
d3	0050951	.0017198	-2.96	0.003	0084695	0017208
d4	005283	.0016341	-3.23	0.001	0084893	0020768
_cons	.0045477	.0012997	3.50	0.000	.0019976	.0070979

# . reg Retail d1 d2 d3 d4, robust

Number of obs	=	1,125
F(4, 1120)	=	2.96
Prob > F	=	0.0191
R-squared	=	0.0166
Root MSE	=	.01062
	F(4, 1120) Prob > F R-squared	F(4, 1120) = Prob > F = R-squared =

Retail	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	. Interval]
d1	003448	.0011279	-3.06	0.002	0056611	0012348
d2	0031929	.0010864	-2.94	0.003	0053245	0010613
d3	0038395	.0012328	-3.11	0.002	0062583	0014206
d4	0030712	.0011154	-2.75	0.006	0052596	0008828
_cons	.0035528	.0009487	3.74	0.000	.0016913	.0054143

# . reg Telecomm d1 d2 d3 d4, robust

Linear regression	Number of obs	=	1,125
	F(4, 1120)	=	2.20
	Drob > E	_	0 0674

Prob > F = 0.0674 R-squared = 0.0111 Root MSE = .01105

Telecomm	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0020643	.0012165	-1.70	0.090	0044512	.0003226
d2	0027683	.001156	-2.39	0.017	0050364	0005002
d3	0035034	.0012727	-2.75	0.006	0060005	0010063
d4	0019457	.0011654	-1.67	0.095	0042322	.0003409
_cons	.0023874	.0010114	2.36	0.018	.0004029	.0043718

# . reg Transport d1 d2 d3 d4, robust

Linear regression	Number of obs	=	1,125
	F(4, 1120)	=	2.35
	Prob > F	=	0.0522
	R-squared	=	0.0116
	Root MSE	=	.014

Transport	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	0033566	.0014468	-2.32	0.021	0061955	0005178
d2	0029012	.0014503	-2.00	0.046	0057467	0000557
d3	0045974	.0015674	-2.93	0.003	0076728	001522
d4	0023617	.0014415	-1.64	0.102	00519	.0004666
_cons	.0030868	.0012059	2.56	0.011	.0007207	.0054529

# . reg Insurance d1 d2 d3 d4, robust

Linear regression	Number of obs	=	1,125
	F(4, 1120)	=	6.60
	Prob > F	=	0.0000
	R-squared	=	0.0287
	Root MSE	=	.0191

Insurance	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	. Interval]
d1 d2 d3 d4	0047659 0061173 0085322 0092081	.0019651 .0019485 .0020997 .001976	-2.43 -3.14 -4.06 -4.66	0.015 0.002 0.000 0.000	0086215 0099403 012652 0130852	0009103 0022943 0044124 005331
_cons	.0063177	.0016172	3.91	0.000	.0031445	.0094908

# . reg Indstrlinv d1 d2 d3 d4, robust

Linear regression	Number of obs	=	1,125
	F(4, 1120)	=	4.04
	Prob > F	=	0.0029
	R-squared	=	0.0211
	Root MSE	=	.01371

Indstrlinv	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	004823	.0015204	-3.17	0.002	0078063	0018398
d2	0031717	.0015057	-2.11	0.035	006126	0002173
d3	00597	.0016145	-3.70	0.000	0091377	0028022
d4	0037423	.0014766	-2.53	0.011	0066395	0008451
_cons	.0041468	.0013131	3.16	0.002	.0015704	.0067232

#### . reg Mediapblsh d1 d2 d3 d4, robust

Linear regression	Number of obs	=	1,125
	F(4, 1120)	=	2.09
	Prob > F	=	0.0802
	R-squared	=	0.0090
	Root MSE	=	.01799

Mediapblsh	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0043488	.0018102	-2.40	0.016	0079005	0007971
d2	0025947	.0018692	-1.39	0.165	0062623	.0010729
d3	0043329	.0018995	-2.28	0.023	0080599	000606
d4	0044558	.0017747	-2.51	0.012	007938	0009737
_cons	.0035627	.0014518	2.45	0.014	.0007142	.0064113

#### . reg multiinv d1 d2 d3 d4, robust

Linear regression Number of obs = 1,125

F(4, 1120) = 4.78 Prob > F = 0.0008 R-squared = 0.0231 Root MSE = .01673

multiinv	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0058386	.0017801	-3.28	0.001	0093313	0023459
d2	0036521	.0017662	-2.07	0.039	0071175	0001867
d3	0075851	.0018983	-4.00	0.000	0113098	0038604
d4	0053965	.0018003	-3.00	0.003	0089289	0018641
_cons	.0049824	.0015158	3.29	0.001	.0020083	.0079566

#### . reg multiinv d1 d2 d3 d4, robust

Linear regression Number of obs = 1,125

Number of obs = 1,125 F(4, 1120) = 4.78 Prob > F = 0.0008 R-squared = 0.0231 Root MSE = .01673

multiinv	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	0058386	.0017801	-3.28	0.001	0093313	0023459
d2	0036521	.0017662	-2.07	0.039	0071175	0001867
d3	0075851	.0018983	-4.00	0.000	0113098	0038604
d4	0053965	.0018003	-3.00	0.003	0089289	0018641
_cons	.0049824	.0015158	3.29	0.001	.0020083	.0079566

# . reg Petroindst d1 d2 d3 d4, robust

Linear regression	Number of obs	=	1,125
	F(4, 1120)	=	3.60
	Prob > F	=	0.0064
	R-squared	=	0.0187
	Root MSE	_	01686

Petroindst	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1 d2	0058254	.0018549 .0018919	-3.14 -1.91	0.002 0.056	0094648	002186
d2 d3	0036147 0067649	.0018919	-3.29	0.056	0073267 0107997	.0000974 00273
d3 d4	0067649	.0020364	-3.29	0.020	010/99/ 0078316	00273
_cons	.004671	.0016567	2.82	0.005	.0014204	.0079215

# . reg Realestateinv d1 d2 d3 d4, robust

inear regression	Number of obs	=	1,125
	F(4, 1120)	=	2.48
	Prob > F	=	0.0423
	R-squared	=	0.0123
	Root MSE	=	.01252

Realestate~v	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0023745	.001357	-1.75	0.080	005037	.000288
d2	002743	.0013511	-2.03	0.043	005394	0000919
d3	004361	.0014158	-3.08	0.002	0071389	0015831
d4	0023911	.0013531	-1.77	0.077	0050459	.0002638
_cons	.0027045	.0011556	2.34	0.019	.0004371	.004972

# . reg Agric d2 d3 d4 d5, robust

Linear regression

Number of obs	=	876
F(4, 871)	=	1.18
Prob > F	=	0.3190
R-squared	=	0.0047
Root MSE	=	.01514

Agric	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	0020771	.0017042	-1.22	0.223	005422	.0012677
d3	000855	.0018105	-0.47	0.637	0044083	.0026984
d4	0009397	.0017026	-0.55	0.581	0042814	.0024019
d5	.0010167	.0017126	0.59	0.553	0023446	.0043779
_cons	.000681	.0013493	0.50	0.614	0019673	.0033293

# . reg BanksFin d2 d3 d4 d5, robust

Linear regression

Number of obs	=	876
F(4, 871)	=	1.25
Prob > F	=	0.2886
R-squared	=	0.0051
Root MSE	=	.0129

BanksFin	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	0003392	.0013925	-0.24	0.808	0030723	.0023939
d3	.000098	.0015442	0.06	0.949	0029328	.0031288
d4	.0003132	.0014466	0.22	0.829	002526	.0031525
d5	.0022559	.0014563	1.55	0.122	0006023	.0051142
_cons	0005152	.0011224	-0.46	0.646	0027182	.0016877

#### . reg BuildingCnstr d2 d3 d4 d5, robust

Linear regression Number of obs = 876F(4, 871) = 0.23

Prob > F = 0.9222 R-squared = 0.0009 Root MSE = .01681

BuildingCn~r	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	0003384	.0018902	-0.18	0.858	0040483	.0033715
d3	.0004991	.0020701	0.24	0.810	0035638	.004562
d4	0005219	.0019318	-0.27	0.787	0043135	.0032696
d5	.0007879	.0018916	0.42	0.677	0029246	.0045005
_cons	0005904	.0015371	-0.38	0.701	0036074	.0024265

#### . reg Cement d2 d3 d4 d5, robust

Linear regression Number of obs = **876** 

F(4, 871) = 1.33 Prob > F = 0.2574 R-squared = 0.0044 Root MSE = .0125

Cement	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	0006088	.0013793	-0.44	0.659	003316	.0020984
d3	0002243	.0016202	-0.14	0.890	0034043	.0029557
d4	.0001575	.0014225	0.11	0.912	0026344	.0029495
d5	.0018039	.0014208	1.27	0.205	0009846	.0045924
_cons	0007477	.0011689	-0.64	0.523	003042	.0015466

#### . reg Energy d2 d3 d4 d5, robust

Linear regressio	n Number of obs	=	876
	F(4 871)	_	0 62

F(4, 871) = 0.62 Prob > F = 0.6456 R-squared = 0.0028 Root MSE = .01632

Energy	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.0000195	.0019204	0.01	0.992	0037496	.0037887
d3	0016171	.0019956	-0.81	0.418	0055339	.0022997
d4	0008088	.00174	-0.46	0.642	0042238	.0026063
d5	.0009197	.0018959	0.49	0.628	0028014	.0046409
_cons	.0009566	.0014906	0.64	0.521	0019689	.0038821

#### . reg Hotel d2 d3 d4 d5, robust

Linear	regression	Number of obs	=	876

F(4, 871) = 0.26 Prob > F = 0.9016 R-squared = 0.0009 Root MSE = .02259

Hotel	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	0012779	.0024728	-0.52	0.605	0061311	.0035754
d3	.0001915	.0027011	0.07	0.943	0051099	.005493
d4	.0006093	.0026854	0.23	0.821	0046614	.0058799
d5	.0003454	.0026382	0.13	0.896	0048326	.0055234
_cons	0001554	.002082	-0.07	0.941	0042416	.0039309

# . reg Retail d2 d3 d4 d5, robust

Linear regression	Number of obs	=	876
	F(4, 871)	=	1.73
	Prob > F	=	0.1421
	R-squared	=	0.0078
	Root MSF	=	. 01436

Retail	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	002584	.0016053	-1.61	0.108	0057346	.0005667
d3	0023801	.0017163	-1.39	0.166	0057487	.0009885
d4	0030035	.0016049	-1.87	0.062	0061534	.0001464
d5	0002128	.0016111	-0.13	0.895	0033749	.0029493
_cons	.0017261	.0012648	1.36	0.173	0007563	.0042085

# . reg Telecomm d2 d3 d4 d5, robust

Linear regression	Number of obs	=	876
	F(4, 871)	=	0.51
	Prob > F	=	0.7315
	R-squared	=	0.0026
	Root MSE	=	.01528

Telecomm	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	0014844	.0016183	-0.92	0.359	0046606	.0016918
d3	002255	.0018209	-1.24	0.216	0058289	.001319
d4	0006931	.0017747	-0.39	0.696	0041763	.00279
d5	0006448	.0017057	-0.38	0.705	0039925	.0027028
_cons	.0005589	.0013325	0.42	0.675	0020565	.0031742

# . reg Transport d2 d3 d4 d5, robust

Linear regression	Number of obs	=	876
	F(4, 871)	=	0.81
	Prob > F	=	0.5205
	R-squared	=	0.0038

Root MSE

= .01943

Transport	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	0005454	.0019936	-0.27	0.784	0044583	.0033676
d3	001575	.002265	-0.70	0.487	0060205	.0028705
d4	0017566	.0020677	-0.85	0.396	0058148	.0023016
d5	.001557	.0021837	0.71	0.476	002729	.005843
_cons	.0010367	.0015665	0.66	0.508	0020378	.0041112

# . reg Insurance d2 d3 d4 d5, robust

Linear regression	Number of obs	=	876
	F(4, 871)	=	0.66
	Prob > F	=	0.6199
	R-squared	=	0.0034
	Root MSE	=	.01912

Insurance	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	0027064	.0022321	-1.21	0.226	0070874	.0016746
d3	0008302	.0023277	-0.36	0.721	0053987	.0037384
d4	0021008	.0020884	-1.01	0.315	0061998	.0019981
d5	0028666	.0021135	-1.36	0.175	0070147	.0012816
_cons	.0018934	.0017097	1.11	0.268	0014622	.005249

#### . reg Indstrlinv d2 d3 d4 d5, robust

Linear regression	Number of obs	=	876
	F(4, 871)	=	1.31
	Prob > F	=	0.2636
	R-squared	=	0.0051
	Root MSF	=	.01815

Indstrlinv	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2 d3 d4 d5 _cons	0010047 .0014171 0010247 .0021758 000296	.0020692 .0021871 .002043 .0020087	-0.49 0.65 -0.50 1.08 -0.18	0.627 0.517 0.616 0.279 0.855	0050659 0028756 0050344 0017667 0034729	.0030564 .0057097 .0029851 .0061182 .0028809

# . reg Mediapblsh d2 d3 d4 d5, robust

Linear regression	Number of obs	=	876
	F(4, 871)	=	0.14
	Prob > F	=	0.9655
	R-squared	=	0.0007
	Root MSE	=	.02772

Mediapblsh	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.0001453	.0030916	0.05	0.963	0059226	.0062132
d3	.0017995	.0030713	0.59	0.558	0042286	.0078276
d4	0002611	.0028852	-0.09	0.928	0059238	.0054016
d5	.0000319	.002822	0.01	0.991	0055068	.0055707
_cons	0004483	.0021088	-0.21	0.832	0045873	.0036907

#### . reg multiinv d2 d3 d4 d5, robust

Linear	regression	Number of obs	=	876
		F(4, 871)	=	0.95

Prob > F = 0.4326 R-squared = 0.0042

Root MSE = .0169

multiinv	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	.0010495	.001843	0.57	0.569	0025677	.0046668
d3	.0010313	.0019398	0.53	0.595	0027759	.0048385
d4	.000174	.0019167	0.09	0.928	0035878	.0039359
d5	.0030854	.001879	1.64	0.101	0006026	.0067734
_cons	00131	.0014386	-0.91	0.363	0041334	.0015135

#### . reg Petroindst d2 d3 d4 d5, robust

Linear regression Number of obs = **876** 

F(4, 871) = 2.77 Prob > F = 0.0263 R-squared = 0.0101 Root MSE = .01632

Petroindst	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	0022706	.0018404	-1.23	0.218	0058828	.0013415
d3	0016161	.0020065	-0.81	0.421	0055542	.0023219
d4	.0004058	.0019006	0.21	0.831	0033246	.0041361
d5	.0024123	.001879	1.28	0.200	0012757	.0061002
_cons	.0000709	.0015213	0.05	0.963	0029149	.0030568

# . reg Realestateinv d2 d3 d4 d5, robust

Linear regression Number of obs = 876

F(4, 871) = 0.92 Prob > F = 0.4498 R-squared = 0.0034 Root MSE = .01753

Realestate~v	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d2	0015502	.0019863	-0.78	0.435	0054486	.0023482
d3	0006544	.0021465	-0.30	0.761	0048673	.0035585
d4	0013215	.0019797	-0.67	0.505	0052071	.002564
d5	.0012889	.0019783	0.65	0.515	0025938	.0051717
_cons	.0009578	.0015913	0.60	0.547	0021655	.004081

# *Table 2:*

#### . reg Agric Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

Agric	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0033539	.0011438	2.93	0.003	.0011098	.0055981
_cons	0000328	.0003472	-0.09	0.925	0007142	.0006485

#### . reg BanksFin Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

BanksFin	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.003262	.0011464	2.85	0.005	.0010127	.0055114
_cons	0004845	.0003403	-1.42	0.155	0011521	

#### . reg BuildingCnstr Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

BuildingCn~r	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0043151	.0013392	3.22	0.001	.0016875	.0069428
_cons	0010262	.0004023	-2.55	0.011	0018156	0002368

#### . reg Cement Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

Cement	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0009292	.0009881	0.94	0.347	0010095	.002868
_cons	.0005348	.0003277	1.63	0.103	0001082	.0011779

#### . reg Energy Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

Energy	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0031608	.0008828	3.58	0.000	.0014286	.0048931
_cons	0003491	.0003465	-1.01	0.314	0010289	.0003307

#### . reg Hotel Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

Hotel	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0045051	.0013917	3.24	0.001	.0017744	.0072358
_cons	.0000426	.0005022	0.08	0.932	0009427	.0010279

#### . reg Retail Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

Retail	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0033882	.0009993	3.39	0.001	.0014275	.0053488
_cons	.0001647	.0003176	0.52	0.604	0004585	.0007878

### . reg Telecomm Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

Telecomm	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0025717	.0010615	2.42	0.016	.0004889	.0046544
_cons	0001843	.0003264	-0.56	0.572	0008248	.0004562

#### . reg Transport Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

Transport	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0033052	.0012778	2.59	0.010	.000798	.0058124
_cons	0002184	.0004272	-0.51	0.609	0010567	.0006198

#### . reg Insurance Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

Insurance	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0071562	.0017192	4.16	0.000	.0037831	.0105294
_cons	0008386	.0005892	-1.42	0.155	0019946	.0003174

#### . reg Indstrlinv Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

Indstrlinv	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0044271	.0013693		0.001	.0017404	.0071137
_cons	0002803	.000394		0.477	0010534	.0004929

#### . reg Mediapblsh Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

Mediapblsh	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.003932	.0015559	2.53	0.012	.0008793	.0069848
_cons	0003693	.0005644	-0.65	0.513	0014768	

#### . reg multiinv Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

multiinv	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0056181	.0015936		0.000	.0024913	.0087448
_cons	0006357	.000498		0.202	0016128	.0003415

#### . reg Petroindst Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

Petroindst	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0051138	.0017216	2.97	0.003	.0017359	.0084917
_cons	0004429	.000476	-0.93	0.352	0013769	.0004911

#### . reg Realestateinv Dsat if Date >td(1jan2009) & Date< td(27june2013), noheader robust

Realestate~v	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsat	.0029687	.0012114	2.45	0.014	.0005919	.0053454
_cons	0002642	.000368	-0.72	0.473	0009863	.0004579

#### . reg Agric Dsun if Date >td(27june2013), robust

Linear regres	sion			Number of	obs =	876
				F(1, 874)	=	0.24
				Prob > F	=	0.6230
				R-squared	=	0.0004
				Root MSE	=	.01515
		Robust				
Agric	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
Dsun _cons	.0007144 0000334	.0014528 .0005443	0.49 -0.06	0.623 0.951	002137 0011017	.0035659 .0010349
. reg BanksFi	n Dsun if Date	e >td(27june	2013),	robust		
Linear regres	sion			Number of	obs =	876
				F(1, 874)	=	0.23
				Prob > F	=	0.6323
				R-squared	=	0.0003
				Root MSE	=	.01291
		Robust				
BanksFin	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
Dsun _cons	0005812 .000066	.0012144 .0004682	-0.48 0.14	0.632 0.888	0029646 000853	.0018022 .0009849
. reg Buildin	gCnstr Dsun if	f Date >td(2	7june2013	3), robust		
Linear regres	sion			Number of		876
				F(1, 874)	=	0.00
				Prob > F	=	0.9492
				R-squared		0.0000
				Root MSE	=	.01679

[95% Conf. Interval]

.0031267

.0006862

-.0033365

-.0016573

P>|t|

0.949

0.416

t

-0.06

-0.81

Robust

Std. Err.

.0016465

.000597

Coef.

-.0001049

-.0004856

BuildingCn∼r

Dsun

\_cons

# . reg Cement Dsun if Date >td(27june2013), robust

Linear regression	Number of obs	=	876
	F(1, 874)	=	0.05
	Prob > F	=	0.8214
	R-squared	=	0.0001
	Root MSE	=	.01251

Cement	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsun	0002817	.0012474	-0.23	0.821	0027301	.0021666
_cons	000466	.0004409	-1.06	0.291	0013313	.0003994

#### . reg Energy Dsun if Date >td(27june2013), robust

Linear regression	Number of obs	=	876
	F(1, 874)	=	0.05
	Prob > F	=	0.8155
	R-squared	=	0.0001
	Root MSE	=	.01632

Energy	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsun	.0003729	.0015973	0.23	0.815	0027621	.0035079
_cons	.0005837	.0005807	1.01	0.315	000556	.0017234

### . reg Hotel Dsun if Date >td(27june2013), robust

Linear regression	Number of obs	=	876
	F(1, 874)	=	0.00
	Prob > F	=	0.9889
	R-squared	=	0.0000
	Root MSE	=	.02256

Hotel	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Dsun	.0000311	.0022269	0.01	0.989	0043396	.0044017
_cons	0001865	.0007996	-0.23	0.816	0017557	

# . reg Retail Dsun if Date >td(27june2013), robust

Linear regress	sion			Number of		876
				F(1, 874)	) =	2.25
				Prob > F	=	0.1339
				R-square		0.0032
				Root MSE	=	.01437
		Robust				
Retail	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
Dsun	.0020478	.001365	1.50	0.134	0006313	.0047269
_cons	0003218	.0005187	-0.62	0.535	0013398	.0006963
. reg Telecomm	n Dsun if Date	e >td(27june	2013),	robust		
Linear regress	sion			Number of	f obs =	876
				F(1, 874)	) =	0.77
				Prob > F	=	0.3791
				R-square	= t	0.0011
				Root MSE	=	.01526
		Robust				
Telecomm	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
Dsun	.0012677	.0014405	0.88	0.379	0015595	.0040949
_cons	0007089	.0005527	-1.28	0.200	0017936	.0003759
. reg Transpo	rt Dsun if Da	te >td(27jun	e2013),	robust		
Linear regress	sion			Number of	f obs =	876
				F(1, 874)	) =	0.11
				Prob > F	=	0.7349
				R-square	= t	0.0001
				Root MSE	=	.01943
		Robust				
Transport	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
Dsun	.0005833	.0017224	0.34	0.735	0027972	.0039638
_cons	.0004534	.0007219	0.63	0.530	0009635	.0018703

# . reg Insurance Dsun if Date >td(27june2013), robust

. reg insurant	ce DSun IT Da	te >ta(2/jun	e2013),	robust			
Linear regress	sion			Number of	obs	=	876
•				F(1, 874)	)	=	1.34
				Prob > F		=	0.2480
				R-squared	ł	=	0.0020
				Root MSE		=	.0191
		Robust					
Insurance	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
Dsun	.0021259	.0018392	1.16	0.248	0014	1839	.0057357
_cons	0002325	.0006854	-0.34	0.734	0015	777	.0011126
. reg Indstrl	inv Dsun if Da	ate >td(27ju	ne2013),	robust			
Linear regress	sion			Number of		=	876
				F(1, 874)	)	=	0.05
				Prob > F		=	0.8244
				R-squared	t	=	0.0001
				Root MSE		=	.01816
		Robust					
Indstrlinv	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
Dsun	0003868	.0017427	-0.22	0.824	0038	8071	.0030335
_cons	.0000909	.0006526	0.14	0.889	06	119	.0013717
. reg Mediapbl	lsh Dsun if Da	ate >td(27ju	ne2013),	robust			
Linear regress	sion			Number of	f obs	=	876
				F(1, 874)		=	0.03
				Prob > F		=	0.8559
				R-squared	i	=	0.0000
				Root MSE		=	.02768
		Dahorat					
Mediapblsh	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
Dsun	000427	.0023498	-0.18	0.856	0056	388	.0041849
_cons	0000213	.0010439	-0.02	0.984	0026	701	.0020274

# . reg multiinv Dsun if Date >td(27june2013), robust

Linear regress	sion			Number of		876
				F(1, 874)	=	0.73
				Prob > F	=	0.3944
				R-squared	=	0.0010
				Root MSE	=	.0169
		Robust				
multiinv	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
Dsun	0013318	.0015631	-0.85	0.394	0043996	.0017361
_cons	.0000218	.0006171	0.04	0.972	0011894	.001233
. reg Petroino	dst Dsun if Da	ate >td(27ju	ne2013),	robust		
Linear regress	sion			Number of	obs =	876
				F(1, 874)	=	0.03
				Prob > F	=	0.8704
				R-squared	=	0.0000
				Root MSE	=	.01637
		Robust				
Petroindst	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
Dsun	.0002653	.0016252	0.16	0.870	0029245	.003455
_cons	0001943	.0005786	-0.34	0.737	00133	.0009413
. reg Realesta	ateinv Dsun i	f Date >td(2	7june201	3), robust	:	
Linear regress	sion			Number of	obs =	876
				F(1, 874)	=	0.11
				Prob > F	=	0.7423
				R-squared	=	0.0002
				Root MSE	=	.01753
		Robust				
Realestate~v	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
Dsun	.0005615	.0017073	0.33	0.742	0027893	.0039123
_cons	.0003963	.0006255	0.63	0.527	0008314	.0016239

*Table 3:* 

#### . reg Energy sun mon tues wed if date1 >td(1jan2009) & date1< td(27june2013)

Source	SS	df	MS	Number of ob - F(4, 1120)	s = =	1,125 2.35
Model	.003817694	4	.000954423	•	=	0.0523
Residual	.454312175	1,120	.000405636		=	0.0083
				- Adj R-square	ed =	0.0048
Total	.458129869	1,124	.000407589	Root MSE	=	.02014
Energy	Coef.	Std. Err.	t	P> t  [95%	Conf.	Interval]
sun mon tues wed	0053865 003844 0038211 0045235	.0019031 .001901 .001901	-2.02 -2.01	0.0050091 0.0430075 0.0450075 0.0180082	739 511	0016524 000114 0000912 0007895
_cons	.0038787	.0013487	2.88	0.004 .0012	324	.0065249

# . reg Materials sun mon tues wed if date1 >td(1jan2009) & date1< td(27june2013)

Source SS df MS Number of obs = 1,125

				– F(4,	1120)	=	3.63
Model	.002098647	4	.000524662	2 Prob	> F	=	0.0060
Residual	.161761877	1,120	.00014443	R-sq	uared	=	0.0128
				– Adj	R-squared	=	0.0093
Total	.163860524	1,124	.000145783	Root	MSE	=	.01202
Materials	Coef.	Std. Err.	t	P> t	[95% Co	nf.	Interval]
sun	0022862	.0011356	-2.01	0.044	004514	3	000058
mon	002181	.0011343	-1.92	0.055	004406	7	.0000447
tues	0042848	.0011343	-3.78	0.000	006510	4	0020591
wed	0026384	.0011356	-2.32	0.020	004866	5	0004102
_cons	.0025519	.0008048	3.17	0.002	.000972	9	.004131

# . reg Capitalgoods sun mon tues wed if date1 >td(1jan2009) & date1< td(27june2013)

Source	SS	df	MS		er of ob		1,125
Model Residual	.00916592 .696609952	4 1,120	.00229148	Prob R-sq	1120) > F uared R-square	= = = d =	3.68 0.0055 0.0130 0.0095
Total	.705775872	1,124	.000627914	_		=	.02494
Capitalgoods	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
sun mon tues wed	0054924 0029329 0078348 0069842	.0023566 .002354 .002354 .0023566	-2.33 -1.25 -3.33 -2.96	0.020 0.213 0.001 0.003	0101 0075 0124 011	516 535	0008686 .0016858 003216 0023605

.0016701

.0048054

\_cons

#### . reg Transportation sun mon tues wed if date1 >td(1jan2009) & date1< td(27june2013)

2.88

0.004

.0015286

.0080822

Source	SS	df	MS		per of obs	=	1,125
				- F(4,	1120)	=	0.72
Model	.000671845	4	.000167961	L Prob	) > F	=	0.5787
Residual	.261463923	1,120	.00023345	R-so	quared	=	0.0026
				- Adj	R-squared	=	-0.0010
Total	.262135768	1,124	.000233217	7 Root	MSE	=	.01528
Transporta∼n	Coef.	Std. Err.	t	P> t	[95% Co	nf.	Interval]
sun	0021132	.0014438	-1.46	0.144	00494	6	.0007196
mon	0019903	.0014422	-1.38	0.168	0048	2	.0008393
tues	0012836	.0014422	-0.89	0.374	004113	2	.001546
wed	0008748	.0014438	-0.61	0.545	003707	6	.0019579
weu		.0010232	1.73	0.084	000238	_	.0037768

#### . reg Consumerdurables sun mon tues wed if date1 >td(1jan2009) & date1< td(27june2013)

Source	SS	df	MS		er of ob: 1120)	s = =	1,125 4.52
Model	.00420635	4	.001051587	Prob	> F	=	0.0013
Residual	.26085793	1,120	.000232909		uared R-square	= d =	0.0159 0.0124
Total	.26506428	1,124	.000235822	Root	MSE	=	.01526
Consumerdu~s	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
sun	0025532	.0014421	-1.77	0.077	0053	827	.0002763
mon	0033615	.0014405	-2.33	0.020	0061	879	0005352
tues	0053543	.0014405	-3.72	0.000	0081	806	0025279
wed	005062	.0014421	-3.51	0.000	0078	915	0022326
_cons	.0032318	.001022	3.16	0.002	.0012	266	.005237

#### . reg Retailing sun mon tues wed if date1 >td(1jan2009) & date1< td(27june2013)

Source	SS	df	MS	Number of obs	=	1,125
Model	.008838878	4	.002209719	F(4, 1120) Prob > F	=	6.02 0.0001
Residual	.411391001	1,120	.000367313	R-squared	=	0.0210
Total	.420229879	1,124	.00037387	Adj R-squared Root MSE	=	0.0175 .01917

Retailing	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval]
sun mon tues wed _cons	0074774 0054853 0078613 005581 .006407	.001811 .001809 .001809 .001811	-4.13 -3.03 -4.35 -3.08 4.99	0.000 0.002 0.000 0.002	0110307 0090346 0114107 0091343 .0038889	0039241 0019359 0043119 0020277 .0089252

#### . reg Foodandbeverage sun mon tues wed if date1 >td(1jan2009) & date1< td(27june2013)

	Source	SS	df	MS	Number of obs	=	1,125
-					F(4, 1120)	=	7.99
	Model	.008462579	4	.002115645	Prob > F	=	0.0000
	Residual	.296403682	1,120	.000264646	R-squared	=	0.0278
-					Adj R-squared	=	0.0243
	Total	.304866261	1,124	.000271233	Root MSE	=	.01627

Foodandbev~e	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
sun mon tues wed _cons	0047355 0051855 007985 0069444 .0056792	.0015372 .0015355 .0015355 .0015372	-3.08 -3.38 -5.20 -4.52 5.21	0.002 0.001 0.000 0.000 0.000	0077516 0081982 0109978 0099605 .0035417	0017194 0021727 0049723 0039283 .0078166

#### . reg Realestate sun mon tues wed if date1 >td(1jan2009) & date1< td(27june2013)

Source	SS	df	MS		er of obs 1120)	=	1,125 3.07
Model Residual	.002066967 .18848939	4 1,120	.000516742 .000168294	Prob R-sq	> F uared	=	0.0157 0.0108
Total	. 190556357	1,124	.000169534	-	R-squared MSE	=	0.0073 .01297
Realestate	Coef.	Std. Err.	t	P> t	[95% Co	onf.	Interval]
sun mon tues wed _cons	0020154 0034201 0037065 0031706 .0032581	.0012258 .0012245 .0012245 .0012258 .0008687	-1.64 -2.79 -3.03 -2.59 3.75	0.100 0.005 0.003 0.010 0.000	004420 005822 00610 005575	26 99 58	.0003898 0010175 0013039 0007655 .0049626

# . reg Consumerservices sun mon tues wed if date1 >td(1jan2009) & date1< td(27june2013)

1,125 4.73	s = =	ber of ob , 1120)		MS	df	SS	Source
0.0009	=	, 1120) b > F		.0014082	4	.005633001	Model
0.0166	=	quared	' <b>5</b> R-sc	.00029747	1,120	.333172294	Residual
0.0131	ed =	R-square	— Adj				
.01725	=	t MSE	8 Root	.00030142	1,124	.338805295	Total
Interval]	Conf.	[95%	P> t	t	Std. Err.	Coef.	Consumerse~s
0011756	571	007	0.007	-2.68	.0016297	0043733	sun
0019949	833	0083	0.001	-3.19	.001628	0051891	mon
0027476	136	009	0.000	-3.65	.001628	0059418	tues
0028932	886	0092	0.000	-3.74	.0016297	0060909	wed
0020932				4.63	.001155	.0053458	

#### . reg Foodandstaples sun mon tues wed if date1 >td(1jan2009) & date1< td(27june2013)

Source	SS	df	MS	Numb	er of obs	=	1,125
				– F(4,	1120)	=	2.13
Model	.003020059	4	.00075501	5 Prob	) > F	=	0.0744
Residual	.396085226	1,120	.000353648	R-so	quared	=	0.0076
				– Adj	R-squared	=	0.0040
Total	.399105285	1,124	.00035507	6 Root	MSE	=	.01881
Foodandsta~s	Coef.	Std. Err.	t	P> t	[95% Con	f.	Interval]
sun	.0028199	.001777	1.59	0.113	0006666		.0063065
mon	.0051248	.001775	2.89	0.004	.001642		.0086075
tues	.0020648	.001775	1.16	0.245	0014179		.0055475
wed	.0023694	.001777	1.33	0.183	0011171		.005856

#### . reg Healthcare sun mon tues wed if date1 >td(1jan2009) & date1< td(27june2013)

-1.27 0.204

.0012593

-.0040728

.0008689

Source	SS	df	MS	Number of obs	=	1,125
				F(4, 1120)	=	1.33
Model	.001646363	4	.000411591	Prob > F	=	0.2550
Residual	.345384479	1,120	.000308379	R-squared	=	0.0047
				Adj R-squared	=	0.0012
Total	.347030841	1,124	.000308746	Root MSE	=	.01756
·						

Healthcare	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
sun mon tues wed _cons	0031929 0031162 0028019 0016176 .0026301	.0016593 .0016575 .0016575 .0016593	-1.92 -1.88 -1.69 -0.97 2.24	0.055 0.060 0.091 0.330 0.026	0064487 0063684 0060541 0048734 .0003227	.0000628 .000136 .0004502 .0016382 .0049374

#### . reg Diversifiedfinancials sun mon tues wed if date1 >td(1jan2009) & date1< td(27june2013)

Source	SS	df	MS	Number of obs	=	1,125
				F(4, 1120)	=	4.77
Model	.007175817	4	.001793954	Prob > F	=	0.0008
Residual	.420977241	1,120	.000375873	R-squared	=	0.0168
				Adj R-squared	=	0.0132
Total	.428153058	1,124	.000380919	Root MSE	=	.01939

Diversifie~s	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
sun mon tues wed _cons	0046675 0045519 0072147 0066121 .0050703	.001832 .0018299 .0018299 .001832	-2.55 -2.49 -3.94 -3.61 3.91	0.011 0.013 0.000 0.000 0.000	0082619 0081424 0108052 0102065 .002523	001073 0009614 0036242 0030176 .0076176

#### *Table 3.1:*

\_cons

-.001602

#### . reg Energy sun mon tues wed if date1 >td(1jan2009) & date1< td(27june2013)

Source	SS	df	MS	Number of ob	s =	1,123
Model Residual	.004017774 .217186031	4 1,118	.001004444	R-squared	= = =	5.17 0.0004 0.0182 0.0147
Total	.221203805	1,122	.000197151	– Adj R-square L Root MSE	= =	.01394
Energy	Coef.	Std. Err.	t	P> t  [95%	Conf.	Interval]
sun mon tues wed _cons	0033644 0042245 0054111 0017707 .0030111	.0013185 .0013171 .0013171 .00132	-2.55 -3.21 -4.11 -1.34 3.22	0.0110059 0.0010068 0.0000079 0.1800043 0.001 .0011	087 953 606	0007774 0016403 0028269 .0008192 .0048465

# . reg Materials sun mon tues wed if date1 >td(1jan2009) & date1< td(27june2013)

Source	SS	df	MS		er of obs	s =	-,
Model Residual	.004311463 .208528109	4 1,120	.001077866	Frob R-sq	1120) > F uared R-squared	= = = 1 =	0.0001 0.0203
Total	.212839572	1,124	.000189359	-	MSE	=	
Materials	Coef.	Std. Err.	t	P> t	[95% (	Conf.	Interval]
sun mon tues wed _cons	0042531 0030784 0059488 0040076 .0038118	.0012893 .0012879 .0012879 .0012893 .0009137	-3.30 -2.39 -4.62 -3.11 4.17	0.001 0.017 0.000 0.002 0.000	00678 00566 00847 00653	)54 /58 374	0017233 0005513 0034218 0014778 .0056047

#### . reg Capitalgoods sun mon tues wed if date1 >td(1jan2009) & date1< td(27june2013)

	Source	SS	df	MS	Number of obs	=	1,125
_					F(4, 1120)	=	7.08
	Model	.005209019	4	.001302255	Prob > F	=	0.0000
	Residual	.206128839	1,120	.000184044	R-squared	=	0.0246
_					Adj R-squared	=	0.0212
	Total	.211337857	1,124	.000188023	Root MSE	=	.01357

Capitalgoods	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
sun mon tues wed _cons	0041691 0037786 0062465 0054708 .0038167	.0012819 .0012805 .0012805 .0012819	-3.25 -2.95 -4.88 -4.27 4.20	0.001 0.003 0.000 0.000	0066843 006291 008759 007986 .0020342	0016539 0012662 0037341 0029556 .0055991

#### . reg Transportation sun mon tues wed if date1 >td(1jan2009) & date1< td(27june2013)

	Source	SS	df	MS		=	1,125
-					F(4, 1120)	=	4.83
	Model	.008316918	4	.00207923	Prob > F	=	0.0007
	Residual	.481897451	1,120	.000430266	R-squared	=	0.0170
_					Adj R-squared	=	0.0135
	Total	.490214369	1,124	.000436134	Root MSE	=	.02074

Transporta~n	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
sun mon tues wed _cons	0058937 0046679 0078359 0067918 .005946	.00196 .0019579 .0019579 .00196	-3.01 -2.38 -4.00 -3.47 4.28	0.003 0.017 0.000 0.001 0.000	0097395 0085094 0116774 0106376 .0032205	002048 0008264 0039944 0029461 .0086714

# . reg Consumerdurables sun mon tues wed if date1 >td(1jan2009) & date1< td(27june2013)

Source	SS	df	MS		er of obs	=	1,125
				- F(4,	1120)	=	3.56
Model	.008278227	4	.002069557	Prob	> F	=	0.0068
Residual	.651896606	1,120	.000582051	. R-so	uared	=	0.0125
				- Adj	R-squared	=	0.0090
Total	.660174833	1,124	.000587344	Root	MSE	=	.02413
Consumerdu~s	Coef.	Std. Err.	t	P> t	[95% Co	nf.	Interval]
Consumerdu~s sun	Coef. 0039924	.0022797	-1.75	P> t  0.080	[95% Co		
						4	.0004805
sun	0039924	.0022797	-1.75	0.080	008465	4 6	.0004805
sun mon	0039924 0039536	.0022797	-1.75 -1.74	0.080 0.083	008465 008421	4 6 7	.0004805 .0005144 0031487 0025593

# . reg Retailing sun mon tues wed if date1 >td(1jan2009) & date1< td(27june2013)

Source	SS	df	MS	Number of obs	=	1,12
				F(4, 1120)	=	1.5
Model	.001198852	4	.000299713	Prob > F	=	0.175
Residual	.211723168	1,120	.000189039	R-squared	=	0.005
				Adj R-squared	=	0.002
Total	.21292202	1.124	.000189432	Root MSE	=	.0137

Retailing	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
sun	0022501	.0012992	-1.73	0.084	0047992	.000299
mon	0024457	.0012978	-1.88	0.060	004992	.0001006
tues	0029536	.0012978	-2.28	0.023	0054999	0004073
wed	0024368	.0012992	-1.88	0.061	0049859	.0001123
_cons	.002386	.0009207	2.59	0.010	.0005795	.0041925

#### . reg Foodandbeverage sun mon tues wed if date1 >td(1jan2009) & date1< td(27june2013)

Source	SS	df	MS		er of ob	s =	1,125
-					1120)	=	6.61
Model	.006299668	4	.001574917	Prob	> F	=	0.0000
Residual	.266860486	1,120	.000238268			=	0.0231
				- Adj	R-square	d =	0.0196
Total	.273160154	1,124	.000243025	Root	MSE	=	.01544
Foodandbev~e	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
sun	0050693	.0014586	-3.48	0.001	0079	311	0022074
mon	0060489	.001457	-4.15	0.000	0089	<b>07</b> 6	0031902
tues	0067721	.001457	-4.65	0.000	0096	308	0039134
wed	0043754	.0014586	-3.00	0.003	0072	372	0015135
_cons	.0047915	.0010337	4.64	0.000	.0027	633	.0068196

#### . reg Telecommunication sun mon tues wed if date1 >td(1jan2009) & date1< td(27june2013)

	Source	SS	df	MS		=	1,123
						=	4.17
	Model	.003255491	4	.000813873		=	0.0023
R	esidual	.218240253	1,118	.000195206		=	0.0147
					Adj R-squared	=	0.0112
	Total	.221495744	1,122	.000197412	Root MSE	=	.01397

Telecommun~n	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
sun mon tues wed _cons	0036499 0037365 0051396 0034271 .0034123	.0013217 .0013202 .0013188 .0013202	-2.76 -2.83 -3.90 -2.60 3.65	0.006 0.005 0.000 0.010 0.000	0062432 0063269 0077271 0060175 .0015765	0010567 0011462 0025521 0008367 .005248

#### . reg Realestate sun mon tues wed if date1 >td(1jan2009) & date1< td(27june2013)

	Source	SS	df	MS	Number of obs	=	1,125
_					F(4, 1120) Prob > F	=	3.76
	Model	.002618718	4	.000654679		=	0.0048
	Residual	.195005492	1,120	.000174112	R-squared	=	0.0133
_					Adj R-squared	=	0.0097
	Total	.19762421	1,124	.000175822	Root MSE	=	.0132

Realestate	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
sun	0028787	.0012468	-2.31	0.021	0053251	0004323
mon	0025724	.0012455	-2.07	0.039	0050161	0001287
tues	0047238	.0012455	-3.79	0.000	0071675	0022801
wed	003203	.0012468	-2.57	0.010	0056494	0007566
_cons	.0027027	.0008836	3.06	0.002	.000969	.0044365

# *Table 3.2:*

# . reg Energy mon tues wed thurs if date1 >td(27june2013) & date1< td(6january2017)

Source	SS	df	MS		er of obs	=	876	
Model Residual	.001825776 .498180574	4 871	.00045644	4 Prob 4 R-squ	F(4, 871) : Prob > F : R-squared : Adj R-squared :		0.80 0.5266 0.0037	
Total	.50000635	875	.000571430	-	•	=	-0.0009 .02392	
Energy	Coef.	Std. Err.	t	P> t	[95% Co	nf.	Interval]	
mon	0015784	.0025604	-0.62	0.538	006603	7	.0034468	

Energy	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
mon tues wed thurs _cons	0015784 0012759 .0009467 0032806 .0010658	.0025604 .0025604 .0025532 .0025604 .001813	-0.62 -0.50 0.37 -1.28 0.59	0.538 0.618 0.711 0.200 0.557	0066037 0063011 0040644 0083058 0024927	.0034468 .0037494 .0059577 .0017446

# . reg Materials mon tues wed thurs if date1 >td(27june2013) & date1< td(6january2017)

Source	SS	df	MS	Number of obs	=	876
				F(4, 871)	=	0.53
Model	.000419842	4	.00010496	Prob > F	=	0.7138
Residual	.172532827	871	.000198086	R-squared	=	0.0024
				Adj R-squared	=	-0.0022
Total	.172952669	875	.00019766	Root MSE	=	.01407
Materials	Coef.	Std. Err.	t P	> t  [95% Co	onf.	Interval]
mon	0004927	.0015068	-0.33 0	.7440034	15	.0024646
tues	000449	.0015068	-0.30 0	.766003406	53	.0025083
wed	.0001667	.0015025	0.11 0	.912002782	22	.0031157
	.0014176	.0015068	0.94 0	.347001539	97	.0043749
thurs						

#### . reg Capitalgoods mon tues wed thurs if date1 >td(27june2013) & date1< td(6january2017)

	Source	SS	df	MS	Number of obs	=	876
-					F(4, 871)	=	0.22
	Model	.000456093	4	.000114023	Prob > F	=	0.9298
	Residual	.460515517	871	.00052872	R-squared	=	0.0010
-					Adj R-squared	=	-0.0036
	Total	.460971611	875	.000526825	Root MSE	=	.02299

[95% Conf. Interval]	P> t	t	Std. Err.	Coef.	Capitalgoods
0063688 .0032943	0.532	-0.62	.0024617	0015373	mon
0059439 .0037192 0070219 .0026139	0.651 0.370	-0.45 -0.90	.0024617 .0024547	0011123 002204	tues wed
0062578 .0034052 0028402 .0040023	0.562	-0.58	.0024617	0014263	thurs
	0.562 0.739	-0.58 0.33	.0024617 .0017432	0014263 .0005811	thurs _cons

#### . reg Transportation mon tues wed thurs if date1 >td(27june2013) & date1< td(6january2017)

Source	SS	df	MS		C1 01 0D3	= 876
Model Residual	.000573825 .313707247	4 871	.000143456 .000360169	Prob R-sq	> F uared	= 0.40 = 0.8099 = 0.0018 = -0.0028
Total	.314281072	875	.000359178	_		= .01898
Transporta~n	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval]
mon tues wed	0006856 .0006768 0009257	.0020318 .0020318 .002026	0.33	0.736 0.739 0.648	0046734 0033109 0049022	.0033021 .0046645 .0030507

-0.84

0.14

0.404

0.885

-.0056842

-.0026153

.0022912

.0030322

.0020318

.0014387

wed thurs

\_cons

-.0016965

.0002084

#### . reg Consumerdurables mon tues wed thurs if date1 >td(27june2013) & date1< td(6january2017)

Source	SS	df	MS	Number of obs	=	876
				F(4, 871)	=	0.31
Model	.000415047	4	.000103762	Prob > F	=	0.8738
Residual	.29504771	871	.000338746	R-squared	=	0.0014
				Adj R-squared	=	-0.0032
Total	.295462757	875	.000337672	Root MSE	=	.01841

Consumerdu~s	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
mon tues wed thurs _cons	0001929 .0016535 .0000562 0000848 0008678	.0019704 .0019704 .0019648 .0019704	-0.10 0.84 0.03 -0.04 -0.62	0.922 0.402 0.977 0.966 0.534	0040602 0022138 0038002 0039521 0036063	.0036744 .0055208 .0039126 .0037825 .0018707

#### . reg Consumerservices mon tues wed thurs if date1 >td(27june2013) & date1< td(6january2017)

Source	SS	df	MS	Number of obs	=	876
				F(4, 871)	=	0.56
Model	.00078512	4	.00019628	Prob > F	=	0.6910
Residual	.304735527	871	.000349869	R-squared	=	0.0026
				Adj R-squared	=	-0.0020
Total	.305520647	875	.000349166	Root MSE	=	.0187

Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
0011145	.0020025	-0.56	0.578	0050448	.0028157
0024674	.0020025	-1.23	0.218	0063977	.0014628
.0001612	.0019968	0.08	0.936	003758	.0040803
0010981	.0020025	-0.55	0.584	0050283	.0028322
.0002219	.001418	0.16	0.876	0025612	.003005
	0011145 0024674 .0001612 0010981	0011145 .0020025 0024674 .0020025 .0001612 .0019968 0010981 .0020025	0011145 .0020025 -0.56 0024674 .0020025 -1.23 .0001612 .0019968 0.08 0010981 .0020025 -0.55	0011145 .0020025 -0.56 0.578 0024674 .0020025 -1.23 0.218 .0001612 .0019968 0.08 0.936 0010981 .0020025 -0.55 0.584	0011145       .0020025       -0.56       0.578      0050448        0024674       .0020025       -1.23       0.218      0063977         .0001612       .0019968       0.08       0.936      003758        0010981       .0020025       -0.55       0.584      0050283

#### . reg Retailing mon tues wed thurs if date1 >td(27june2013) & date1< td(6january2017)

	Source	SS	df	MS	Number of obs	=	876
_					F(4, 871)	=	1.46
	Model	.003618481	4	.00090462	Prob > F	=	0.2136
	Residual	.541014894	871	.000621142	R-squared	=	0.0066
_					Adj R-squared	=	0.0021
	Total	.544633375	875	.000622438	Root MSE	=	.02492

Retailing	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
mon tues wed thurs _cons	0022395 005816 0038397 00121	.0026682 .0026682 .0026607 .0026682	-0.84 -2.18 -1.44 -0.45 0.56	0.402 0.030 0.149 0.650 0.577	0074763 0110528 0090617 0064468 0026536	.0029973 0005792 .0013824 .0040269

#### . reg Foodandstaples mon tues wed thurs if date1 >td(27june2013) & date1< td(6january2017)

Source	SS	df	MS	Number of obs	=	876
				F(4, 871)	=	0.59
Model	.002284199	4	.00057105	Prob > F	=	0.6669
Residual	.837088622	871	.000961066	R-squared	=	0.0027
				Adj R-squared	=	-0.0019
Total	.839372821	875	.000959283	Root MSE	=	.031
·						

Foodandsta~s	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
mon tues wed thurs _cons	0003138 .0012173 0036092 0011611 .0005844	.0033189 .0033189 .0033095 .0033189 .0023502	-0.09 0.37 -1.09 -0.35 0.25	0.925 0.714 0.276 0.727 0.804	0068278 0052967 0101048 0076751 0040283	.0062002 .0077313 .0028864 .0053529

#### . reg Foodandbeverage mon tues wed thurs if date1 >td(27june2013) & date1< td(6january2017)

Source	ss	df	MS	Number of obs	=	876
				F(4, 871)	=	0.49
Model	.000634858	4	.000158715	Prob > F	=	0.7421
Residual	.281340412	871	.000323009	R-squared	=	0.0023
				Adj R-squared	=	-0.0023
Total	.28197527	875	.000322257	Root MSE	=	.01797

Foodandbev~e	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
mon	0007454	.0019241	-0.39	0.699	0045218	.003031
tues	.0007371	.0019241	0.38	0.702	0030393	.0045135
wed	0004285	.0019187	-0.22	0.823	0041943	.0033372
thurs	0018391	.0019241	-0.96	0.339	0056155	.0019373
_cons	.0002109	.0013625	0.15	0.877	0024633	.002885

#### . reg Healthcare mon tues wed thurs if date1 >td(27june2013) & date1< td(6january2017)

Source	SS	df	MS		er of obs 871)	=	876 1.36
Model Residual	.001625402 .26060071	4 871	.0004063 .00029919	<ul><li>5 Prob</li><li>7 R-sq</li></ul>	Prob > F R-squared Adj R-squared		0.2467 0.0062 0.0016
Total	.262226112	875	.00029968	-	MSE	=	.0173
Healthcare	Coef.	Std. Err.	t	P> t	[95% Coi	nf.	Interval]
mon tues wed thurs _cons	0016867 0012949 000359 .0022119 .0004139	.0018518 .0018518 .0018466 .0018518	-0.91 -0.70 -0.19 1.19 0.32	0.363 0.485 0.846 0.233 0.752	0053213 0049294 0039833 0014223	4 3 7	.0019478 .0023397 .0032653 .0058464

#### . reg Diversifiedfinancials mon tues wed thurs if date1 >td(27june2013) & date1< td(6january2017)

Source	SS	df	MS	Number of ob	s =	876
Model	.000549837	4	.000137459	- F(4, 871) Prob > F	=	0.30 0.8787
Residual	.400411343	871	.000137459		=	0.0014
				– Adj R-square	d =	-0.0032
Total	.40096118	875	.000458241	L Root MSE	=	.02144
Diversifies	Coof	C+d Enn		D- I+I [050.	Conf	Intonvol1

Diversifie~s	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
mon	.0007926	.0022954	0.35	0.730	0037126	.0052978
tues	.0014537	.0022954	0.63	0.527	0030515	.0059589
wed	000704	.002289	-0.31	0.758	0051965	.0037885
thurs	.001163	.0022954	0.51	0.613	0033422	.0056682
_cons	0005936	.0016254	-0.37	0.715	0037838	.0025967

#### . reg Realestate mon tues wed thurs if date1 >td(27june2013) & date1< td(6january2017)

	Source	SS	df	MS	Number of obs	=	876
-					F(4, 871)	=	0.48
	Model	.000643492	4	.000160873	Prob > F	=	0.7525
	Residual	.293630058	871	.000337118	R-squared	=	0.0022
_					Adj R-squared	=	-0.0024
	Total	.294273551	875	.000336313	Root MSE	=	.01836

Realestate	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
mon tues wed thurs _cons	0017391 0016291 0015531 .0002024 .0011458	.0019657 .0019657 .0019601 .0019657	-0.88 -0.83 -0.79 0.10 0.82	0.377 0.407 0.428 0.918 0.411	0055971 0054871 0054002 0036556 0015861	.0021189 .0022289 .002294 .0040604

#### . reg Energy mon tues wed thurs if date1 >td(27june2013) & date1< td(6january2017)

	Source	SS	df	MS	Number of obs	=	876
_					F(4, 871)	=	0.10
	Model	.000108323	4	.000027081	Prob > F	=	0.9832
	Residual	.241099656	871	.000276808	R-squared	=	0.0004
_					Adj R-squared	=	-0.0041
	Total	.241207979	875	.000275666	Root MSE	=	.01664

Energy	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
mon tues wed thurs _cons	.0005019 .0002913 .0002822 .0010535	.0017812 .0017812 .0017762 .0017812 .0012613	0.28 0.16 0.16 0.59 -0.31	0.778 0.870 0.874 0.554 0.754	002994 0032046 0032038 0024424 0028715	.0039978 .0037872 .0037683 .0045494

#### . reg Materials mon tues wed thurs if date1 >td(27june2013) & date1< td(6january2017)

	Source	SS	df	MS	Number of obs	=	876
_					F(4, 871)	=	0.67
	Model	.000666264	4	.000166566	Prob > F	=	0.6120
	Residual	.216119776	871	.000248128	R-squared	=	0.0031
_					Adj R-squared	=	-0.0015
	Total	.216786039	875	.000247755	Root MSE	=	.01575

Materials	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
mon tues wed thurs _cons	0015224 0003083 .0000627 .0012056 0003207	.0016864 .0016864 .0016816 .0016864	-0.90 -0.18 0.04 0.71 -0.27	0.367 0.855 0.970 0.475 0.788	0048322 0036182 0032378 0021042 0026645	.0017875 .0030015 .0033632 .0045155 .0020231

#### . reg Capitalgoods mon tues wed thurs if date1 >td(27june2013) & date1< td(6january2017)

Source	SS	df	MS		Number of obs		876
Model Residual	.000190041 .202031063	4 871	.0000475	1 Prob 3 R-squ	F(4, 871) Prob > F R-squared Adj R-squared		0.20 0.9358 0.0009 -0.0036
Total	.202221103	875	.0002311	_	Root MSE		.01523
Capitalgoods	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
mon	0007991	.0016305	-0.49	0.624	0039	993	.002401

Capitalgoods	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
mon tues wed thurs _cons	0007991 0001049 0009415 .0002436 0003017	.0016305 .0016305 .0016259 .0016305	-0.49 -0.06 -0.58 0.15 -0.26	0.624 0.949 0.563 0.881 0.794	0039993 0033051 0041326 0029565 0025678	.002401 .0030952 .0022497 .0034438

#### . reg Transportation mon tues wed thurs if date1 >td(27june2013) & date1< td(6january2017)

SS	df	MS			=	876
.001423157 .428485801	4 871		9 Prob 7 R-sq	> F uared	=	0.72 0.5762 0.0033
. 429908957	875	.00049132	-	•	=	-0.0013 .02218
Coef.	Std. Err.	t	P> t	[95% Con	ıf.	Interval]
0012338 .0000984	.0023745	-0.52 0.04	0.603 0.967			.0034267
.0018903	.0023678	0.80	0.425	002757		.0065376
	.001423157 .428485801 .429908957 Coef. 0012338 .0000984	.001423157 4 .428485801 871  .429908957 875  Coef. Std. Err. 0012338 .0023745 .0000984 .0023745	.001423157	F(4, 001423157	F(4, 871)	F(4, 871)   =

# . reg Consumerdurables mon tues wed thurs if date1 >td(27june2013) & date1< td(6january2017)

	Source	SS	df	MS		=	876
-	Model	.002019635	4	.000504909	F(4, 871) Prob > F	=	0.83 0.5049
	Residual	.528585907	-		R-squared	=	0.0038
-					Adj R-squared	=	-0.0008
	Total	.530605543	875	.000606406	Root MSE	=	.02463

Consumerdu~s	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
mon tues	.0032236	.0026374	1.22	0.222 0.694	0019527 0041389	.0083999
wed	0013885	.0026299	-0.53	0.598	0065502	.0037732
thurs _cons	.0002654 0010059	.0026374 .0018676	0.10 -0.54	0.920 0.590	0049109 0046713	.0054417 .0026596

#### . reg Retailing mon tues wed thurs if date1 >td(27june2013) & date1< td(6january2017)

Source	SS	df	MS	Number of		876
Model Residual	.000558871 .315149738	4 871	.000139718		=	0.0018
Total	.315708609	875	.00036081		=	.01902
Retailing	Coef.	Std. Err.	t	P> t  [9	5% Conf.	Interval]
mon tues wed thurs _cons	0009295 0003896 0021661 0000798 0001375	.0020364 .0020364 .0020307 .0020364 .001442	-0.19 -1.07 -0.04	0.8480 0.2860 0.9690	049264 043865 061517 040766 029677	.0030674 .0036073 .0018195 .0039171

#### . reg Foodandbeverage mon tues wed thurs if date1 >td(27june2013) & date1< td(6january2017)

Source	SS	df	MS	Number of obs	=	876
				F(4, 871)	=	0.65
Model	.000738838	4	.00018471	Prob > F	=	0.6271
Residual	.247556641	871	.000284221	R-squared	=	0.0030
				Adj R-squared	=	-0.0016
Total	.248295479	875	.000283766	Root MSE	=	.01686

Foodandbev~e	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
mon tues wed thurs _cons	0012682 0009064 0010103 .0012359 0001412	.0018049 .0018049 .0017998 .0018049	-0.70 -0.50 -0.56 0.68 -0.11	0.482 0.616 0.575 0.494 0.912	0048107 0044488 0045427 0023065 0026496	.0022742 .0026361 .0025221 .0047783 .0023673

#### . reg Telecommunication mon tues wed thurs if date1 >td(27june2013) & date1< td(6january2017)

	Source	SS	df	MS	Number of obs	=	876
_					F(4, 871)	=	0.62
	Model	.000734348	4	.000183587	Prob > F	=	0.6470
	Residual	.25715849	871	.000295245	R-squared	=	0.0028
_					Adj R-squared	=	-0.0017
	Total	.257892838	875	.000294735	Root MSE	=	.01718

Telecommun~n	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
mon	0016764	.0018395	-0.91	0.362	0052869	.001934
tues	0026073	.0018395	-1.42	0.157	0062178	.0010031
wed	0010562	.0018344	-0.58	0.565	0046565	.0025441
thurs	0004629	.0018395	-0.25	0.801	0040733	.0031476
_cons	.0008618	.0013026	0.66	0.508	0016948	.0034184

#### . reg Realestate mon tues wed thurs if date1 >td(27june2013) & date1< td(6january2017)

Source	SS	df	MS	Number of obs	=	876 0.63
Model	.000834655	4	.000208664	Prob > F	=	0.6435
Residual	.289972519	871	.000332919	R-squared Adj R-squared	=	0.0029 -0.0017
Total	.290807174	875	.000332351	Root MSE	=	.01825

Realestate	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
mon	0015266	.0019534	-0.78	0.435	0053605	.0023073
tues	0007793	.0019534	-0.40	0.690	0046132	.0030546
wed	0013303	.0019479	-0.68	0.495	0051534	.0024927
thurs	.0011406	.0019534	0.58	0.559	0026933	.0049745
_cons	.0006251	.0013832	0.45	0.651	0020898	.0033399

# <u>Chapter 4:</u> <u>Table 1:</u> . reg Return Eidalfitr, robust

inear regress	ion			Number	of obs	=	2,745
-				F(1, 27	43)	=	6.34
				Prob >	F	=	0.0119
				R-squar	ed	=	0.0027
				Root MS	E	=	.01115
		Robust					
Return	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
Eidalfitr	.004166	.0016544	2.52	0.012	.0009	219	.0074101
_cons	.0001019	.0002146	0.47	0.635	0003	189	.0005226
	10 10 14 1						
. reg Return d	11 d2 d3 d4 d	5, robust					
Linear regress	ion			Number	of obs	=	2,745
				F(5, 27	739)	=	7.36
				Prob >	F	=	0.0000
				R-squar	red	=	0.0039
				Root MS	SE	=	.01115
		Robust					
Return	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
I							
d1	.0079039	.0013816	5.72	0.000	.0051	1948	.010613
d1 d2	.0079039 .0057757	.0013816 .0050365	5.72 1.15	0.000 0.252	.0051 0040		
						999	.0156514
d2	.0057757	.0050365	1.15	0.252	0040	999 1775	.0156514 .011148
d2 d3	.0057757 .0039853	.0050365 .0036529	1.15 1.09	0.252 0.275	0040 0031	999 1775 2503	.010613 .0156514 .011148 .0077836

#### . reg Return Eidaladha, robust

Linear regress	sion			Number F(1, 27 Prob > R-squar Root MS	43) F ed	= = =	2,745 0.08 0.7726 0.0000 .01117
Return	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
Eidaladha _cons	0003209 .0001918	.00111 .0002163	-0.29 0.89	0.773 0.375	0024 0002		.0018557 .000616
. reg Return o	d1 d2 d3 d4 d	5, robust					
Linear regres	sion			Number F(5, 27 Prob > R-squar Root MS	F red	= = = =	2,745 2.71 0.0189 0.0010 .01117

Return	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	.0044143	.0013726	3.22	0.001	.0017228	.0071057
d2	0016845	.0021207	-0.79	0.427	0058429	.0024739
d3	0017702	.0014175	-1.25	0.212	0045496	.0010092
d4	0025397	.0029634	-0.86	0.392	0083504	.0032711
d5	0000243	.0031428	-0.01	0.994	0061868	.0061383
_cons	.0001918	.0002165	0.89	0.376	0002327	.0006163

Linear regression	Number of obs	=	2,745
	F(1, 2743)	=	0.40
	Prob > F	=	0.5252
	R-squared	=	0.0001
	Root MSE	=	.01117

Return	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationaday	.00075	.0011803	0.64	0.525	0015644	.0030643
_cons	.0001703	.0002162	0.79	0.431	0002535	

Linear regression	Number of obs	=	2,745
	F(5, 2739)	=	1.51
	Prob > F	=	0.1840
	R-squared	=	0.0013
	Root MSE	=	.01117

Return	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	.0024157	.0020646	1.17	0.242	0016327	.0064641
d2	.0006545	.0025078	0.26	0.794	0042628	.0055718
d3	0038525	.0020724	-1.86	0.063	0079162	.0002112
d4	-7.57e-06	.0027511	-0.00	0.998	0054019	.0053868
d5	.0045398	.0028254	1.61	0.108	0010004	.0100799
_cons	.0001703	.0002163	0.79	0.431	0002539	.0005945

Linear regression	Number of obs	=	2,745
	F(1, 2743)	=	5.76
	Prob > F	=	0.0164
	R-squared	=	0.0018
	Root MSE	=	.01116

Return	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr	.0033363	.0013896	2.40	0.016	.0006115	.0060611
_cons	.0001185	.0002155	0.55	0.582	000304	

Linear regression	Number of obs	=	2,745
	F(5, 2739)	=	3.14
	Prob > F	=	0.0079
	R-squared	=	0.0043
	Root MSE	=	.01115

Return	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6	.0107949	.0032197	3.35	0.001	.0044816	.0171082
d7	.0037676	.0018193	2.07	0.038	.0002002	.0073349
d8	.0018454	.0036096	0.51	0.609	0052323	.0089232
d9	0002229	.0027718	-0.08	0.936	005658	.0052122
d10	.0004964	.0024188	0.21	0.837	0042465	.0052394
_cons	.0001185	.0002156	0.55	0.583	0003043	.0005413

#### . reg Return Eidaladha, robust

Linear regression	Number of obs	=	2,745
	F(1, 2743)	=	3.96
	Prob > F	=	0.0468
	R-squared	=	0.0023
	Root MSE	=	.01115

Return	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	. Interval]
Eidaladha	0038098	.001915	-1.99	0.047	0075649	0000548
_cons	.0002617	.0002137	1.22	0.221	0001574	.0006808

Linear regression	Number of obs	=	2,745
	F(5, 2739)	=	1.67
	Prob > F	=	0.1394
	R-squared	=	0.0042
	Root MSE	=	.01115

Return	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0072262	.0066881	-1.08	0.280	0203405	.005888
d2	.0024161	.0029647	0.81	0.415	0033972	.0082293
d3	0028832	.00213	-1.35	0.176	0070598	.0012935
<b>d4</b>	0048291	.0034663	-1.39	0.164	0116259	.0019678
d5	0065268	.0039231	-1.66	0.096	0142194	.0011658
_cons	.0002617	.0002139	1.22	0.221	0001577	.0006811

Linear regress	sion			Number F(1, 27 Prob > R-squar Root MS	43) F ed	= = =	2,745 0.02 0.8836 0.0000 .01117
		Robust					
Return	Coef.	Std. Err.	t	P> t	[95% Co	nf.	Interval]
Nationalday2 _cons	0002233 .0001898	.0015247 .0002153	-0.15 0.88	0.884 0.378	00321 000232		.0027664
. reg Return o	d6 d7 d8 d9 d	10, robust					
Linear regress	sion			Number	of obs	=	2,745
				F(5, 27	39)	=	2.58
				Prob >	F	=	0.0247
				R-squar	ed	=	0.0020
				Root MS	E	=	.01116
Return	Coef.	Robust Std. Err.	t	P> t	[95% Co	nf.	Interval]
d6	0007331	.0043519	-0.17	0.866	009266	3	.0078001
d7	.0025127	.0012402	2.03	0.043	.00008		.0049445
d8	0057712	.0036308	-1.59	0.112	012890	5	.0013482
d9	001664	.0038025	-0.44	0.662	0091	.2	.0057921
d10	.0045391	.0018416	2.46	0.014	.00092	8	.0081502
_cons	.0001898	.0002154	0.88	0.378	000232	6	.0006123

Linear regression Number of obs = 1,999F(1, 1997) = 15.44

Prob > F = 0.0001 R-squared = 0.0047 Root MSE = .01337

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr	.0065535	.0016676	3.93	0.000	.003283	.009824
_cons	.0002519	.0003033	0.83	0.406	000343	.0008467

#### . reg Returns d1 d2 d3 d4 d5, robust

Linear regression Number of obs = 1,999

Number of obs = 1,999 F(5, 1993) = 4.30 Prob > F = 0.0007 R-squared = 0.0060 Root MSE = .01337

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	.0122621	.0034084	3.60	0.000	.0055777	.0189465
d2	.0042649	.0025476	1.67	0.094	0007313	.0092611
d3	.0080069	.0045008	1.78	0.075	0008198	.0168337
d4	.0056594	.0036825	1.54	0.124	0015625	.0128813
d5	.0025741	.0029669	0.87	0.386	0032444	.0083926
_cons	.0002519	.0003036	0.83	0.407	0003436	.0008473

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	8.65
	Prob > F	=	0.0033
	R-squared	=	0.0033
	Root MSE	=	.01224

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr	.005043	.0017148	2.94	0.003	.0016799	.008406
_cons	0000506	.0002771	-0.18	0.855	0005941	.0004929

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	4.79
	Prob > F	=	0.0002
	R-squared	=	0.0047
	Root MSE	=	.01224

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	.0099667	.0023727	4.20	0.000	.0053134	.01462
d2	.0042651	.0023653	1.80	0.072	0003736	.0089038
d3	.0068467	.0039283	1.74	0.081	0008572	.0145507
d4	.0002784	.0024037	0.12	0.908	0044356	.0049924
d5	.003858	.0057572	0.67	0.503	0074328	.0151488
_cons	0000506	.0002774	-0.18	0.855	0005946	.0004935

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	4.92
	Prob > F	=	0.0266
	R-squared	=	0.0007
	Root MSE	=	.01514

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr	.0027954	.0012598	2.22	0.027	.0003247	.0052661
_cons	0004088	.0003447	-1.19	0.236	0010848	.0002673

R-squared = 0	Linear regression	egression Number of obs	=	1,999
R-squared = 0		F(5, 1993)	=	3.63
		Prob > F	=	0.0028
Root MSE = .6		R-squared	=	0.0011
***************************************		Root MSE	=	.01516

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	.0054776	.0019303	2.84	0.005	.0016919	.0092632
d2	.0023505	.0009951	2.36	0.018	.0003989	.004302
d3	.0042733	.0027623	1.55	0.122	001144	.0096906
d4	.0028273	.0013082	2.16	0.031	.0002617	.005393
d5	0009517	.004512	-0.21	0.833	0098005	.0078971
_cons	0004088	.0003451	-1.18	0.236	0010855	.000268

d2

d3

d4

d5

\_cons

.0061657

.0012149

.0029565

.000544

.0000863

.0027896

.0009541

.0011518

.0028424

.0002629

Linear regres	Coef.	Robust Std. Err.	t	Number of F(5, 199 Prob > F R-square Root MSE	93) = ed	= = = = = Conf.	1,999 3.26 0.0062 0.0020 .01155
Linear regres	sion			F(5, 199 Prob > F R-square	93) = ed	= = =	3.26 0.0062 0.0020
Linear regres	sion			F(5, 199 Prob > F R-square	93) = ed	=	3.26 0.0062 0.0020
Linear regres	sion			F(5, 199	93)	=	3.26
Linear regres	sion						-
Linear regres	sion			Number o	of obs	=	1,999
. reg Returns	d1 d2 d3 d4	d5, robust					
_cons	.0000863	.0002626	0.33	0.742	0004	1288	.0006014
Eidalfitr	.0030622	.0010293	2.98	0.003	.001		.0050808
Returns	Coef.	Std. Err.	t	P> t	[95%	Cont.	Interval]
Datuma	Conf	Robust		D. I.I.	[050	Conf	Tata
				Root MSE	=	=	.01154
				R-square		=	0.0014
				Prob > F		=	0.0030
				F(1, 199		=	8.85
				-/			

2.21

1.27

2.57

0.19

0.33

0.027

0.203

0.010

0.848

0.743

.0006949

.0006975

-.0050304

-.0004293

-.0006561

.0116366

.003086

.0052154

.0061184

.0006019

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	4.23
	Prob > F	=	0.0398
	R-squared	=	0.0026
	Root MSE	=	.01349

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr	.0048854	.0023748	2.06	0.040	.0002279	.0095428
_cons	.000337	.0003042	1.11	0.268	0002596	.0009335

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	1.19
	Prob > F	=	0.3109
	R-squared	=	0.0046
	Root MSE	=	.01349

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	.0048349	.0054842	0.88	0.378	0059206	.0155904
d2	.0024891	.003682	0.68	0.499	0047318	.00971
d3	.004148	.0026	1.60	0.111	0009509	.009247
d4	.000091	.0019704	0.05	0.963	0037733	.0039553
d5	.0128638	.008573	1.50	0.134	0039493	.0296768
_cons	.000337	.0003045	1.11	0.269	0002602	.0009341

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	0.01
	Prob > F	=	0.9209
	R-squared	=	0.0000
	Root MSE	=	.01911

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr	.0002442	.0024599	0.10	0.921	00458	.0050684
_cons	.0003987	.0004333	0.92	0.358	0004512	

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	0.22
	Prob > F	=	0.9521
	R-squared	=	0.0002
	Root MSE	=	.01913

Interval]	[95% Conf.	P> t	t	Robust Std. Err.	Coef.	Returns
.0070166	0072521	0.974	-0.03	.0036378	0001177	d1
.0118176	0078475	0.692	0.40	.0050137	.0019851	d2
.0087056	0031648	0.360	0.92	.0030264	.0027704	d3
.0105968	0122831	0.885	-0.14	.0058333	0008432	d4
.0131058	0182528	0.748	-0.32	.0079949	0025735	d5
.0012494	0004521	0.358	0.92	.0004338	.0003987	_cons

Linear regression Number of obs = 1,999F(1, 1997) = 4.67

Prob > F = 0.0307 R-squared = 0.0013 Root MSE = .01584

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr	.0041284	.0019094	2.16	0.031	.0003837	.0078731
_cons	.0002378	.0003594	0.66	0.508	0004671	.0009427

#### . reg Returns d1 d2 d3 d4 d5, robust

Linear regression Number of obs = 1,999

F(5, 1993) = 1.89 Prob > F = 0.0931 R-squared = 0.0016 Root MSE = .01585

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	.0034308	.0030351	1.13	0.258	0025216	.0093832
d2	.0007751	.0019931	0.39	0.697	0031337	.0046839
d3	.0061655	.0032391	1.90	0.057	0001868	.0125178
d4	.004388	.0021384	2.05	0.040	.0001943	.0085817
d5	.0058827	.007623	0.77	0.440	009067	.0208325
_cons	.0002378	.0003598	0.66	0.509	0004678	.0009434

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	1.61
	Prob > F	=	0.2044
	R-squared	=	0.0003
	Root MSE	=	.01919

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr	.002305	.0018156	1.27	0.204	0012556	.0058656
_cons	.000316	.0004365	0.72	0.469	0005401	.0011721

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	3.29
	Prob > F	=	0.0058
	R-squared	=	0.0014
	Root MSE	=	.0192

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	004282	.0032026	-1.34	0.181	0105628	.0019989
d2	.0060651	.0021924	2.77	0.006	.0017654	.0103648
d3	.008685	.0033018	2.63	0.009	.0022095	.0151604
d4	0004887	.0030139	-0.16	0.871	0063994	.0054221
d5	.0015456	.0055079	0.28	0.779	0092563	.0123475
_cons	.000316	.000437	0.72	0.470	000541	.001173

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	2.75
	Prob > F	=	0.0976
	R-squared	=	0.0006
	Root MSE	=	.02275

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr	.0039382	.0023758	1.66	0.098	0007212	.0085976
_cons	.0000777	.000517	0.15	0.881	0009363	.0010917

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	1.40
	Prob > F	=	0.2219
	R-squared	=	0.0013
	Root MSE	=	.02276

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	.0039602	.0031609	1.25	0.210	0022388	.0101591
d2	.0021975	.0056971	0.39	0.700	0089754	.0133704
d3	.0077606	.0051069	1.52	0.129	0022549	.0177761
d4	.0087543	.0052253	1.68	0.094	0014933	.019002
d5	0029817	.0053932	-0.55	0.580	0135585	.0075951
_cons	.0000777	.0005176	0.15	0.881	0009373	.0010927

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	1.22
	Prob > F	=	0.2692
	R-squared	=	0.0002
	Root MSE	=	.01688

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr	.0018036	.0016318	1.11	0.269	0013966	.0050038
_cons	.0001054	.0003839	0.27	0.784	0006476	.0008584

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	2.70
	Prob > F	=	0.0192
	R-squared	=	0.0010
	Root MSE	=	.01689

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	.0043235	.001533	2.82	0.005	.001317	.0073299
d2	0017706	.0022445	-0.79	0.430	0061724	.0026312
d3	.0031185	.0020421	1.53	0.127	0008864	.0071234
d4	.0060063	.0036638	1.64	0.101	0011789	.0131915
d5	0026596	.0056072	-0.47	0.635	0136561	.0083369
_cons	.0001054	.0003843	0.27	0.784	0006483	.0008591

d3

d4

d5

\_cons

.006352

.0021604

.0002912

.0001311

.005707

.0027058

.0084963

.000377

Linear regress	ion			Number	of obs	=	1,999
_				F(1, 19	97)	=	3.68
				Prob >	F	=	0.0553
				R-squar	ed	=	0.0014
				Root MS	Ε	=	.01663
		Robust					
Returns	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
Eidalfitr	.0044294	.0023099	1.92	0.055	000	1006	.0089595
_cons	.0001311	.0003766	0.35	0.728	000	6075	.0008697
. reg Returns	d1 d2 d3 d4 (	d5, robust					
. reg Returns Linear regress		d5, robust		Number F(5, 19	93)	=	1,999 10.46
-		d5, robust		F(5, 19 Prob >	93) F	=	10.46 0.0000
-		d5, robust		F(5, 19	93) F	=	10.46
-		d5, robust Robust		F(5, 19 Prob > R-squar	93) F	= = =	10.46 0.0000 0.0020
-			t	F(5, 19 Prob > R-squar	993) F red SE	= = =	10.46 0.0000 0.0020

1.11

0.80

0.03

0.35

0.266

0.425

0.973

0.728

-.0048403

-.003146

-.0163714

-.0006082

.0175444

.0074668

.0169538

.0008704

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	1.53
	Prob > F	=	0.2160
	R-squared	=	0.0004
	Root MSE	=	.01492

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr	.0022416	.0018111	1.24	0.216	0013103	.0057934
_cons	.0003412	.0003387	1.01	0.314	000323	.0010054

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	2.63
	Prob > F	=	0.0221
	R-squared	=	0.0013
	Root MSE	=	.01493

Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
.0052119	.0026193	1.99	0.047	.0000752	.0103487
.0034041	.0014956	-2.28	0.023	0063373	000471
.0049799	.0057477	0.87	0.386	0062922	.016252
.0032491	.0019416	1.67	0.094	0005586	.0070568
.001171	.0052585	0.22	0.824	0091417	.0114838
.0003412	.000339	1.01	0.314	0003236	.001006
	.0052119 .0034041 .0049799	.0052119 .0026193 .0034041 .0014956 .0049799 .0057477 .0032491 .0019416 .001171 .0052585	.0052119 .0026193 1.99 .0034041 .0014956 -2.28 .0049799 .0057477 0.87 .0032491 .0019416 1.67 .001171 .0052585 0.22	.0052119 .0026193 1.99 0.047 .0034041 .0014956 -2.28 0.023 .0049799 .0057477 0.87 0.386 .0032491 .0019416 1.67 0.094 .001171 .0052585 0.22 0.824	.0052119 .0026193 1.99 0.047 .0000752 .0034041 .0014956 -2.28 0.0230063373 .0049799 .0057477 0.87 0.3860062922 .0032491 .0019416 1.67 0.0940005586 .001171 .0052585 0.22 0.8240091417

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	0.08
	Prob > F	=	0.7774
	R-squared	=	0.0000
	Root MSE	=	.01245

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr	.0003877	.001371	0.28	0.777	002301	.0030764
_cons	.0004922	.0002829	1.74	0.082	0000625	

# . reg Returns d1 d2 d3 d4 d5, robust

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	0.46
	Prob > F	=	0.8072
	R-squared	=	0.0006

Root MSE = .01246

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	.0023961	.0041079	0.58	0.560	0056601	.0104523
d2	.0013397	.0018622	0.72	0.472	0023124	.0049917
d3	.0008576	.0018225	0.47	0.638	0027167	.0044319
d4	.0010125	.0025213	0.40	0.688	0039323	.0059572
d5	0036674	.003564	-1.03	0.304	010657	.0033222
_cons	.0004922	.0002832	1.74	0.082	0000631	.0010475

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	8.04
	Prob > F	=	0.0046
	R-squared	=	0.0024
	Root MSE	=	.01305

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr	.0045572	.0016069	2.84	0.005	.0014059	.0077086
_cons	0001289	.000296	-0.44	0.663	0007094	.0004516

Linear regression	Number of obs	=	1.999
Linear regression	F(5, 1993)	=	5.15
	Prob > F	=	0.0001
	R-squared	=	0.0044
	Root MSE	=	.01305

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	.0089857	.0029793	3.02	0.003	.0031429	.0148286
d2	.0086639	.0022447	3.86	0.000	.0042617	.0130661
d3	.0055154	.00495	1.11	0.265	0041924	.0152232
d4	0015386	.0019644	-0.78	0.434	0053912	.0023139
d5	.0011598	.003139	0.37	0.712	0049962	.0073159
_cons	0001289	.0002963	-0.43	0.664	00071	.0004522

Linear regress	sion			Number F(1, 19 Prob > R-squar Root MS	97) = F = ed =	1,999 0.48 0.4895 0.0001 .01658
Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr _cons	.0012099 .0004428	.0017503 .0003768	0.69 1.18	0.489 0.240	0022228 0002961	.0046426 .0011817
. reg Returns		d5, robust		Number F(5, 19 Prob > R-squar Root MS	93) = F = ed =	1,999 0.71 0.6161 0.0007 .01659
Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1 d2 d3 d4 d5 _cons	.0046162 .0037564 0007834 0030188 .0014791 .0004428	.0036685 .0038707 .0030708 .0033264 .0044666	1.26 0.97 -0.26 -0.91 0.33 1.17	0.208 0.332 0.799 0.364 0.741 0.240	0025782 0038346 0068057 0095423 0072805 0002968	.0118107 .0113475 .0052388 .0035047 .0102388 .0011824

# Table 2 (Post):

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	3.57
	Prob > F	=	0.0591
	R-squared	=	0.0009
	Root MSE	=	.0134

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr	.002869	.0015189	1.89	0.059	0001098	.0058478
_cons	.0003256	.0003042	1.07	0.285	000271	.0009222

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	3.96
	Prob > F	=	0.0014
	R-squared	=	0.0027
	Root MSE	=	.0134

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6	.0090607	.0022936	3.95	0.000	.0045626	.0135587
d7	.0037414	.0026036	1.44	0.151	0013647	.0088475
d8	.0027863	.0036793	0.76	0.449	0044293	.0100019
d9	0034354	.0030471	-1.13	0.260	0094113	.0025405
d10	.0021919	.0033368	0.66	0.511	004352	.0087358
_cons	.0003256	.0003045	1.07	0.285	0002716	.0009228

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	5.58
	Prob > F	=	0.0182
	R-squared	=	0.0038
	Root MSE	=	.01223

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr	.0053877	.0022803	2.36	0.018	.0009157	.0098596
_cons	0000575	.0002754	-0.21	0.835	0005975	.0004826

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	2.75
	Prob > F	=	0.0174
	R-squared	=	0.0086
	Root MSE	=	.01222

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6	.0167595	.0081936	2.05	0.041	.0006907	.0328284
d7	.0024154	.0019462	1.24	0.215	0014013	.0062322
d8	.0009786	.0028255	0.35	0.729	0045626	.0065198
d9	.0005161	.0047088	0.11	0.913	0087186	.0097508
d10	.0062687	.002196	2.85	0.004	.001962	.0105753
_cons	0000575	.0002756	-0.21	0.835	0005981	.0004831

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	18.24
	Prob > F	=	0.0000
	P-squared	_	0 0020

R-squared = Root MSE = .01513

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr	.0058694	.0013745	4.27	0.000	.0031738	.008565
_cons	0004703	.0003442	-1.37	0.172	0011452	.0002047

# . reg Returns d6 d7 d8 d9 d10, robust

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	6.08
	Prob > F	=	0.0000
	R-squared	=	0.0037

R-squared Root MSE .01514

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6	.0108558	.0024175	4.49	0.000	.0061147	.015597
d7	.0073087	.0033125	2.21	0.027	.0008123	.0138051
d8	.0040978	.0025323	1.62	0.106	0008684	.0090641
d9	.0029574	.0034008	0.87	0.385	0037122	.0096269
d10	.0041272	.0022229	1.86	0.064	0002322	.0084866
_cons	0004703	.0003445	-1.37	0.172	0011459	.0002054

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	3.61
	Prob > F	=	0.0577
	R-squared	=	0.0006
	Root MSE	=	.01155

	Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
E	idalfitr _cons	.002037 .0001068	.0010728 .0002627	1.90 0.41	0.058 0.684	0000669 0004083	.0041409

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	1.85
	Prob > F	=	0.0999
	R-squared	=	0.0015
	Root MSE	=	.01155

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6	.0065553	.0022914	2.86	0.004	.0020615	.011049
d7	.0001775	.0016876	0.11	0.916	0031322	.0034872
d8	.0001362	.0017343	0.08	0.937	003265	.0035374
d9	.0005755	.0023935	0.24	0.810	0041186	.0052696
d10	.0027405	.0026144	1.05	0.295	0023868	.0078677
_cons	.0001068	.0002629	0.41	0.685	0004088	.0006225

regression Number of obs	=	1,999
F(1, 1997)	=	0.78
Prob > F	=	0.3778
R-squared	=	0.0001
Root MSE	=	.01351
	F(1, 1997) Prob > F R-squared	F(1, 1997) = Prob > F = R-squared =

Return	s	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfit		.0010565	.0011976	0.88	0.378	0012921	.0034051
_con		.0004136	.0003074	1.35	0.179	0001894	.0010165

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	2.11
	Prob > F	=	0.0615
	R-squared	=	0.0007
	Root MSE	=	.01352

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6	.0039665	.0026689	1.49	0.137	0012677	.0092007
d7	.0011204	.0030176	0.37	0.710	0047976	.0070384
d8	0025171	.0020757	-1.21	0.225	0065878	.0015537
d9	0004142	.0029241	-0.14	0.887	0061489	.0053204
d10	.0031269	.0012132	2.58	0.010	.0007476	.0055063
_cons	.0004136	.0003078	1.34	0.179	00019	.0010171

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	4.35
	Prob > F	=	0.0371
	R-squared	=	0.0013
	Root MSE	=	.0191

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr	.0048989	.0023482	2.09	0.037	.0002938	.0095041
_cons	.0003055	.0004333	0.71	0.481	0005443	.0011553

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	4.00
	Prob > F	=	0.0013
	R-squared	=	0.0022
	Root MSE	=	.01911

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6	.0115602	.0029755	3.89	0.000	.0057247	.0173956
d7	.0045817	.0020926	2.19	0.029	.0004777	.0086856
d8	.0064686	.0080143	0.81	0.420	0092486	.0221858
d9	.0003312	.0045515	0.07	0.942	0085949	.0092573
d10	.001553	.0051265	0.30	0.762	0085009	.011607
_cons	.0003055	.0004338	0.70	0.481	0005451	.0011562

Linear regres	sion			Number of of F(1, 1997) Prob > F R-squared Root MSE	obs = = = = = = =	1,999 4.00 0.0457 0.0010 .01584
Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr _cons	.0035503 .0002494	.0017757 .0003598	2.00 0.69		.0000678 .0004562	.0070328
. reg Returns	d6 d7 d8 d9	d10, robust				
linear regress						
	SION			Number of a	obs =	1.999
Linear regres	sion			Number of ( F(5, 1993)	obs = =	1,999 3.09
Linear regress	sion			Number of ( F(5, 1993) Prob > F		-
Linear regress	sion			F(5, 1993) Prob > F	=	3.09
Linear regres:	sion			F(5, 1993)	=	3.09 0.0088
Returns	Coef.	Robust Std. Err.	t	F(5, 1993) Prob > F R-squared Root MSE	= = =	3.09 0.0088 0.0024 .01585
			t 3.68	F(5, 1993) Prob > F R-squared Root MSE	= = =	3.09 0.0088 0.0024 .01585
Returns	Coef.	Std. Err.		F(5, 1993) Prob > F R-squared Root MSE  P> t  0.000	= = = = [95% Conf.	3.09 0.0088 0.0024 .01585
Returns d6 d7 d8	Coef. .0105532 .0011008 .0059049	Std. Err0028665 .0024739 .0056381	3.68	F(5, 1993) Prob > F R-squared Root MSE  P> t   0.000 0.656 0.295	= = = = [95% Conf.	3.09 0.0088 0.0024 .01585 Interval] .0161749 .0059525 .0169621
Returns d6 d7 d8 d9	Coef0105532 .0011008 .00590490013513	Std. Err0028665 .0024739 .0056381 .0039953	3.68 0.44 1.05 -0.34	F(5, 1993) Prob > F R-squared Root MSE  P> t   0.000 0.656 0.295 0.735	= = = = [95% Conf. .0049315 .0037508 .0051523	3.09 0.0088 0.0024 .01585 Interval] .0161749 .0059525 .0169621 .0064841
Returns d6 d7 d8	Coef. .0105532 .0011008 .0059049	Std. Err0028665 .0024739 .0056381	3.68 0.44 1.05	F(5, 1993) Prob > F R-squared Root MSE  P> t   0.000 0.656 0.295 0.735 0.388	= = = = [95% Conf. .0049315 .0037508	3.09 0.0088 0.0024 .01585 Interval] .0161749 .0059525 .0169621

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	12.63
	Prob > F	=	0.0004
	R-squared	=	0.0028
	Poot MSE	_	01017

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr	.0072581	.0020421	3.55	0.000	.0032532	.011263
_cons	.0002169	.0004356	0.50	0.619	0006374	.0010711

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	6.06
	Prob > F	=	0.0000
	R-squared	=	0.0053
	Root MSE	=	.01916

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6	.0206454	.0040301	5.12	0.000	.0127418	.028549
d7	.0028394	.0027665	1.03	0.305	0025862	.0082649
d8	.0048298	.0049068	0.98	0.325	0047932	.0144527
d9	.0056053	.0043966	1.27	0.202	0030171	.0142277
d10	.0023706	.0020894	1.13	0.257	001727	.0064682
_cons	.0002169	.000436	0.50	0.619	0006382	.0010719

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	3.05
	Prob > F	=	0.0807
	R-squared	=	0.0004

Root MSE = .02275

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr	.0032341	.0018506	1.75	0.081	0003952	.0068633
_cons	.0000918	.000518	0.18	0.859	000924	.0011076

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	0.78
	Prob > F	=	0.5671
	R-squared	=	0.0008
	Root MSE	=	.02277

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6	.0095113	.0060077	1.58	0.114	0022708	.0212934
d7	.0018169	.0026707	0.68	0.496	0034207	.0070544
d8	.0009219	.0028937	0.32	0.750	0047531	.006597
d9	.002676	.0028142	0.95	0.342	002843	.0081951
d10	.0012442	.0038072	0.33	0.744	0062222	.0087106
_cons	.0000918	.0005185	0.18	0.859	0009251	.0011087

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	13.41
	Prob > F	=	0.0003
	R-squared	=	0.0026
	Root MSE	=	.01686

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr	.0060991	.0016654	3.66	0.000	.0028329	.0093653
_cons	.0000194	.0003834	0.05	0.960	0007325	.0007714

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	5.85
	Prob > F	=	0.0000
	R-squared	=	0.0039
	Root MSE	=	.01687

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6	.0123615	.0039913	3.10	0.002	.004534	.020189
d7	.0061676	.0029293	2.11	0.035	.0004228	.0119124
d8	.0046254	.0012837	3.60	0.000	.0021079	.0071429
d9	0010225	.0031043	-0.33	0.742	0071104	.0050655
d10	.0083634	.0043067	1.94	0.052	0000827	.0168095
_cons	.0000194	.0003838	0.05	0.960	0007333	.0007722

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	3.52
	Prob > F	=	0.0609
	R-squared	=	0.0008
	Root MSE	=	.01663

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr	.0033849	.001805	1.88	0.061	000155	.0069247
_cons	.000152	.0003779	0.40	0.688	0005891	

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	2.72
	Prob > F	=	0.0186
	R-squared	=	0.0024
	Root MSE	=	.01664

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6	.0101845	.0033389	3.05	0.002	.0036363	.0167327
d7	.0017491	.0028132	0.62	0.534	003768	.0072662
d8	.0036984	.0032332	1.14	0.253	0026424	.0100391
d9	0039638	.0048089	-0.82	0.410	0133949	.0054672
d10	.0052562	.0035713	1.47	0.141	0017477	.0122602
_cons	.000152	.0003782	0.40	0.688	0005898	.0008938

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	2.08
	Prob > F	=	0.1492
	R-squared	=	0.0005
	Root MSE	=	.01492

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr	.0024767	.0017163	1.44	0.149	0008891	.0058426
_cons	.0003365	.0003388	0.99	0.321	000328	.001001

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	2.05
	Prob > F	=	0.0687
	R-squared	=	0.0032
	Root MSE	=	.01492

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6	.0126728	.0043241	2.93	0.003	.0041927	.021153
d7	.003052	.0043325	0.70	0.481	0054448	.0115487
d8	0006335	.002413	-0.26	0.793	0053658	.0040989
d9	0026934	.0026391	-1.02	0.308	007869	.0024822
d10	0000143	.001677	-0.01	0.993	0033031	.0032746
_cons	.0003365	.0003392	0.99	0.321	0003287	.0010017

Linear regres	sion	Number of obs	=	1,999
		F(1, 1997)	=	2.64
		Prob > F	=	0.1043
		R-squared	=	0.0008
		Root MSE	=	.01245

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr	.0025026	.0015399	1.63	0.104	0005174	.0055227
_cons	.0004499	.0002824	1.59	0.111	0001039	.0010037

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	3.94
	Prob > F	=	0.0015
	R-squared	=	0.0053
	Root MSE	=	.01243

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6	.0129368	.0038152	3.39	0.001	.0054547	.0204189
d7	.0017651	.0026081	0.68	0.499	0033498	.0068799
d8	0027014	.0021196	-1.27	0.203	0068583	.0014555
d9	0035706	.00222	-1.61	0.108	0079243	.0007831
d10	.0040834	.0022309	1.83	0.067	0002917	.0084585
_cons	.0004499	.0002827	1.59	0.112	0001045	.0010043

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	6.03
	Prob > F	=	0.0142
	R-squared	=	0.0009
	Root MSF	=	. 01306

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr	.0028566	.0011635	2.46	0.014	.0005748	.0051384
_cons	0000948	.0002971	-0.32	0.750	0006775	.0004878

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	1.88
	Prob > F	=	0.0941
	R-squared	=	0.0015
	Root MSE	=	.01307

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6	.0069329	.0029995	2.31	0.021	.0010504	.0128154
d7	.0022429	.0024653	0.91	0.363	0025919	.0070777
d8	.0009223	.0030567	0.30	0.763	0050724	.006917
d9	.0018217	.001274	1.43	0.153	0006769	.0043202
d10	.0023633	.0018265	1.29	0.196	0012187	.0059453
_cons	0000948	.0002974	-0.32	0.750	0006781	.0004884

Linear regress	sion			Number of of F(1, 1997) Prob > F R-squared Root MSE	obs = = = = = =	1,999 5.59 0.0182 0.0015 .01657
Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidalfitr _cons	.0045327 .0003763	.0019176 .0003762	2.36 1.00		.0007721 .0003614	.0082933
. reg Returns		d10, robust		Number of of form of the following series of the follo	obs = = = = = =	1,999 2.45 0.0316 0.0022 .01658
Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6 d7 d8 d9 d10 _cons	.0104594 .0045313 .0016986 .00258 .0033943 .0003763	.0033209 .0036265 .0042031 .0043283 .0047584 .0003765	3.15 1.25 0.40 0.60 0.71 1.00	0.212 0.686 0.551 0.476	.0039465 .0025809 .0065443 .0059085 .0059376	.0169723 .0116435 .0099415 .0110684 .0127262

# Table 3 (Pre):

Linear regression	Number of obs	=	1,924
	F(1, 1922)	=	2.04
	Prob > F	=	0.1532
	R-squared	=	0.0005
	Root MSE	=	.01346

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	.0023011	.0016105	1.43	0.153	0008575	.0054597
_cons	.0002022	.0003112	0.65	0.516	0004081	.0008124

# . reg Returns d1 d2 d3 d4 d5, robust

Linear regression	Number of obs	=	1,924
	F(5, 1918)	=	0.69
	Prob > F	=	0.6342
	R-squared	=	0.0008

Root MSE = .01347

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	.0038319	.0028663	1.34	0.181	0017894	.0094532
d2	.0029388	.0037026	0.79	0.427	0043228	.0102004
d3	.0000992	.002076	0.05	0.962	0039722	.0041707
d4	.0045966	.0044679	1.03	0.304	0041659	.0133591
d5	.0002579	.0036167	0.07	0.943	0068352	.0073509
_cons	.0002022	.0003115	0.65	0.516	0004087	.000813

Linear regression	Number of obs	=	1,924
	F(1, 1922)	=	2.73
	Prob > F	=	0.0987
	R-squared	=	0.0007
	Root MSE	=	.01231

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	.0025359	.0015349	1.65	0.099	0004744	.0055462
_cons	0000469	.0002844	-0.16	0.869	0006046	.0005109

Linear regression	Number of obs	=	1,924
	F(5, 1918)	=	1.36
	Prob > F	=	0.2346
	R-squared	=	0.0018
	Root MSE	=	.01232

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	.0065197	.0035921	1.81	0.070	0005252	.0135646
d2	0021303	.0022567	-0.94	0.345	0065562	.0022956
d3	.0007302	.0023956	0.30	0.761	003968	.0054284
d4	.0051623	.0037751	1.37	0.172	0022415	.0125661
d5	.0029667	.0036131	0.82	0.412	0041192	.0100527
_cons	0000469	.0002847	-0.16	0.869	0006052	.0005115

Linear regression	Number of obs	=	1,924
	F(1, 1922)	=	0.23
	Prob > F	=	0.6334
	R-squared	=	0.0000
	Root MSE	=	.01534

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	0006197	.0012992	-0.48	0.633	0031676	.0019283
_cons	0003964	.0003552	-1.12	0.265	0010931	.0003003

Linear regression	Number of obs	=	1,924
	F(5, 1918)	=	1.50
	Prob > F	=	0.1850
	R-squared	=	0.0007
	Root MSE	=	.01535

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0030664	.001968	-1.56	0.119	006926	.0007932
d2	0050853	.0026604	-1.91	0.056	0103028	.0001322
d3	.0006312	.0021324	0.30	0.767	0035508	.0048133
d4	.0012923	.0031684	0.41	0.683	0049217	.0075063
d5	.0027803	.0026479	1.05	0.294	0024128	.0079734
_cons	0003964	.0003556	-1.11	0.265	0010938	.000301

Linear regression	Number of obs	=	1,924
	F(1, 1922)	=	0.21
	Prob > F	=	0.6457
	R-squared	=	0.0000
	Root MSE	=	.01169

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	0004408	.0009587	-0.46	0.646	0023211	.0014394
_cons	.0001085	.0002708	0.40	0.689	0004226	.0006395

Linear regression	Number of obs	=	1,924
	F(5, 1918)	=	4.02
	Prob > F	=	0.0012
	R-squared	=	0.0011
	Root MSE	=	.0117

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	.0045803	.0014346	3.19	0.001	.0017668	.0073938
d2	0018809	.001476	-1.27	0.203	0047756	.0010138
d3	003525	.0016591	-2.12	0.034	0067789	0002712
d4	0021067	.0012514	-1.68	0.092	004561	.0003476
d5	.0014455	.0025827	0.56	0.576	0036196	.0065107
_cons	.0001085	.0002711	0.40	0.689	0004231	.0006401

Linear regress	sion			Number of F(1, 1922) Prob > F R-squared Root MSE		1,924 0.00 0.9931 0.0000 .01352
Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha _cons	9.81e-06 .0003739	.0011354 .0003131	0.01 1.19		0022168 0002402	.0022365
. reg Returns	d1 d2 d3 d4	d5, robust				
Linear regress	sion			Number of	obs =	1,924
				F(5, 1918)	=	1.12
				Prob > F	=	0.3458
				R-squared	=	0.0004
				Root MSE	=	.01353
Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0029272	.0024316	-1.20	0.229 -	.0076961	.0018417
d1 d2	0023272	.0032245	-0.22		0070356	.0056121
d2	.0017942	.0020369	0.88		0022006	.005789
d4	0014864	.0017432	-0.85		0049052	.0019325
d5	.0029606	.0018797	1.57	0.115	000726	.0066471
_cons	.0003739	.0003134	1.19	0.233 -	0002408	.0009885
	I					

Linear regression	Number of obs	=	1,924
	F(1, 1922)	=	0.09
	Prob > F	=	0.7696
	R-squared	=	0.0000
	Root MSF	_	01028

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	0004742	.0016186	-0.29	0.770	0036485	.0027001
_cons	.0003915	.0004466	0.88	0.381	0004845	.0012674

Linear regression	Number of obs	=	1,924
	F(5, 1918)	=	1.67
	Prob > F	=	0.1397
	R-squared	=	0.0006
	Root MSE	=	.0193

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	001789	.0045057	-0.40	0.691	0106257	.0070477
d2	0043966	.0022379	-1.96	0.050	0087856	-7.61e-06
d3	0018347	.003055	-0.60	0.548	0078261	.0041568
d4	0006659	.003149	-0.21	0.833	0068417	.0055098
d5	.0061275	.0031715	1.93	0.053	0000924	.0123473
_cons	.0003915	.0004471	0.88	0.381	0004854	.0012683

Linear regression	Number of obs	=	1,924
	F(1, 1922)	=	0.16
	Prob > F	=	0.6867
	R-squared	=	0.0000
	Root MSE	=	.01596

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	.000519	.0012866	0.40	0.687	0020042	.0030423
_cons	.0002583	.0003698	0.70	0.485	000467	

Linear regression	Number of obs	=	1,924
	F(5, 1918)	=	0.67
	Prob > F	=	0.6461
	R-squared	=	0.0003
	Root MSE	=	.01598

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	.0024312	.0021036	1.16	0.248	0016945	.0065568
d2	0025619	.0021233	-1.21	0.228	0067261	.0016024
d3	.0004012	.0019142	0.21	0.834	003353	.0041553
d4	.0000134	.0026741	0.01	0.996	0052311	.0052579
d5	.0025844	.0039388	0.66	0.512	0051405	.0103092
_cons	.0002583	.0003702	0.70	0.485	0004678	.0009843

Linear regression	Number of obs	=	1,924
	F(1, 1922)	=	0.25
	Prob > F	=	0.6147
	R-squared	=	0.0001
	Root MSE	=	.0194

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	0012601	.0025031	-0.50	0.615	0061691	.0036489
_cons	.000309	.0004481	0.69	0.491	0005698	.0011878

Linear regression	Number of obs	=	1,924
	F(5, 1918)	=	1.58
	Prob > F	=	0.1620
	R-squared	=	0.0020
	Root MSE	=	.0194

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	0056321	.0039954	-1.41	0.159	0134679	.0022037
d2	0066052	.0042218	-1.56	0.118	0148849	.0016745
d3	0013756	.0039782	-0.35	0.730	0091777	.0064266
d4	0041265	.0053191	-0.78	0.438	0145583	.0063054
d5	.0108143	.0064916	1.67	0.096	0019171	.0235456
_cons	.000309	.0004486	0.69	0.491	0005708	.0011887

Linear regression	Number of obs	=	1,924
	F(1, 1922)	=	2.02
	Prob > F	=	0.1551
	R-squared	=	0.0003
	Poot MSE	_	02301

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	0032445	.0022811	-1.42	0.155	0077183	.0012293
_cons	.0001331	.0005325	0.25	0.803	0009112	.0011774

Linear regression	Number of obs	=	1,924
	F(5, 1918)	=	2.83
	Prob > F	=	0.0149
	R-squared	=	0.0011
	Root MSE	=	.02302

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	0036028	.0022369	-1.61	0.107	0079898	.0007842
d2	0042646	.0015223	-2.80	0.005	0072501	001279
d3	0087267	.0047561	-1.83	0.067	0180544	.0006011
d4	0050729	.0058372	-0.87	0.385	0165207	.006375
d5	.0053933	.0062715	0.86	0.390	0069064	.0176929
_cons	.0001331	.000533	0.25	0.803	0009123	.0011785

Linear regression	Number of obs	=	1,924
	F(1, 1922)	=	0.21
	Prob > F	=	0.6463
	R-squared	=	0.0000
	Root MSE	=	.01708

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	.0008644	.0018833	0.46	0.646	0028291	.0045579
_cons	.0000954	.000395	0.24	0.809	0006792	.0008701

Linear regression	Number of obs	=	1,924
	F(5, 1918)	=	2.01
	Prob > F	=	0.0739
	R-squared	=	0.0010
	Root MSE	=	.01709

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	.0031294	.001894	1.65	0.099	0005851	.0068439
d2	003459	.0036395	-0.95	0.342	0105968	.0036788
d3	0034115	.001584	-2.15	0.031	006518	000305
<b>d4</b>	.001458	.0030851	0.47	0.637	0045925	.0075085
d5	.0069287	.0064609	1.07	0.284	0057423	.0195997
_cons	.0000954	.0003954	0.24	0.809	00068	.0008709

Linear regression	Number of obs	=	1,924
	F(1, 1922)	=	1.55
	Prob > F	=	0.2130
	R-squared	=	0.0003
	Root MSE	=	.01677

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	.0023483	.0018852	1.25	0.213	0013489	.0060455
_cons	.0000881	.0003878	0.23	0.820	0006724	.0008487

Linear regression	Number of obs	=	1,924
	F(5, 1918)	=	1.44
	Prob > F	=	0.2067
	R-squared	=	0.0013
	Root MSE	=	.01678

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	.0045793	.0024258	1.89	0.059	0001782	.0093367
d2	0034281	.0027604	-1.24	0.214	0088417	.0019855
d3	.0002646	.0015591	0.17	0.865	002793	.0033222
d4	.0026451	.0038884	0.68	0.496	0049808	.010271
d5	.0079995	.0064092	1.25	0.212	0045703	.0205693
_cons	.0000881	.0003882	0.23	0.820	0006732	.0008494

Linear regress	ion	Numbe	r of	obs	=	1,924
		E/1 1	1022	١	_	0 02

F(1, 1922) = 0.02 Prob > F = 0.8999 R-squared = 0.0000 Root MSE = .01507

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	0001726	.0013719	-0.13	0.900	0028632	.0025181
_cons	.0003613	.0003489	1.04	0.301	000323	.0010456

#### . reg Returns d1 d2 d3 d4 d5, robust

Linear regression Number of obs = 1,924F(5, 1918) = 0.51

Number of obs = 1,924 F(5, 1918) = 0.51 Prob > F = 0.7703 R-squared = 0.0003 Root MSE = .01508

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	.0025773	.0029869	0.86	0.388	0032806	.0084352
d2	0010271	.0025073	-0.41	0.682	0059444	.0038903
d3	0012692	.0017627	-0.72	0.472	0047262	.0021877
<b>d4</b>	.0016053	.0018232	0.88	0.379	0019703	.0051809
d5	0023563	.0045368	-0.52	0.604	0112539	.0065413
_cons	.0003613	.0003493	1.03	0.301	0003237	.0010463

Linear regression	Number of obs	=	1,924
	F(1, 1922)	=	0.54
	Prob > F	=	0.4613
	R-squared	=	0.0001
	Root MSE	=	.01258

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	0010484	.001423	-0.74	0.461	0038392	.0017423
_cons	.000537	.0002909	1.85	0.065	0000335	.0011075

#### . reg Returns d1 d2 d3 d4 d5, robust

.000537

\_cons

Linear regression	Number of obs	=	1,924
	F(5, 1918)	=	0.80
	Prob > F	=	0.5511
	R-squared	=	0.0005

Root MSE

0.065

-.0000341

.01259

.001108

Robust Returns Coef. Std. Err. [95% Conf. Interval] t P>|t| d1 .0002222 .0023744 0.09 0.925 -.0044345 .0048788 d2 -.0037251 .0021168 -1.76 0.079 -.0078765 .0004263 d3 .0040178 -.0016392 -0.41 0.683 -.009519 .0062406 d4 -.0015168 .0037833 -0.40 0.689 -.0089367 .0059031 d5 .0015981 .0022097 0.72 0.470 -.0027356 .0059318

1.84

.0002912

Linear regression	Number of obs	=	1,924
	F(1, 1922)	=	0.05
	Prob > F	=	0.8196
	R-squared	=	0.0000
	Root MSE	=	.01314

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	.0002512	.0011011	0.23	0.820	0019084	.0024107
_cons	0001466	.0003043	-0.48	0.630	0007435	.0004503

Linear regression	Number of obs	=	1,924
	F(5, 1918)	=	5.24
	Prob > F	=	0.0001
	R-squared	=	0.0007
	Root MSE	=	.01315

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	.0046277	.0009585	4.83	0.000	.0027479	.0065076
d2	.0014639	.0030477	0.48	0.631	0045134	.0074411
d3	0002234	.0015776	-0.14	0.887	0033174	.0028706
d4	0008238	.0020219	-0.41	0.684	0047891	.0031415
d5	0031633	.0024375	-1.30	0.195	0079437	.0016171
_cons	0001466	.0003047	-0.48	0.630	0007441	.0004509

Linear regress	sion			Number	of obs	=	1,924
				F(1, 19		=	0.03
				Prob >		=	0.8676
				R-squar		=	0.0070
				Root MS		=	.01674
				KOUL MS	· E	_	.01074
		Robust					
Returns	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
Eidaladha	.0002566	.0015393	0.17	0.868	002	7623	.0032756
_cons	.0004769	.0003877	1.23	0.219	0002	2834	.0012372
. reg Returns	d1 d2 d3 d4 d	d5, robust					
Linear regress	sion			Number	of obs	=	1,924
				F(5, 19	18)	=	1.26
				Prob >	F	=	0.2798
				R-squar	ed	=	0.0006
				Root MS	E	=	.01676
		Robust					
Returns	Coef.	Std. Err.	t	P> t	[95%	Cont.	Interval]
<b>d1</b>	.0006332	.0019349	0.33	0.744	003	1616	.0044279
d2	0037157	.0018913	-1.96	0.050	007	7425	-6.42e-06
d3	0018718	.0029423	-0.64	0.525	007	6422	.0038986
d4	.0056387	.0042458	1.33	0.184	002	6881	.0139655
d5	.0006526	.0036148	0.18	0.857	0064	4368	.007742
_cons	.0004769	.0003881	1.23	0.219	0002	2842	.001238

# Table 3 (Post):

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	0028229	.0024167	-1.17	0.243	0075624	.0019167
_cons	.0004395	.0003018	1.46	0.145	0001524	.0010313

#### . reg Returns d1 d2 d3 d4 d5, robust

Root MSE = .0134

Interval]	[95% Conf.	P> t	t	Robust Std. Err.	Coef.	Returns
.0084767	0211159	0.402	-0.84	.0075447	0063196	d1
.0114324	006894	0.627	0.49	.0046723	.0022692	d2
.010088	0095114	0.954	0.06	.0049969	.0002883	d3
.0016993	011932	0.141	-1.47	.0034753	0051164	d4
.0038137	0142853	0.257	-1.13	.0046144	0052358	d5
.0010319	000153	0.146	1.45	.0003021	.0004395	_cons

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	11.73
	Prob > F	=	0.0006
	R-squared	=	0.0096
	Root MSE	=	.0122

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	0085821	.0025063	-3.42	0.001	0134973	0036669
_cons	.0002221	.0002737	0.81	0.417	0003147	.0007589

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	4.03
	Prob > F	=	0.0012
	R-squared	=	0.0137
	Root MSE	=	.01219

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	017662	.0068687	-2.57	0.010	0311327	0041914
d2	0005098	.0041176	-0.12	0.901	008585	.0075655
d3	0089399	.0028996	-3.08	0.002	0146264	0032533
d4	0091194	.0052934	-1.72	0.085	0195006	.0012617
d5	0066793	.0060229	-1.11	0.268	0184911	.0051326
_cons	.0002221	.000274	0.81	0.418	0003153	.0007594

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	2.47
	Prob > F	=	0.1161
	R-squared	=	0.0019
	Root MSE	=	.01513

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	0046596	.0029642	-1.57	0.116	0104729	.0011537
_cons	0002596	.0003401	-0.76	0.445	0009267	.0004075

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	0.88
	Prob > F	=	0.4931
	R-squared	=	0.0037
	Root MSE	=	.01514

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0104389	.0099018	-1.05	0.292	0298579	.00898
d2	.0020951	.0060028	0.35	0.727	0096773	.0138675
d3	0016457	.0023372	-0.70	0.481	0062293	.0029379
d4	004814	.004677	-1.03	0.303	0139863	.0043583
d5	0084945	.0065941	-1.29	0.198	0214265	.0044374
_cons	0002596	.0003405	-0.76	0.446	0009273	.0004082

R-squared = 0.0017 Root MSE = .01154

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	0034018	.0020672	-1.65	0.100	007456	.0006523
_cons	.0002157	.00026	0.83	0.407	0002943	.0007256

#### . reg Returns d1 d2 d3 d4 d5, robust

Linear regression Number of obs = 1,999F(5, 1993) = 1.42

> Prob > F = 0.2147 R-squared = 0.0037

> > .01154

Root MSE

Robust Returns Coef. Std. Err. t P>|t| [95% Conf. Interval] .0064076 **d1** -.0091548 .0079354 -1.15 0.249 -.0247173 d2 -.0002893 .0030906 -0.090.925 -.0063505 .0057719 d3 -.0026114 .0014427 -1.81 0.070 -.0054408 .0002179 0.25 d4 .0007804 .0031011 0.801 -.0053014 .0068621 -.0057339 .0036275 -1.58 0.114 -.012848 .0013801 d5 \_cons .0002157 .0002603 0.83 0.407 -.0002948 .0007262

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	4.13
	Prob > F	=	0.0423
	R-squared	=	0.0021
	Root MSF	=	0135

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	0043989	.0021652	-2.03	0.042	0086452	0001525
_cons	.0005227	.0003049	1.71	0.087	0000753	.0011207

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	2.06
	Prob > F	=	0.0678
	R-squared	=	0.0030
	Root MSE	=	.0135

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0092933	.005126	-1.81	0.070	0193462	.0007595
d2	0023301	.0069682	-0.33	0.738	0159957	.0113355
d3	005049	.0023649	-2.13	0.033	009687	0004111
d4	004787	.0030134	-1.59	0.112	0106967	.0011226
d5	0005347	.0045375	-0.12	0.906	0094334	.0083639
_cons	.0005227	.0003052	1.71	0.087	0000759	.0011213

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	0.14
	Prob > F	=	0.7113
	R-squared	=	0.0001
	Root MSE	=	.01911

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	0012517	.003382	-0.37	0.711	0078843	.0053809
_cons	.0004286	.0004307	1.00	0.320	0004161	.0012733

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	0.68
	Prob > F	=	0.6409
	R-squared	=	0.0018
	Root MSE	=	.01911

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	0078312	.0106194	-0.74	0.461	0286576	.0129952
d2	.000137	.0055418	0.02	0.980	0107314	.0110054
d3	.0081203	.0063729	1.27	0.203	0043779	.0206185
d4	0003627	.0067363	-0.05	0.957	0135736	.0128482
d5	0063219	.0057724	-1.10	0.274	0176424	.0049986
_cons	.0004286	.0004312	0.99	0.320	000417	.0012742

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	4.34
	Prob > F	=	0.0374
	R-squared	=	0.0029
	Root MSE	=	.01583

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	0060983	.0029282	-2.08	0.037	011841	0003556
_cons	.0004424	.0003563	1.24	0.214	0002563	.0011411

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	1.50
	Prob > F	=	0.1881
	R-squared	=	0.0040
	Root MSE	=	.01583

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	0121155	.0101863	-1.19	0.234	0320925	.0078615
d2	000699	.0056968	-0.12	0.902	0118713	.0104732
d3	0045151	.0027512	-1.64	0.101	0099106	.0008804
d4	0062774	.0040551	-1.55	0.122	0142301	.0016752
d5	0068845	.0065904	-1.04	0.296	0198092	.0060402
_cons	.0004424	.0003566	1.24	0.215	000257	.0011418

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	1.97
	Prob > F	=	0.1607
	R-squared	=	0.0016
	Root MSE	=	.01918

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	005554	.0039577	-1.40	0.161	0133157	.0022077
_cons	.0004732	.0004303	1.10	0.272	0003706	.0013171

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Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0081271	.0126428	-0.64	0.520	0329216	.0166674
d2	.0031959	.0078626	0.41	0.684	0122239	.0186157
d3	0035066	.0034228	-1.02	0.306	0102193	.0032061
d4	0069236	.0063414	-1.09	0.275	0193601	.0055128
d5	0124086	.0098991	-1.25	0.210	0318222	.007005
_cons	.0004732	.0004307	1.10	0.272	0003715	.0013179

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	1.88
	Prob > F	=	0.1704
	R-squared	=	0.0005
	Root MSF	=	. 02275

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	0034529	.0025179	-1.37	0.170	0083909	.0014851
_cons	.0002256	.0005168	0.44	0.662	0007879	.0012391

inear regression	Number of obs	=	1,999
	F(5, 1993)	=	0.44
	Prob > F	=	0.8212
	R-squared	=	0.0007
	Root MSE	=	.02277

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0064907	.007101	-0.91	0.361	0204169	.0074355
d2	004923	.0056617	-0.87	0.385	0160265	.0061805
d3	.0000318	.0027214	0.01	0.991	0053053	.0053689
d4	0018758	.003243	-0.58	0.563	0082359	.0044843
d5	0040067	.007054	-0.57	0.570	0178407	.0098272
_cons	.0002256	.0005173	0.44	0.663	0007889	.0012401

Number of obs	=	1,999
F(1, 1997)	=	1.02
Prob > F	=	0.3135
R-squared	=	0.0006
Root MSE	=	.01688
	F(1, 1997) Prob > F R-squared	F(1, 1997) = Prob > F = R-squared =

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	0030075	.0029829	-1.01	0.313	0088575	.0028425
_cons	.0002017	.0003805	0.53	0.596	0005445	

inear regression	Number of obs	=	1,999
	F(5, 1993)	=	0.54
	Prob > F	=	0.7446
	R-squared	=	0.0011
	Root MSE	=	.01689

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	0057725	.0097868	-0.59	0.555	0249658	.0134209
d2	.0006452	.0044333	0.15	0.884	0080491	.0093395
d3	0006522	.0031136	-0.21	0.834	0067585	.0054541
d4	0056903	.0038864	-1.46	0.143	0133122	.0019315
d5	0035677	.0086886	-0.41	0.681	0206075	.013472
_cons	.0002017	.0003809	0.53	0.597	0005452	.0009486

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	2.03
	Prob > F	=	0.1545
	R-squared	=	0.0014
	Root MSE	=	.01663

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	0044605	.0031316	-1.42	0.155	0106021	.0016811
_cons	.000309	.0003741	0.83	0.409	0004247	.0010427

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	1.27
	Prob > F	=	0.2753
	R-squared	=	0.0029
	Root MSE	=	.01663

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0088171	.0113959	-0.77	0.439	0311662	.013532
d2	.0043146	.0030609	1.41	0.159	0016884	.0103175
d3	0053643	.0042847	-1.25	0.211	0137673	.0030387
d4	005605	.0057665	-0.97	0.331	0169141	.005704
d5	0068305	.0062458	-1.09	0.274	0190796	.0054185
_cons	.000309	.0003745	0.83	0.409	0004255	.0010434

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	0052921	.0027684	-1.91	0.056	0107213	.0001371
_cons	.000492	.0003356	1.47	0.143	0001662	.0011501

#### . reg Returns d1 d2 d3 d4 d5, robust

Root MSE = .0149

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	0121923	.0094339	-1.29	0.196	0306937	.0063091
d2	.0041298	.0041075	1.01	0.315	0039257	.0121853
d3	0039889	.0015331	-2.60	0.009	0069955	0009823
d4	0039528	.004889	-0.81	0.419	0135409	.0056353
d5	0104563	.0060596	-1.73	0.085	0223402	.0014276
_cons	.000492	.0003359	1.46	0.143	0001669	.0011508

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	0.84
	Prob > F	=	0.3603
	R-squared	=	0.0007
	Root MSE	=	.01245

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	0023929	.0026154	-0.91	0.360	0075222	.0027364
_cons	.0005478	.0002791	1.96	0.050	5.09e-07	.0010952

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	0.27
	Prob > F	=	0.9310
	R-squared	=	0.0017
	Root MSE	=	.01245

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0071277	.0091554	-0.78	0.436	0250828	.0108274
d2	0011066	.0050121	-0.22	0.825	010936	.0087228
d3	0008931	.0033974	-0.26	0.793	007556	.0057698
d4	.0006186	.0049967	0.12	0.901	0091808	.0104179
d5	0034556	.0044458	-0.78	0.437	0121746	.0052633
_cons	.0005478	.0002794	1.96	0.050	-4.03e-08	.0010957

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	2.04
	Prob > F	=	0.1535
	R-squared	=	0.0013
	Root MSE	=	.01305

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Eidaladha	003393	.0023764	-1.43	0.154	0080535	.0012675
_cons	.0000302	.000294	0.10	0.918	0005464	.0006068

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	0.88
	Prob > F	=	0.4955
	R-squared	=	0.0037
	Root MSE	=	.01305

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0110611	.0080429	-1.38	0.169	0268345	.0047123
d2	.0029033	.004672	0.62	0.534	0062592	.0120658
d3	0025173	.0028602	-0.88	0.379	0081265	.0030919
<b>d4</b>	0017935	.0037819	-0.47	0.635	0092103	.0056233
d5	0044965	.0042219	-1.07	0.287	0127763	.0037834
_cons	.0000302	.0002943	0.10	0.918	0005469	.0006074

### . reg Returns Eidaladha, robust

Linear regress	sion			Number	of obs	=	1,999
				F(1, 19	97)	=	0.75
				Prob >	F	=	0.3882
				R-squar	ed	=	0.0008
				Root MS	E	=	.01657
		Robust					
Returns	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
Eidaladha	003316	.0038418	-0.86	0.388	0108	8504	.0042183
_cons	.0005334	.0003701	1.44	0.150	000	1925	.0012592
. reg Returns	d1 d2 d3 d4	d5, robust					
Linear regres	sion			Number F(5, 19 Prob > R-squar	93) F ed	= = =	1,999 0.72 0.6111 0.0035
Linear regres	sion			F(5, 19 Prob >	93) F ed	=	0.72 0.6111
Linear regress	sion	Robust		F(5, 19 Prob > R-squar	93) F ed	= = =	0.72 0.6111 0.0035
Linear regress	coef.	Robust Std. Err.	t	F(5, 19 Prob > R-squar	93) F ed E	= = =	0.72 0.6111 0.0035
			t -0.80	F(5, 19 Prob > R-squar Root MS	93) F ed E	= = = = Conf.	0.72 0.6111 0.0035 .01657
Returns	Coef.	Std. Err.		F(5, 19 Prob > R-squar Root MS	93) F ed E [95%	= = = = Conf.	0.72 0.6111 0.0035 .01657
Returns d1	Coef. 0087931	Std. Err.	-0.80	F(5, 19 Prob > R-squar Root MS P> t	93) Feed E [95%	= = = = Conf.	0.72 0.6111 0.0035 .01657 Interval]
Returns d1 d2	Coef. 0087931 .0076595	.0109779 .0089681	-0.80 0.85	F(5, 19 Prob > R-squar Root MS P> t  0.423 0.393	93) Feed E [95% 030; 009	= = = = Conf. 3224 9284 9073	0.72 0.6111 0.0035 .01657 Interval] .0127363 .0252473
Returns d1 d2 d3	Coef0087931 .00765950031379	Std. Err0109779 .0089681 .0034518	-0.80 0.85 -0.91	F(5, 19 Prob > R-squar Root MS P> t  0.423 0.393 0.363	93) F ed E [95%030:0099	Conf. 3224 9284 9073	0.72 0.6111 0.0035 .01657 Interval] .0127363 .0252473 .0036316

# Table 4 (Pre):

Linear regressi	ion	Number of obs	=	1,919
		F(1, 1917)	=	0.64

Prob > F = 0.4223 R-squared = 0.0002 Root MSE = .01348

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationaday	.0015558	.0019386	0.80	0.422	0022461	.0053578
_cons	.0002022	.0003112	0.65	0.516	0004081	.0008124

#### . reg Returns d1 d2 d3 d4 d5, robust

Linear regression

Number of obs = 1,919 F(5, 1913) = 1.25 Prob > F = 0.2854 Prob > F = 0.2854 R-squared = 0.0020 Root MSE = .01349

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0004969	.0021648	-0.23	0.818	0047426	.0037488
d2	.0025829	.0041236	0.63	0.531	0055042	.0106701
d3	0048782	.0036001	-1.36	0.176	0119388	.0021824
d4	.0020999	.003936	0.53	0.594	0056194	.0098192
d5	.0098546	.0051721	1.91	0.057	0002889	.0199982
_cons	.0002022	.0003115	0.65	0.516	0004087	.000813

Linear regression	Number of obs	=	1,919
	F(1, 1917)	=	2.30
	Prob > E	_	0 1200

Prob > F = 0.1299 R-squared = 0.0005 Root MSE = .01231

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationaday	0023566	.0015555	-1.52	0.130	0054073	.000694
_cons	0000469	.0002844	-0.16	0.869	0006046	.0005109

#### . reg Returns d1 d2 d3 d4 d5, robust

.0046022

-.0000469

d5

\_cons

Linear regression Number of obs = 1,919F(5, 1913) = 2.29

Prob > F = 0.0436 R-squared = 0.0020

-.0016382

-.0006052

.01232

.0108426

.0005115

Root MSE

0.148

0.869

Robust Returns Coef. Std. Err. P>|t| [95% Conf. Interval] t **d1** -.003387 .0026195 -1.29 0.196 -.0085244 .0017505 d2 -.0016313 .0020712 -0.79 0.431 -.0056933 .0024307 d3 -.0078256 -2.60 0.009 -.0137289 -.0019223 .00301 -.0023818 -.0101958 d4 .0039843 -0.600.550 .0054322

1.45

-0.16

.0031819

.0002847

Linear regression Number of obs 1,919 F(1, 1917) 0.03 Prob > F 0.8681 =

> 0.0000 R-squared = Root MSE .01538

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationaday	0003314	.0019957	-0.17	0.868	0042454	.0035826
_cons	0003964	.0003552	-1.12	0.265	0010931	.0003003

#### . reg Returns d1 d2 d3 d4 d5, robust

Linear regression Number of obs 1,919 F(5, 1913) 1.39

Prob > F 0.2267 R-squared = 0.0016 Root MSE .01539

=

Robust [95% Conf. Interval] Returns Coef. Std. Err. t P>|t| .0005065 .002593 0.845 -.004579 .0055919 d1 0.20 d2 .0033902 0.972 -.0065301 .0067677 .0001188 0.04 d3 -.0083784 .0051033 -1.64 0.101 -.018387 .0016303 d4 -.0002046 .0041321 -0.05 0.961 -.0083084 .0078992 2.04 .0037447 0.042 .0149712 d5 .0076271 .000283 \_cons -.0003964 .0003556 -1.11 0.265 -.0010938 .000301

Linear regression	Number of obs	=	1,919
	F(1, 1917)	=	0.16
	Prob > F	=	0.6916
	R-squared	=	0.0000

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationaday	0005192	.0013086	-0.40	0.692	0030856	.0020472
_cons	.0001085	.0002708	0.40	0.689	0004226	.0006395

#### . reg Returns d1 d2 d3 d4 d5, robust

_inear regression	Number of obs	=	1,919
	F(5, 1913)	=	1.76
	Prob > F	=	0.1181
	R-squared	=	0.0009

R-squared = **0.0009** Root MSE = **.01172** 

Root MSE = .01171

Interval]	[95% Conf.	P> t	t	Robust Std. Err.	Coef.	Returns
.0091661	0058069	0.660	0.44	.0038173	.0016796	d1
.0020106	0049331	0.409	-0.83	.0017703	0014613	d2
001014	008979	0.014	-2.46	.0020306	0049965	d3
.0037706	0051604	0.760	-0.31	.0022769	0006949	d4
.0088575	0017448	0.188	1.32	.002703	.0035564	d5
.0006401	0004231	0.689	0.40	.0002711	.0001085	_cons

Linear regression	Number of obs	=	1,919
	F(1, 1917)	=	1.81
	Prob > F	=	0.1793
	R-squared	=	0.0005

R-squared = **0.0005** Root MSE = **.01356** 

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationaday	0025279	.0018815	-1.34	0.179	0062179	.0011621
_cons	.0003739	.0003131	1.19	0.233	0002402	.0009879

### . reg Returns d1 d2 d3 d4 d5, robust

Linear regression	Number of obs	=	1,919
	F(5, 1913)	=	0.70
	Drob > E	_	0 6200

Prob > F = 0.6200 R-squared = 0.0014 Root MSE = .01357

Interval]	[95% Conf.	P> t	t	Robust Std. Err.	Coef.	Returns
.0021944	0035988	0.635	-0.48	.0014769	0007022	d1
.0038242	0069829	0.567	-0.57	.0027552	0015794	d2
.0040725	0201322	0.193	-1.30	.0061709	0080299	d3
.0050119	0122626	0.411	-0.82	.0044041	0036254	d4
.0072643	0031398	0.437	0.78	.0026525	.0020622	d5
.0009885	0002408	0.233	1.19	.0003134	.0003739	_cons

regression Number of	obs =	1,919
F(1, 1917	·) =	0.00
Prob > F	=	0.9669
R-squared	=	0.0000
Root MSE	=	.01933
	F(1, 1917 Prob > F R-squared	F(1, 1917) = Prob > F = R-squared =

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationaday	000094	.0022651	-0.04	0.967	0045364	.0043483
_cons	.0003915	.0004466	0.88	0.381	0004845	.0012674

Linear regression	Number of obs	=	1,919
	F(5, 1913)	=	2.09
	Prob > F	=	0.0635
	R-squared	=	0.0011
	Root MSE	=	.01933

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	.0026878	.002082	1.29	0.197	0013955	.006771
d2	.0009964	.0055985	0.18	0.859	0099835	.0119763
d3	009729	.003755	-2.59	0.010	0170933	0023646
d4	.0002577	.0053409	0.05	0.962	0102169	.0107324
d5	.006399	.0046737	1.37	0.171	0027672	.0155652
_cons	.0003915	.0004471	0.88	0.381	0004854	.0012683

Linear regression	Number of obs	=	1,919
	F(1, 1917)	=	0.45
	Prob > F	=	0.5011
	R-squared	=	0.0002
	Root MSE	=	.01603

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationaday	0016341	.0024285	-0.67	0.501	0063968	.0031286
_cons	.0002583	.0003698	0.70	0.485	000467	.0009836

Linear regression	Number of obs	=	1,919
	F(5, 1913)	=	2.74
	Prob > F	=	0.0180
	R-squared	=	0.0024
	Root MSE	=	.01603

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
<b>d1</b>	0030285	.0033395	-0.91	0.365	0095779	.003521
d2	0030724	.0027497	-1.12	0.264	0084651	.0023203
d3	0099185	.0051844	-1.91	0.056	0200862	.0002492
d4	0000971	.0070942	-0.01	0.989	0140103	.0138161
d5	.0098621	.0035247	2.80	0.005	.0029494	.0167748
_cons	.0002583	.0003702	0.70	0.485	0004678	.0009843

Linear regression	Number of obs	=	1,919
	F(1, 1917)	=	0.19
	Prob > F	=	0.6602
	R-squared	=	0.0001
	Root MSE	=	.01942

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationaday	.0012059	.0027429	0.44	0.660	0041735	.0065853
_cons	.000309	.0004481	0.69	0.491	0005698	.0011878

#### . reg Returns d1 d2 d3 d4 d5, robust

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	0009824	.0047124	-0.21	0.835	0102244	.0082597
d2	.0005928	.0019754	0.30	0.764	0032814	.004467
d3	0051356	.0092796	-0.55	0.580	0233348	.0130636
d4	.0033124	.0051393	0.64	0.519	0067667	.0133916
d5	.0096497	.0047207	2.04	0.041	.0003915	.018908
_cons	.000309	.0004486	0.69	0.491	0005708	.0011887

Linear regression	Number of obs	=	1,919
	F(1, 1917)	=	0.05
	Prob > F	=	0.8310
	R-squared	=	0.0000
	Root MSE	=	.02304

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationaday	0005647	.0026453	-0.21	0.831	0057526	.0046233
_cons	.0001331	.0005325	0.25	0.803	0009112	.0011774

Linear regression	Number of obs	=	1,919
	F(5, 1913)	=	2.33
	Prob > F	=	0.0402
	R-squared	=	0.0012
	Root MSE	=	.02305

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	.0050041	.0034234	1.46	0.144	0017098	.011718
d2	0026442	.0012194	-2.17	0.030	0050358	0002527
d3	0070136	.0066547	-1.05	0.292	0200647	.0060376
d4	0064134	.0046293	-1.39	0.166	0154923	.0026656
d5	.0100055	.0080892	1.24	0.216	0058591	.02587
_cons	.0001331	.000533	0.25	0.803	0009123	.0011785

Linear regression	Number of obs	=	1,919
	F(1, 1917)	=	0.02
	Prob > F	=	0.8788
	R-squared	=	0.0000
	Root MSE	=	.0171

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationaday	0003427	.0022474	-0.15	0.879	0047503	.004065
_cons	.0000954	.000395	0.24	0.809	0006792	.0008701

Linear regression	Number of obs	=	1,919
	F(5, 1913)	=	1.73
	Prob > F	=	0.1235
	R-squared	=	0.0020
	Root MSE	=	.0171

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	.0031314	.0031064	1.01	0.314	0029609	.0092237
d2	0021871	.0040798	-0.54	0.592	0101884	.0058141
d3	009076	.0046587	-1.95	0.052	0182126	.0000607
d4	0021023	.0035139	-0.60	0.550	0089938	.0047892
d5	.0102935	.0058	1.77	0.076	0010816	.0216685
_cons	.0000954	.0003954	0.24	0.809	00068	.0008709

Linear regression	Number of obs	=	1,919
	F(1, 1917)	=	0.01
	Prob > F	=	0.9267
	R-squared	=	0.0000
	Root MSE	=	.01677

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationaday	.0001717	.0018675	0.09	0.927	0034908	.0038343
_cons	.0000881	.0003878	0.23	0.820	0006724	.0008487

Linear regression	Number of obs	=	1,919
	F(5, 1913)	=	3.06
	Prob > F	=	0.0094
	R-squared	=	0.0009
	Root MSE	=	.01679

Interval]	[95% Conf.	P> t	t	Robust Std. Err.	Coef.	Returns
.0052398	0058425	0.915	-0.11	.0028254	0003014	d1
.0108805	0077245	0.739	0.33	.0047432	.001578	d2
0020728	0070807	0.000	-3.58	.0012767	0045768	d3
.0040707	0085468	0.487	-0.70	.0032168	0022381	d4
.0190476	003764	0.189	1.31	.0058157	.0076418	d5
.0008495	0006732	0.820	0.23	.0003882	.0000881	_cons

n Number of obs =	1,919
F(1, 1917) =	0.70
Prob > F =	0.4030
R-squared =	0.0001
Root MSE =	.01509
C	F(1, 1917) = Prob > F = R-squared =

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationaday	0013892	.0016607	-0.84	0.403	0046463	.0018678
_cons	.0003613	.0003489	1.04	0.301	000323	.0010456

Linear regression	Number of obs	=	1,919
	F(5, 1913)	=	3.20
	Prob > F	=	0.0070
	R-squared	=	0.0022
	Root MSE	=	.01509

Interval]	[95% Conf.	P> t	t	Robust Std. Err.	Coef.	Returns
.001759	0054864	0.313	-1.01	.0018472	0018637	d1
.0017176	010386	0.160	-1.40	.0030857	0043342	d2
001258	0123445	0.016	-2.41	.0028264	0068013	d3
.0020414	006458	0.308	-1.02	.0021669	0022083	d4
.0181685	.0022147	0.012	2.51	.0040673	.0101916	d5
.0010463	0003237	0.301	1.03	.0003493	.0003613	_cons

Linear regression	Number of obs	=	1,919
	F(1, 1917)	=	1.12
	Prob > F	=	0.2892
	R-squared	=	0.0003
	Root MSE	=	.0126

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationaday	0017371	.0016385	-1.06	0.289	0049504	.0014763
_cons	.000537	.0002909	1.85	0.065	0000335	.0011075

Linear regression	Number of obs	=	1,919
	F(5, 1913)	=	1.43
	Prob > F	=	0.2097
	R-squared	=	0.0019
	Root MSE	=	.0126

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	.0007311	.0022717	0.32	0.748	0037241	.0051862
d2	0012502	.001727	-0.72	0.469	0046372	.0021368
d3	0081605	.0038148	-2.14	0.033	0156421	0006789
d4	0032977	.0037945	-0.87	0.385	0107395	.004144
d5	.0042979	.0039311	1.09	0.274	0034118	.0120076
_cons	.000537	.0002912	1.84	0.065	0000341	.0011081

Linear regression	Number of obs	=	1,919
	F(1, 1917)	=	0.02
	Prob > F	=	0.8752
	R-squared	=	0.0000
	Root MSE	=	.0132

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationaday	0003205	.0020409	-0.16	0.875	0043231	.0036822
_cons	0001466	.0003043	-0.48	0.630	0007435	.0004503

inear regression	Number of obs	=	1,919
	F(5, 1913)	=	1.68
	Prob > F	=	0.1363
	R-squared	=	0.0019
	Root MSE	=	.0132

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	.0008791	.0039612	0.22	0.824	0068896	.0086477
d2	0025275	.003609	-0.70	0.484	0096056	.0045505
d3	0040857	.003865	-1.06	0.291	0116657	.0034944
d4	0035296	.0049558	-0.71	0.476	013249	.0061897
d5	.0092579	.0037246	2.49	0.013	.0019531	.0165627
_cons	0001466	.0003047	-0.48	0.630	0007441	.0004509

Linear regression

				F(1, 19 Prob > R-squar Root MS	F ed	= = = =	0.39 0.5301 0.0001 .01679
Returns	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
Nettenada	0014078	.0022417	-0.63	0.530	0058	042	.0029887
Nationaday _cons	.0004769	.0003877	1.23	0.219	0002	834	.0012372
_cons	.0004769		1.23				
_cons	.0004769		1.23	Number	of obs	=	1,919
_cons	.0004769		1.23	Number F(5, 19	of obs		1,919 1.62
_cons	.0004769		1.23	Number	of obs 013) F	= =	

Number of obs = 1,919

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d1	.0014435	.0028063	0.51	0.607	0040602	.0069472
d2	0012693	.0025887	-0.49	0.624	0063464	.0038077
d3	0076921	.0041267	-1.86	0.062	0157854	.0004012
d4	0052684	.0072317	-0.73	0.466	0194513	.0089145
d5	.0071785	.0038317	1.87	0.061	0003363	.0146933
_cons	.0004769	.0003881	1.23	0.219	0002842	.001238

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	0.13
	Prob > F	=	0.7154
	R-squared	=	0.0000
	Root MSE	=	.0134

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationalday2	0006532	.0017914	-0.36	0.715	0041665	.0028601
_cons	.0003961	.0003037	1.30	0.192	0001996	

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	4.52
	Prob > F	=	0.0004
	R-squared	=	0.0040
	Root MSE	=	.01339

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6	0045587	.0024054	-1.90	0.058	009276	.0001586
d7	.0073816	.003053	2.42	0.016	.0013942	.0133689
d8	0064392	.0053643	-1.20	0.230	0169594	.0040809
d9	0055044	.0027533	-2.00	0.046	0109041	0001047
d10	.0058547	.0021485	2.72	0.006	.0016411	.0100683
_cons	.0003961	.000304	1.30	0.193	0002002	.0009923

\_cons

.0000457

.0002747

Linear regres	sion			Number F(1, 19 Prob > R-squar Root MS	997) F ed	= = =	1,999 0.01 0.9305 0.0000 .01226
Returns	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
Nationalday2 _cons	.0002324	.0026639	0.09 0.17	0.930 0.868	0049 000	9918	.0054567
. reg Returns	d6 d7 d8 d9	d10, robust					
Linear regres	sion			Number	of obs	=	1,999
				F(5, 19	93)	=	3.28
				Prob >	F	=	0.0059
				R-squar		=	0.0039
				Root MS	SE	=	.01225
Returns	Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
d6	.0023186	.0102262	0.23	0.821	017	7365	.0223738
d7	.00363	.0019537	1.86	0.063	000	2015	.0074615
d7 d8	.00363 0086977	.0019537 .0038113	1.86 -2.28	0.063 0.023	000; 016;		.0074615 0012232
						1721	

0.17

0.868

-.0004931

.0005845

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	0.50
	Prob > F	=	0.4802
	R-squared	=	0.0003
	Root MSE	=	.01515

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationalday2	0019846	.0028108	-0.71	0.480	007497	.0035278
_cons	0003131	.000341	-0.92	0.359	0009818	.0003556

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	7.40
	Prob > F	=	0.0000
	R-squared	=	0.0064
	Root MSE	=	.01512

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6	0059489	.0039433	-1.51	0.132	0136822	.0017845
d7	.0047464	.0024586	1.93	0.054	0000754	.0095682
d8	0137354	.0079576	-1.73	0.084	0293416	.0018708
d9	0047995	.0079854	-0.60	0.548	0204601	.010861
d10	.0098142	.0018671	5.26	0.000	.0061525	.0134759
_cons	0003131	.0003413	-0.92	0.359	0009825	.0003562

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	1.83
	Prob > F	=	0.1764
	R-squared	=	0.0008
	Root MSF	=	.01155

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationalday2	0023101	.0017083	-1.35		0056602	.0010401
_cons	.0001938	.0002612	0.74		0003185	.0007062

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	1.19
	Prob > F	=	0.3138
	R-squared	=	0.0023
	Root MSE	=	.01155

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6	004483	.0037947	-1.18	0.238	011925	.0029589
d7	.0016689	.0014141	1.18	0.238	0011044	.0044422
d8	0051377	.0039203	-1.31	0.190	012826	.0025505
d9	0051578	.0049623	-1.04	0.299	0148896	.0045741
d10	.0015594	.0029777	0.52	0.601	0042803	.007399
_cons	.0001938	.0002615	0.74	0.459	000319	.0007067

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	0.04
	Prob > F	=	0.8509
	R-squared	=	0.0000

R-squared = **0.0000** Root MSE = **.01351** 

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationalday2	0003969	.0021111	-0.19	0.851	0045371	.0037432
_cons	.0004427	.0003054	1.45	0.147	0001563	.0010416

#### . reg Returns d6 d7 d8 d9 d10, robust

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	0.90
	Proh > F	_	0 4796

Prob > F = 0.4796 R-squared = 0.0011 Root MSE = .01352

Interval]	[95% Conf.	P> t	t	Robust Std. Err.	Coef.	Returns
.0098961	00906	0.931	0.09	.0048329	.000418	d6
.0092408	0042674	0.470	0.72	.003444	.0024867	d7
.0096124	0206062	0.476	-0.71	.0077043	0054969	d8
.0028594	0071095	0.403	-0.84	.0025416	002125	d9
.005984	0005189	0.099	1.65	.0016579	.0027326	d10
.0010422	0001569	0.148	1.45	.0003057	.0004427	cons

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	1.69
	Prob > F	=	0.1939
	R-squared	=	0.0012
	Root MSE	=	.0191

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationalday2	0047652	.003667	-1.30	0.194	0119568	.0024265
_cons	.0004989	.0004295	1.16	0.246	0003434	.0013412

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	1.72
	Prob > F	=	0.1275
	R-squared	=	0.0042
	Root MSE	=	.01909

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6	0099516	.005639	-1.76	0.078	0210106	.0011073
d7	.0014516	.001977	0.73	0.463	0024257	.0053289
d8	0135126	.0121588	-1.11	0.267	0373579	.0103327
d9	0080781	.0101014	-0.80	0.424	0278886	.0117323
d10	.006265	.0036241	1.73	0.084	0008425	.0133724
_cons	.0004989	.0004299	1.16	0.246	0003443	.0013421

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	2.94
	Prob > F	=	0.0866
	R-squared	=	0.0012
	Root MSE	=	.01584

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationalday2	0038859	.0022668	-1.71	0.087	0083315	.0005597
_cons	.0003982	.0003586	1.11	0.267	0003051	.0011014

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	4.68
	Prob > F	=	0.0003
	R-squared	=	0.0055
	Root MSE	=	.01582

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6	0084316	.0034579	-2.44	0.015	015213	0016502
d7	.002178	.0008953	2.43	0.015	.0004222	.0039339
d8	0140937	.0075505	-1.87	0.062	0289015	.0007141
d9	0054843	.0038972	-1.41	0.160	0131274	.0021588
d10	.0064022	.0027074	2.36	0.018	.0010925	.0117119
_cons	.0003982	.000359	1.11	0.267	0003058	.0011021

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	0.34
	Prob > F	=	0.5623
	R-squared	=	0.0002
	Root MSE	=	.01919

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationalday2	.0017804	.0030718	0.58	0.562	0042439	.0078048
_cons	.0003265	.0004336	0.75	0.452	0005239	.0011769

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	4.47
	Prob > F	=	0.0005
	R-squared	=	0.0047
	Root MSE	=	.01917

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6	.0024296	.005015	0.48	0.628	0074057	.0122649
d7	.0138807	.0034854	3.98	0.000	.0070453	.0207162
d8	011803	.0089348	-1.32	0.187	0293254	.0057195
d9	00421	.0067953	-0.62	0.536	0175366	.0091167
d10	.0086046	.0041743	2.06	0.039	.0004182	.016791
_cons	.0003265	.0004341	0.75	0.452	0005248	.0011777

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	2.70
	Prob > F	=	0.1007
	R-squared	=	0.0011
	Root MSE	=	.02274

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationalday2	0054352	.0033097	-1.64	0.101	011926	.0010556
_cons	.0002653	.0005147	0.52	0.606	0007442	.0012748

_inear regression	Number of obs	=	1,999
	F(5, 1993)	=	2.40
	Prob > F	=	0.0352
	R-squared	=	0.0029
	Root MSE	=	.02275

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6	0049611	.002197	-2.26	0.024	0092698	0006524
d7	.0071191	.0049175	1.45	0.148	0025249	.0167632
d8	0100211	.0108669	-0.92	0.357	0313327	.0112905
d9	0124254	.007936	-1.57	0.118	0279891	.0031384
d10	0068877	.0054951	-1.25	0.210	0176643	.003889
_cons	.0002653	.0005153	0.51	0.607	0007452	.0012758

Root MSE

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationalday2	001708	.0025024	-0.68	0.495	0066156	.0031996
_cons	.0001757	.000382	0.46	0.646	0005735	.0009248

#### . reg Returns d6 d7 d8 d9 d10, robust

Linear regression Number of obs = 1,999F(5, 1993) = 1.68

Prob > F = 0.1362 R-squared = 0.0021 Root MSE = .01688

.01688

Robust Returns Coef. Std. Err. P>|t| [95% Conf. Interval] t d6 -.0028983 .0029725 -0.980.330 -.0087279 .0029313 d7 .0036139 .0020229 1.79 0.074 -.0003533 .0075812 d8 0.273 -.0084543 .0077141 -1.10 -.0235829 .0066742 -.0057109 d9 .0073768 -0.77 0.439 -.020178 .0087563 d10 .0049094 .0031864 1.54 0.124 -.0013396 .0111584 \_cons .0001757 .0003824 0.46 0.646 -.0005742 .0009256

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	0.72
	Prob > F	=	0.3959
	R-squared	=	0.0002
	Root MSE	=	.01664

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationalday2	0016699	.0019665	-0.85	0.396	0055264	.0021867
_cons	.0002531	.0003776	0.67	0.503	0004875	.0009938

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	4.70
	Prob > F	=	0.0003
	R-squared	=	0.0034
	Root MSE	=	.01663

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6	0089482	.0026727	-3.35	0.001	0141898	0037066
d7	.0027924	.0013787	2.03	0.043	.0000886	.0054961
d8	0040994	.0041317	-0.99	0.321	0122024	.0040036
d9	0070607	.0046292	-1.53	0.127	0161392	.0020178
d10	.0089667	.0043311	2.07	0.039	.0004726	.0174607
_cons	.0002531	.000378	0.67	0.503	0004882	.0009945

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	3.59
	Prob > F	=	0.0583
	R-squared	=	0.0013
	Root MSE	=	.01492

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationalday2	0039079	.0020626	-1.89	0.058	007953	.0001373
_cons	.0004643	.0003379	1.37	0.170	0001984	.0011269

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	3.93
	Prob > F	=	0.0015
	R-squared	=	0.0058
	Root MSE	=	.0149

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6	006328	.0037137	-1.70	0.089	0136111	.000955
d7	.0073013	.0026216	2.79	0.005	.0021599	.0124427
d8	0136059	.0055305	-2.46	0.014	0244521	0027596
d9	006794	.0041146	-1.65	0.099	0148634	.0012753
d10	0001128	.0022312	-0.05	0.960	0044885	.0042629
_cons	.0004643	.0003382	1.37	0.170	0001991	.0011276

Linear	regression	Number of obs	=	1,999
		F(1, 1997)	=	0.42

Prob > F = 0.5151 R-squared = 0.0002 Root MSE = .01245

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationalday2	0013981	.0021475	-0.65	0.515	0056097	.0028135
_cons	.0005279	.0002808	1.88	0.060	0000228	.0010787

#### . reg Returns d6 d7 d8 d9 d10, robust

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	3.68

Prob > F = 0.0026 R-squared = 0.0048 Root MSE = .01243

Interval]	[95% Conf.	P> t	t	Robust Std. Err.	Coef.	Returns
.00092	0111613	0.097	-1.66	.0030802	0051206	d6
.0053608	0005847	0.115	1.58	.0015158	.002388	d7
.0079338	0171576	0.471	-0.72	.0063971	0046119	d8
.0031602	019165	0.160	-1.41	.0056918	0080024	d9
.0134002	.0033126	0.001	3.25	.0025718	.0083564	d10
.0010792	0000233	0.061	1.88	.0002811	.0005279	cons

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	1.06
	Prob > F	=	0.3033
	R-squared	=	0.0004
	Poot MSE	_	01306

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationalday2	0019271	.0018716	-1.03	0.303	0055977	.0017435
_cons	8.76e-07	.0002956	0.00	0.998	0005789	.0005807

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	2.37
	Prob > F	=	0.0376
	R-squared	=	0.0026
	Root MSE	=	.01306

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6	0031845	.0033032	-0.96	0.335	0096626	.0032936
d7	.002768	.0017417	1.59	0.112	0006477	.0061837
d8	0063168	.0066385	-0.95	0.341	0193359	.0067023
d9	0063364	.0037336	-1.70	0.090	0136586	.0009859
d10	.0034342	.001621	2.12	0.034	.0002552	.0066132
_cons	8.76e-07	.0002959	0.00	0.998	0005795	.0005813

Linear regression	Number of obs	=	1,999
	F(1, 1997)	=	0.17
	Prob > F	=	0.6846
	R-squared	=	0.0001
	Root MSE	=	.01658

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Nationalday2	0012088	.002975	-0.41	0.685	0070431	.0046256
_cons	.0004912	.0003735	1.31	0.189	0002414	.0012238

Linear regression	Number of obs	=	1,999
	F(5, 1993)	=	2.45
	Prob > F	=	0.0321
	R-squared	=	0.0046
	Root MSE	=	.01656

Returns	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
d6	0037005	.0033978	-1.09	0.276	010364	.0029631
d7	.0068536	.006559	1.04	0.296	0060096	.0197167
d8	0140411	.0086362	-1.63	0.104	030978	.0028958
d9	0023281	.0066292	-0.35	0.725	0153291	.0106729
d10	.0071724	.002697	2.66	0.008	.0018831	.0124617
_cons	.0004912	.0003739	1.31	0.189	0002421	.0012245