The Effects of Derivatives on Firm Financial Risk:

An Analysis of UK Non-Financial Firms

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Any remaining errors are entirely my responsibility.

Vikram Finavker

Declaration of Originality

I hereby declare that this project is entirely my own work and that any additional sources of information have been duly cited.

I hereby declare that any internet sources, published or unpublished works from which I have quoted or drawn reference have been reference fully in the text and in the contents list. I understand that failure to do this will result in a failure of this project due to Plagiarism.

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Date ....

Name of Supervisor: Dr Amrit Judge……………………………

Abstract

The main aim of this thesis is to examine the effects of the use of derivatives on financial risk measures of UK non-financial firms for the period 1999-2010. This question is important in the light of attempts by regulators to curb the use of over-the-counter (OTC) derivatives as a response to the 2008 financial crisis, the introduction of European Market Infrastructure Regulation and more recently the prospect of the introduction of the financial transactions tax. Despite the significant use of derivatives by UK non-financial firms, there is a gap in literature for a study that shows the effect of derivatives use on the financial risk for UK firms. This examination is important in the UK setting as financial distress is more costly for the UK firms due to higher creditors' right in the UK, all else being equal. In this thesis, the effects of foreign currency (FC) and interest rate (IR) derivatives are examined on the 1-year probability of default, 5-year probability of default, total risk, idiosyncratic risk, market risk and foreign exchange (FX) exposure. This thesis contributes to the corporate hedging literature by presenting, to the best of our knowledge, new evidence on the impact of derivatives on firm financial risk.

Chapter 4 of this thesis examines the effects of derivatives use on the total risk, idiosyncratic risk and market risk. The results suggest that a 1% increase in the extent of all derivatives use is associated with a reduction of 2.52% in total risk, 2.22% in idiosyncratic risk and 0.0651 basis points in market risk. A 1% increase in the extent of FC derivatives use is associated with a reduction of 0.0945 basis points in market risk. We also examine the nonlinear effect of derivatives use on financial risk and find inverted U-shaped relationship with reduction in total risk and idiosyncratic risk is associated with low and high derivatives use. We also control for the problem of endogeneity by matching derivative users with non-users using a propensity score matching method. Our results suggest that derivative users have a statistically lower 5.50% to 6.80% total risk and 4.08% and 5.17% idiosyncratic risk. We provide empirical evidence that is consistent with the notion that firms use derivatives for hedging and not for speculation.

In Chapter 5, we examine the effects of derivative use on expected default frequency (EDF). The results show that IR derivatives use has a greater impact on the probability of default than FC derivatives use. Furthermore, we find that hedging with derivatives has a significantly greater impact on near term default (1-year) than long-term (5-year) default probabilities. The interaction of derivatives variable with time dummies reveals that the derivatives use is associated with a large reduction in the probability of default during the period of 2000-2001 and 2007-2009. We also interact our derivatives variable with proxies for credit risk conditions and find that derivatives use has largest negative effect on the probability of default during the period of heightened credit risk conditions. In this chapter endogeneity between the probability of default, derivatives and leverage is addressed using instrumental variable analysis. The results suggest that derivatives use is associated with a reduction in the probability of default. We also use propensity score matching method to match derivative users and non-users and then examine the mean differences on the probability of default for matched firms. The results show that the mean 1-year (5-year) probability of default of derivative users is 1.60% to 2.09% (1.11% to 1.24%) lower across different matching methods than matched non-users. The findings of this chapter will be of interest to public policy makers, financial regulators and corporate as they suggest that firms are using derivatives for hedging purposes rather than speculative ones.

In Chapter 6, we examine the effects of FC derivatives and FC debt on FX exposure. The results show that firms use FC derivatives and FC debt to hedge unexpected changes in FX rates as the use of FC derivatives and FC debt is associated with a significant reduction in FX exposure. The results also indicate that UK non-financial firms' stock returns are sensitive to not only the current but also the time delayed exchange rate changes and that the use of FC derivatives also significantly reduce the sensitivity of stock return to the time delayed exchange rate changes. In respect of FC debt, the evidence suggests that the use of FC debt leads to a significant reduction in FX exposure and supports the view that FC debt works as a natural hedge. We also examined the effect of FC debt on the probability of default and Z-score after showing that FC debt works as a natural hedge.

The empirical examination in this thesis provides an important understanding of the role played by derivatives in UK non-financial firms' risk management policies. This thesis contributes to the existing body of knowledge on risk management by providing a comprehensive examination of the effect of derivatives on UK firms' risk.

Keywords: Bankruptcy, Default Probabilities, Derivatives, Total risk, Foreign Debt, Foreign Exchange Exposure, Hedging, Idiosyncratic Risk, Market Risk, Risk Management, Speculation and Z-score.

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Table of Abbreviations

CCP	Central Counter Parties
CEM	Coarsened Exact Matching
CFO	Chief Financial Officer
CP	Commodity Price
EDF	Expected Default Frequency
FC	Foreign Currency
FC&CP	Foreign Currency and Commodity Price
FC&IR	Foreign Currency and Interest Rate
FCD	Foreign Currency Derivatives
FD	First Difference
FE	Fixed effects
FRS	Financial Reporting Standard
FTT	Financial Transactions Tax
FX	Foreign Exchange
GDP	Gross Domestic Product
GMM	Generalized Method of Moments
IMF	International Monetary Fund
IR	Interest Rate
IR&CP	Interest Rate and Commodity Price
IRD	Interest Rate Derivatives
LIBOR	London Inter-Bank Offer Rate
LM	Lagrange Multiplier

MBA	Master of Business Administration
MNC	Multinational Corporation
OLS	Ordinary least squares
OTC	Over-the-Counter
PSM	Propensity score matching
R&D	Research and development
ROW	Rest of the World
SB	Standardized bias
USD	US dollar
WLS	Weighted Least Squares
2SLS	Two stage least square model

Chapter 1. Introduction

1.1. Introduction

In the current financial climate risk management has become one of the key financial decisions faced by finance directors and corporate treasurers. There has been extensive growth in the use of derivatives by corporations around the world but various stakeholders such as employees, investors, creditors and regulators have become increasingly concerned about how firms use these instruments, particularly in light of the recent financial crisis.[1] These stakeholders are concerned about the stability of their employment, the value of their investments, the ability of the firm to payback its lenders and whether firms are taking excessive financial risks, which could affect the economy as a whole. It follows then that an understanding of the effects of derivatives use on the firm's level of risk is an important area of research.

In today's economic environment firms are serving new markets, which brings new challenges and less explored areas of risk. FX risk, IR risk and CP risk are examples of fresh challenges these new markets offer to corporations that are ready to explore the new avenues and accept the challenges they offer. Encountered with the financial risk of functioning in world markets, many firms choose risk management activities, such as financial derivatives, in order to reduce the unfavourable and unexpected effects of exchange rate, IR and CP volatility. However, the recent financial crisis has shown that there are many instances where firm's senior managers have been encouraged to take on additional financial risks rather than dampen the effects of financial price volatility. In the wake of recent financial crisis of 2007, derivative markets have come under greater scrutiny. The financial crisis points out the important role played by financial derivatives market in recent failures of Lehman Brothers and American Insurance Group in 2008 and brought these financial markets to the attention of regulatory authorities. This brings

[1] *"According to the Bank of International Settlement (BIS), at the end of December 2009 the notional value of outstanding interest rate (IR) and foreign exchange (FX) derivatives held by non-financial customers was $35.6 trillion and $8.8 trillion, respectively. By comparison, at the end of 2000 those numbers were only $6.1 trillion and $3.3 trillion. The International Swaps and Derivatives Association (ISDA) reports that virtually all of the world's largest companies use derivatives to hedge their business and financial risks."Campello, Lin, Ma and Zou (2011, p. 1615)*

criticism for the complex and less transparent nature of financial derivatives market that limits the ability of regulators to identify the level of financial risk.

Financial derivative instruments are widely used risk management instruments. Derivatives can allow businesses to effectively manage exposures to external influences on their business over which they have no control. Derivatives can also be used to speculate on market prices. Derivatives is *"a means of either gaining exposure to or gaining an offset to an underlying asset without either buying or selling the underlying asset" (LCH.Clearnet, stated by House of Lords, 2010, p. 8)*. A derivatives contract involves one party reducing its risk, *"When a derivative contract is entered, one party to the deal typically wants to free itself of a specific risk, linked to its commercial activities, such as currency or interest rate risk, over a given time period. It is 'hedging'; and the more exact that hedge, the better for the hedging party"(The International Swaps and Derivatives Association, stated by House of Lords, 2010, p. 8)*, and other taking on risk associated with an underlying asset, *"The other party to the deal assumes the risk, though it may then 'lay it off' elsewhere, in a process akin to reinsurance. Thus risk passes to those most willing to take it on (including investors, who are used to taking similar risks through other financial instruments)" (The International Swaps and Derivatives Association, stated by House of Lords, 2010, p. 8)*. This allows parties to speculate on the values of underlying assets without having any actual interest in the asset itself. This use of derivatives for speculating on financial prices, coupled with the lack of transparency in the derivatives market as a whole, could lead to increased firm risk. Financial market regulators like European commission are concerned about the potential risk arising from the use of derivative instruments for speculation.

In a seminal work, Modigliani and Miller (1958) show that hedging does not add value to the firm in a perfect capital market. However, in the absence of perfect capital market hedging can increase firm value by reducing expected cost of financial distress, better coordinating financing and investment decisions, reducing corporate tax liability, improving conflict of interest between bondholder and shareholders and maximising the value of manager's wealth portfolio.[2] Corporate hedging theory argues that firms faced

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[2] *See for more details Smith and Stulz (1985), Bessembinder (1991), Froot, Scharfstein and Stein (1993), Géczy, Minton and Schrand (1997) and Graham and Smith (1999)*

with large exposures to interest rates, exchange rates or commodity prices can increase firm value by reducing or eliminating these exposures. Firms can achieve this by using financial and operational hedging strategies. Financial hedging strategies involve use of derivative instruments such as FC derivatives, IR derivatives, commodity price (CP) derivatives and FC debt[3]; whereas operational hedging strategies require physical change of production or change of supplier among others. Operational hedging strategies are normally for a longer period and require huge financial commitments whereas financial hedging strategies do not require huge financial commitments and can be available for both short-term and long-term periods.[4]

Some US studies have examined the question of whether derivatives are being used for hedging or speculation. These studies reported mixed results. Allayannis and Ofek (2001) using a data of US firms for the year 2001 find that use of derivatives significantly reduces the foreign exchange exposure firms face. Guay (1999) also studies US non-financial firms and finds evidence that firms use derivatives to hedge, and not to increase firm financial risk. Guay (1999) finds that in the year following the start of derivatives use firms experience a decline in market risk, idiosyncratic risk and IR risk exposures. In contrast, Hentschel and Kothari (2001) find very little differences in the measures of risk between users and non-users of derivative instruments. They point out that they do not find evidence consistent with the hypothesis that firms use derivatives to speculate on a large scale. However, they do not detect any significant reduction in firms' risks from the use of derivatives either. Bartram, Brown and Conrad (2011) find significantly lower total risk, market risk and cash flow volatility for derivative users compared to matched non-user firms. Recently, Boyer and Marin (2013) and Magee (2013) examine the effect of derivatives use on the market-based measure of default using US data. Both of the studies find negative effect of FC derivatives use on the measure of default. However, both the studies only examine the effect of FC derivatives and do not examine the effects of IR derivatives despite the fact that IR derivatives should have a greater effect on the likelihood of default.

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[3] *To use FC debt as a hedging tool a firms needs to have foreign income.*

[4] *There is no cost to enter into a forwards derivative contract where as there is a premium to buy an options contract in OTC market.*

The discussion above suggests that there is, to the best of our knowledge, very little research on the impact of derivatives on firm financial risk. It also shows that not all categories of derivatives are employed to investigate their effect on firm financial risk. In this thesis, we examine the impact of derivatives use on measures of firm financial risk for a large sample of UK non-financial firms during the period 1999 to 2010. In particular, we examine the effects of any derivative and then separately FC and IR derivatives use on firm risk. This examination is presented in three empirical chapters. All these chapters examine the effect of derivatives on a distinct type of firm risk. The first empirical chapter (Chapter 4) examines the effects of derivatives on firm equity price risks. In particular, the chapter examines whether the use of derivatives lowers firm total risk, market risk and idiosyncratic risk. The second empirical chapter (Chapter 5) examines the effects of derivatives on a market-based measure of the likelihood of default. In this chapter, we use the 1-year and 5-year expected default frequency (EDF) as a measure of the probability of default. The third empirical chapter (Chapter 6) examines the effects of FC derivatives and FC debt use on firm exchange rate exposure and the probability of default. Firm exchange rate exposure is measured by exchange rate betas estimated using the market model.

1.2. Research Rationale

The main reason for conducting this research is to provide a comprehensive analysis of the effects of derivatives use on the firm risk in the context of UK. This is particularly useful to regulators, investors, creditors and employees. We conduct this analysis by examining the effects of derivatives use on the total risk, market risk, idiosyncratic risk, 1-year probability of default, 5-year probability of default and FX exposures. Previous researchers examined the determinants of derivatives use[5] using data for UK firms; however, not much is known about the effects of derivatives on the firm financial risk measures. This gap in the existing literature motivated this study to conduct this research.

This research is very important given the recent financial crisis and the role-played by derivative instruments during this period. Financial regulators have blamed OTC derivative instruments for the systemic failures in global financial markets. In view of this, public policy makers and regulators are planning to curb the use of OTC derivative instruments. The European Market Infrastructure Regulation introduced new regulations governing the

[5] *Judge (2006a), Judge (2006b) and Clark and Judge (2008)*

use of derivative instruments and started a move towards exchange–traded instruments and centralised clearing and therefore daily marking-to-market of firms' derivative positions. Non-financial firms are opposing these new regulations, as the new regulations will increase the cost of firms for using financial derivatives. Non-financial firms argue that they use derivative instruments for reducing their exposure to unanticipated changes in the future prices of currency, interest rates and commodity and hence they should be excluded from the new regulations governing the derivatives use. In a memorandum to House of Lords, British Airways argued that *"The economic effect of the requirement to provide cash collateral/margining is to convert the primary risk for companies from that associated with counterparty exposure into liquidity risk. The adverse effect of the creation of liquidity risk is a reduction in the amount of funds allocated to productive investment in the Company, and curtailment or even elimination of the ability of BA to manage its financial risks (ie hedge) because the liquidity risk generated jeopardises our financial stability"House of Lords (2010).*

Furthermore, this research is very vital due to the prospect of the introduction of the financial transactions tax (FTT). Though FTT will be introduced for financial firms, non-financial firms could be considered financial firms and will be liable to pay the FTT; if non-financial firms carry out activities such as deposit taking, lending, financial leasing or guarantees and commitments and also if the average annual value of their financial transactions is more than 50% of their overall average net turnover (Martin, Tim and Kamal, 2013). Despite the proposal by European Committee to protect non-financial business from the FTT, it has been argued that the introduction of the FTT would unfavourably affect the risk management activities of non-financial firms (PwC, 2013). This indicates that introduction of FTT would lead to reduction in the use of derivatives due to increased costs and will result in unhedged risk for non-financial firms. Given this, the findings of this study are potentially quite significant, because if non-financial firms are actually using derivative instruments for risk management purposes, it could be argued that non-financial firms should be exempted from the new regulations and permitted to use OTC derivatives without any impediments.

The research question of this thesis is very important in a UK context for several reasons. First, the bankruptcy code in UK is creditor friendly which implies, all else being same, that the rules of bankruptcy in the UK make bankruptcy more likely for firms in financial distress. Both UK and US are English-origin countries, however, they have substantially different protection for creditors. In the UK senior creditors are secured by floating charge that gives senior creditors full control of the firm via receivership in the event of bankruptcy (Senbet and Wang, 2012). The UK is also given the highest creditor rights score of 4 by La Porta, Lopez-De-Silanes, Shleifer and Vishny (1998) whereas US is given a creditor rights score of only 1[6]. Hence, all else being equal it is more important for UK firms to manage their firm financial risk than US firms. Second, the UK is a relatively open economy in which its firms trade actively with customers in the EU and further afield. For example, in 2012 UK exports as a percentage of GDP equated to 32% whereas the corresponding figure for the US was only 14%.[7] Third reason for conducting this analysis is that there are no studies that use UK data to explicitly examine whether derivatives are used for hedging or speculative motives. This study is intended to fill this gap.

1.3. Research Questions

This section presents the research questions that are examined in each of the empirical chapters. The main aim of this thesis is to provide a comprehensive understanding of the effects of derivative instruments on the firm financial risks. We organise our aim into three empirical chapters in this thesis and try to answer the research question.

1.3.1. Objective for Chapter 4

The objective for Chapter 4 is to examine the effect of use of derivatives on equity price risk. A few studies examine this question using data for US firms (Guay, 1999; Hentschel and Kothari, 2001), Australian firms (Nguyen and Faff, 2010) and a world-wide sample (Bartram, 2006; Bartram et al., 2011).[8] The results of these studies are rather mixed.

Guay (1999) finds an average reduction of 5% in the stock return volatility of all derivative user firms for a sample of US firms. However, Hentschel and Kothari (2001) fail to find any significant reduction in the total risk for a sample of US derivative users. Bartram (2006) examines the effects of derivatives use on financial risks for a sample of firms across 46 countries and finds significant negative effect of derivatives on the financial

[6] *See La Porta et al. (1998) for more details.*
[7] *Sourced from www.data.worldbank.org.*
[8] *The sample of Bartram (2006) and Bartram et al. (2011) inlcudes UK firms. Bartram et al. (2011) did not examine the research question separately for UK firms and hence it is not clear how derivatives use effect firm finacnial risk measures of UK firms.*

risks. However, the author fails to find any significant negative effect of derivatives on firm risks when a separate examination is performed for UK firms. For a sample of Australian firms Nguyen and Faff (2010) find a nonlinear effect of derivatives use on total risk, market risk and idiosyncratic risk. Bartram et al. (2011) examine the average mean difference between matched derivative users and non-users and find significantly lower standardised total risk, market risk and idiosyncratic risk. In this thesis, a negative sign is expected on the derivatives coefficient if firms are using derivatives for hedging and positive sign if firms use derivatives for speculation.

1.3.2. Objective for Chapter 5

The objective for Chapter 5 is to examine the effect of derivatives on firms' probability of default. We used expected default frequencies as a proxy for the probability of default.[9] A firm might default on its liabilities if it is not in a position to service those liabilities due to IR or cash flow volatility. Hedging theories argue that a firm can reduce its probability of default by hedging its interest rate, foreign exchange or commodity price risk. Therefore, firms that use derivatives for hedging should benefit from a lower probability of default. Boyer and Marin (2013) and Magee (2013) examine the effects of FC derivatives use on the measure of default calculated using an option-based model. Boyer and Marin (2013) use distance to default, equity-implied volatility of assets and moneyness of debt as measures of firm risk. They use a dummy measure for FC derivatives use. Magee (2013) also uses distance to default as a measure for a firm's probability of default and uses a continuous measure of foreign FC derivatives use. Both of the studies find that the use of FC derivatives is associated with a reduction in the probability default. However, neither of the studies examines the effects of IR derivatives use on the probability of default, although it is expected that IR derivatives should have a larger negative effect on the probability of default. In Chapter 5, we examine the effects of derivatives use on the probability of default and extend previous research by examining not only the effects of FC derivatives but also the effects of IR derivatives use on the probability of default. This chapter also examines the importance of derivatives during the period of financial crisis and heightened credit risk conditions and for firms with different levels of pre-derivatives use credit risk.

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[9] *This data is sourced from Moody's. See section 3.3.1.2 for more details.*

1.3.3. Objective for Chapter 6

The objective of Chapter 6 is to investigate the impact of the use of FC derivatives and FC debt on firm exchange rate exposure. FC derivatives are one of the most used financial instruments by firms (Bank for International Settlements, 2007; Bartram, Brown and Fehle, 2009; Bank for International Settlements, 2012). An examination of UK annual reports shows that many firms use FC debt as a means to manage their FX exposure. In Chapter 5 we find that UK firms have higher levels of foreign currency exposure, measured by foreign sales, foreign assets and foreign income, compared to US firms.[10] This suggests that all else being equal UK firms have greater incentives to use FC derivatives and FC debt to manage their foreign exchange exposure.

If FC derivatives are effective in reducing FX exposure, then firms that use FC derivatives should end up with lower FX exposure than what they have started with. We also find anecdotal evidence showing that UK firms use FC debt as a tool for natural hedging against FX exposure. Hence, we expect that the use of FC debt should also reduce FX exposure. Allayannis and Ofek (2001) examine the effects of FC derivatives on FX exposure of US firms. They find significant negative effect of FC derivatives use on FX exposure. They confirm the role of FC debt as a tool for hedging, however, they did not further investigate the role of FC debt in reducing the FX exposure. A recent study by Zhou and Wang (2013) examines the effects of FC derivatives on FX exposure for a sample of UK firms for the year 1999. They find only a weak negative effect of FC derivatives use on FX exposure when they use raw values of FX exposure with p-value of 0.1235.

1.4. Structure of Thesis

The remaining chapters of the thesis are organised as follows:

1.4.1. Chapter 2: Literature Review

provides review of the existing theoretical and empirical research related to the firms' use of derivatives and the effects of derivatives use on the firm financial risks. This chapter is organised around the aim of this thesis that whether the use of derivatives lowers the firm

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[10] *We compared our sample mean for foreign sales, foreign income, foreign assets with studies that used US data (Such as Allayannis and Ofek, 2001; Bartram et al., 2011)*

financial risk. This chapter highlights the gaps in the research and provides a motivation for this thesis.

1.4.2. Chapter 3: Data and Methodology

In Chapter 3, we discuss the sample selection and sample period, the data sources for the variables used in the analysis, measurement of the dependent; independent and control variables, justification for the control variables and comprehensively the methods of estimation used in the empirical chapters. In this chapter we discuss the characteristics of our sample period and explain the importance of this study in the UK setting.

1.4.3. Chapter 4: The Effects of Derivatives Use on Equity Implied Risk

Chapter 4 is the first empirical chapter and examines the effects of derivatives use on the equity-implied risk. In particular, this chapter examines the effects of all, FC and IR derivatives use on the total risk, market risk and idiosyncratic risk. We use both continuous and dummy measures for derivatives use. Different estimation methods are used to examine the research objective. We also use propensity score matching method to match derivative user and non-user firms in order to control the problem of self-selection and endogeneity.

1.4.4. Chapter 5: The Effect of Derivatives Use on The Probability of Default

We examine the effects of derivatives use on the probability of default in Chapter 5. In this chapter, we use 1-year and 5-year expected default frequency as a measure of probability of default. We examine the effects of all, FC and IR derivatives use on the probability of default. We also control for “other” users in the sample of non-user firms. We also create several categories of derivatives use based on the number of derivatives and combinations of derivatives and examine the effects of these new categories on the probability of default. We control for endogeneity between the probability of default, derivatives use and leverage using instrumental variable approach. In particular, we use two stage least square model (2SLS) and Generalized Method of Moments (GMM) methods. To control for the problem of firms self-selection we use treatment effects model, propensity score method and coarsened exact matching method.

1.4.5. Chapter 6: The Effects of FC Derivatives and FC Debt on FX Exposure

In Chapter 6 we examine the effects of FC derivatives and FC debt use on the FX exposure. We calculate weekly and monthly FX exposure following Allayannis and Ofek

(2001). We also calculate lagged FX exposure, FX exposure arising from Sterling/Euro and Sterling/USD exchange rate changes. We create several dummy variables based on firm's use of FC derivatives and FC debt and examine the effects of them on the FX exposure. After establishing that firms use FC debt as a hedging tool, we examine the effects of FC debt on the probability of the default and Z-score.

1.4.6. Chapter 7: Conclusion

Chapter 7 concludes this thesis and summarise the research findings. This chapter provides the contribution of this study to the existing literature. This chapter also provides limitations of this thesis and implication of this study for further research.

Chapter 2. Literature Review

This chapter provides the critical review of literature associated with the motives of firms behind the use of derivatives and the effects of derivatives on firm risk. This section shows the extent to which the research on corporate derivatives is explored over the last many years and the questions researchers tried to answer. The research on financial derivatives has grown from earlier studies examining the determinants of derivatives use to recent studies examining the role of derivative instruments in reducing risk faced by firms. This section also helps us in identifying the gap in literature for a study investigating the effects of derivatives use on the firm financial risk for UK non-financial firms. There is a lack of study showing clear and consistent effect of derivatives use on firm risk. Majority of the literature that we investigate here either use a general derivatives category or use FC derivatives and examine the effect of derivatives on firm financial risk.

2.1. Introduction

Corporate financial theories suggest that firms that have significant exposure to FX, IR and CP can use derivatives to reduce their exposure and in doing so they can reduce the costs associated with financial distress. Derivatives work as a tool to reduce risk for firms that want to reduce their risk, as the risk is born by the counter party who is in best position to bear the risk. This risk reduction benefits firms in many ways such as firms may use more risky but profitable projects by managing the risk that can be hedged with derivatives that could not have been chosen in the absence of hedging with derivatives. Corporate financial theories have portrayed derivatives as a tool to reduce the cost of financial distress by reducing the variability of firm’s future cash flows. However, in reality the use of derivatives dose not closely follow the theory. Firms’ use derivative to manage their cash flow volatility and small firms have more cash flow volatility than large firms and hence higher probability of default. Furthermore, smaller firms have restricted access to capital and hence they need more protection than larger firms do. However, larger firms use more derivatives than smaller firms do. Bartram et al. (2009) find that derivative user firms are larger and more profitable. This little discussion about the use of derivatives shows difference between theory and practical use of derivatives. By relaxing the Modigliani and Miller (1958) assumptions and allowing for capital market imperfections, Smith and Stulz

(1985) provide rationales for why firms may decide to hedge and therefore use derivatives as a means for hedging.[11] Some of the researchers have explained the benefits of risk management.[12] These theories suggest that firms that have huge exposures to IR, FX rates and CP should use derivatives to reduce their exposure and in doing so increase the market value of the firm. Following are few fundamental goals of using derivative instruments.

2.1.1. Minimize Corporate Tax Liability.

Smith and Stulz (1985) argue that by reducing the variability of taxable income, hedging can reduce a firm's expected tax liabilities given that it has a convex tax function. Since tax rates are progressive, smoothing cash flows across tax years reduces the tax percentages and hence minimizes corporate tax liability (Copeland and Joshi, 1996). Stulz (1996) argues that due to the convexity of tax code, a firm has benefit to manage its taxable income so that the taxable income falls within an optimal range. Stulz (1996) also suggests that risk management allows firms to reduce fluctuations in taxable income, which results in lower taxable income in a complete business cycle, by allowing income to fall in optimal range of tax rates. Stulz (1996) and Leland (1998) argue that by reducing the cash-flow volatility, derivatives may increase a firm's debt capacity and provides more tax benefits.

2.1.2. Reduce the Expected Cost of Financial Distress

Finance theories argue that firms should not hedge if shareholders can hedge their risk away by diversifying their portfolio. However, this is true only when shareholders are concerned about the future cash-flow variability caused by changes in FX, IR or CP but if the exposure arising from FX, IR or CP can materially change the probability of bankruptcy for the firms, then it creates big financial implications for shareholders (Stulz, 1996). In this case if a firm has unhedged position then it may see decline in its assets relative to debt and be required to file for bankruptcy. Smith and Stulz (1985) argue that hedging can reduce the expected cost of financial distress. Firm's market value will decrease if cash flow volatility decreases firm's capacity to payback its debt and increases financial distress. Increased financial distress will increase financial distress cost and it will be reflected in the market prices of the firm. However, for a given level of debt, derivatives

[11] Smith and Stulz (1985) show that a firm should hedge for three reasons 1) taxes 2) cost of financial distress and 3) managerial risk aversion.
[12] Smith and Stulz (1985); Froot et al. (1993); Géczy et al. (1997); Guay (1999)

can reduce the volatility of cash flow and hence reduces the cost of financial distress. Stulz (1996) argues that a costless risk management programme that has potential to eliminate the increase in bankruptcy cost can increase the firm value. Ross (1997) and Leland (1998) show that by reducing the likelihood of bankruptcy derivatives may increase a firm's debt capacity, which in turn will increase firm value through debt interest tax shields. Lenders are more likely to lend money to firm that manages its cash flow volatility by hedging (Copeland and Joshi, 1996).

2.1.3. Improve the Co-ordination Between Financing and Investment Policy

Bessembinder (1991) shows that conflicts between shareholder and bondholders can lead to the problem of underinvestment in future positive net present value projects and that derivatives can help the firm reduce this conflict. Derivative can increase the shareholder value by improving the co-ordination between financing and investment policies (Froot et al., 1993). Froot et al. (1993) argue that firms facing costly external finance may use derivatives to reduce the probability that internally generated cash flows are insufficient to cover the cost of planned investments. They argue that if external capital is costly because of capital market imperfection than the internal capital, then there is an advantage in using derivatives. Managing cash flow volatility by hedging, firms control funds available for new projects (Copeland and Joshi, 1996). Stulz (1996) argues that if a firm becomes financial weaker then it would create problem for the firm to raise the finance from the capital market. The cost of borrowing would also go up, if any available, which may result in firm not to continue with a profitable project; hence, creates problem of underinvestment for a firm.

2.1.4. Maximise the Value of Managers Wealth Portfolio

Stulz (1984) states that there are greater benefits for managers to hedge when managerial compensation leaves the managers holding a large portfolio of idiosyncratic firm risk. Managers may not use derivatives to hedge when the equity value of a firm is positively associated with asset volatility. However, when managers hold undiversified financial stock portfolio of the firm, they may hedge non-diversifiable risk, which may not be in the best interest of the shareholders. This shows that the managers' compensation plan can lower managers risk aversion and hence affect hedging decision. Stulz (1996) argues that it is not only the managers who need protection but employees, customers and suppliers with large stakes in the firms need protection from undiversifiable risk that a firm can hedge. If a firm decides to hedge the undiversifiable risk then employees, customers and suppliers would feel confident about the firm which would result in smooth functioning of the firm; otherwise employees would demand more salary to work or reduce their loyalty toward the firm, customers will be reluctant to buy the products due to issue with a firm's ability to fulfil warranty obligations and suppliers would not enter into long-term contracts and will charge more trade-credits (Stulz, 1996).

Over the last two decades several studies have examined the aforementioned theories of corporate hedging (Nance, Smith and Smithson, 1993; Mian, 1996; Géczy et al., 1997; Gay and Nam, 1998; Guay, 1999; Spanò, 2004; Judge, 2006a, 2006b; Purnanandam, 2008; Bartram et al., 2011; Magee, 2013). All of these studies incorporate the use of financial derivatives into their hedging definitions. One problem with this approach is that they have classified derivative users as hedgers; however, firms could potentially be using derivatives for speculation in financial markets and not for hedging. It follows from this that one of the critical basic assumptions of these studies is that risk management activities (such as the use of derivatives) are employed for hedging (that is, risk reduction) rather than speculative purposes. The relationship between derivatives use and firm risk is very complicated. Firms' use of derivatives may be motivated by reasons other than those related to hedging, such as increasing the value of the managers wealth portfolio[13], firms attempting to profit from taking speculative positions[14] and firms matching the risk management strategies of competitors. All these expose firms to the new risks as these types of trade are not linked to any underlying exposure, they have the effect of increasing exposure and in doing so increases the firm risk.

2.2. Why Firms Use Derivatives?

A wider empirical examination is conducted on the use of derivatives by non-financial firms. While some of the studies find that derivatives are used for speculative purposes[15], other studies find that derivatives are used for hedging underlying exposure[16]. These suggest that firms use derivatives for both hedging and speculative motives. Géczy et al.

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[13] See for details Jensen and Meckling (1976); Smith and Stulz (1985); Tufano (1996)

[14] See for details Faulkender (2005); Chernenko and Faulkender (2011)

[15] Stulz (1996) ; Bodnar, Hayt and Marston (1998); Bodnar and Gebhardt (1999); Faulkender (2005); Adam and Fernando (2006); Aabo (2007); Geczy, Minton and Schrand (2007); Adam (2009); Chernenko and Faulkender (2011); Aabo, Hansen and Pantzalis (2012); Allayannis, Lel and Miller (2012); Beber and Fabbri (2012); Lel (2012); Júnior (2013) to name a few.

[16] Guay (1999); Allayannis and Weston (2001); Hagelin and Pramborg (2004); Purnanandam (2008); Nguyen and Faff (2010); Allayannis et al. (2012); Magee (2013) to name a few

(1997) show that firms are more likely to use FC derivatives when they have high cost of financial distress and high volatility of cash flow, which suggests that their sample firms are using derivatives to protect themselves from unanticipated changes in foreign exchange rates that are capable of moving firms into financial distress zone. However, they find no direct evidence that the use of FC derivatives reduces the exposure to foreign exchange risk and hence it may be possible that the use is related to expected gain from speculative use of derivatives. Grant and Marshall (1997) find that their sample firms rarely use derivatives to speculate on market movements. They show that their sample firms use derivatives to reduce the cash flow volatility. Smith, Smithson and Wilford (1989) argue that firms hedge in response to volatile financial markets, reduce taxes, reduce the cost of financial distress, reduce the cost of borrowing and to increase the debt capacity.[17] However, Zhao (2004) finds that firms with high variance cash flow are discouraged to use derivatives even when they face high cost of financial distress.

Hedging is defined as "the acquisition of financial assets that reduce the variance of a firm's payoffs" (Smith and Stulz, 1985). Hentschel and Kothari (2001) define hedging as risk management activity that uses financial derivatives and other instruments in order to mitigate the adverse effects of exchange rate, interest rate and commodity price volatility. Geczy et al. (2007) define hedging with derivatives as *"a position in derivatives market with the intention of reducing firm risk"*. These suggest that firms are using derivatives for hedging when a firm's use of derivatives lowers the firm risk.

Hentschel and Kothari (2001) define speculation as risk management activity that uses financial derivatives and other instruments and increases risk instead of decreasing. O'conner, Wackett and Zammit (2011) define speculation as the strategy to earn additional profits based on a view that the market is mispriced and hence there are gains to be made by trading. Speculation involves using the financial derivatives instruments to gain profit from anticipated changes in the prices of underlying securities. Harrington and Niehaus (2004) argue that firms find derivatives more attractive for speculation as derivatives are extremely liquid and offer the potential for massive leverage. Firms with a very little capital can enter into the derivatives contract to speculate without committing a huge cash as many derivatives contract do not need any upfront fees to enter where as those contract

[17] *cited by Grant and Marshall (1997)*

that require fees need small fraction compared to the underlying value of the derivative instrument. These speculative positions in derivatives market can generate huge profits for firms with very little investment but they also create a potential for huge losses. Geczy et al. (2007) define speculation with derivatives as *"a position in derivatives market with the primary intention of making a profit or increasing risk"*.

As discussed above derivative instruments may be used either to increase or decrease the firm financial risk and hence raises the question that whether managers of non-financial firms use derivative instruments to hedge firm financial risk or whether they use these instruments for speculative motives. If a firm uses derivatives for hedging then it should end up with lower firm financial risks than what it has started with and if it uses derivatives for speculation then it should end up with higher firm financial risks than what it has started with.

Compared to a wider empirical work on the determinants of corporate derivative usage, there are few studies that examined the relationship between the use of derivatives and their impact on the firm risk. These studies are, but not limited to, Guay (1999), Allayannis and Ofek (2001), Hentschel and Kothari (2001), Nguyen and Faff (2010), Bartram et al. (2011), Boyer and Marin (2013), Marin (2013) and Magee (2013). Among these studies, studies prior to year 2013 used equity-based measure of firm financial risk such as total risk, market risk and idiosyncratic risk; whereas the recent studies used both equity-based and market-based measures of firm financial risk such as distance to default. Market-based measure of firm financial risks is calculated using market model such as Black-Scholes option pricing model. The existing studies have tried to examine the motives behind the use of derivatives mainly using US data despite the fact that UK firms are more exposed to pre-derivatives use firm risk[18] and that UK firms use more derivatives[19]. This shows an important gap in the existing literature.

2.3. Managers View and Selective Hedging with Derivatives

Firms would not state that they use derivatives for speculation, if they are, after the increased concern with the losses incurred on the derivatives market and hence it would be

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[18] In our univariate results we show that UK firms have higher levels of pre-derivatives use measures of exposures and firm financial risk measures.
[19] See Bank for International Settlements (2007) report for more details.

difficult to identify if a firm uses derivatives for reasons other than hedging from annual reports. Geczy et al. (2007) examine the information disclosed in the annual reports of the firms and compare it with the same firms that responded to a survey saying they use derivative for speculation and find that the information disclosed in the annual reports, which also meets the minimum disclosure requirements, is not sufficient to determine whether firms use derivatives for speculation. Geczy et al. (2007) report that 40% of the respondent to the survey indicate that they actively trade in derivatives market based on their market views at least some times; where as 7% of the respondent firms frequently speculate. However, when they examine the annual reports they do not find any information suggesting that firms are speculating with derivatives.

Several studies have presented evidence that suggests that non-financial firms engage in selective hedging activities where they incorporate their views of future market price movements in deciding their hedging positions. (Dolde, 1993; Bodnar, Hayt and Marston, 1996; Stulz, 1996; Bodnar et al., 1998; Bodnar and Gebhardt, 1999; Glaum, 2002; Guay and Kothari, 2003; Adam and Fernando, 2006; Brown, Crabb and Haushalter, 2006; Adam, Fernando and Salas, 2008).

Stulz (1996) argue that this practice of selective hedging is inconsistent with the modern risk management theory. Outright speculation may be a rare activity for non-financial firms but there is evidence that managers' future market views affect firms' financial policy decisions. Stulz (1996) calls the practice of managers' attempt to time the financial markets with their risk management policy decisions as "selective hedging". The author says that selective hedging will increase shareholders wealth if managers have private information about the market than other market participants. However, if financial managers do not have this advantage then this type of financial strategy of hedging will merely result in an increase in the variability of cash flow (relative to a fully hedged position) and will potentially reduce shareholders value. The author argues that "selective hedging" firms are those firms whose managers take their market views into consideration while deciding the hedging strategy for the firm. A firm is referred as "selective hedging" firm when it changes 1) time of hedging and/or 2) volume of hedging. Geczy et al. (2007) use a more controlled term for speculation. They argue that a firm is defined as a speculator in derivatives market if a firm *"actively take positions"* in the derivatives market based on their *"market views"*. They argue that there are two important aspects of their definition: 1) *"the word "active" is important, as it does not allow for confusion* *about whether or not hedging is a form of speculation"* and 2) *"the question specifically indicates that the cause for taking positions is a market view."* [20]

Stulz (1996) provides few reasons for selective hedging. First, he notes that it is a rationale approach for managers of firms that are likely to go bankrupt to take speculative positions as they have very little to lose; also the benefits of such actions will go to shareholders while the losses will go to bondholders. Since the firm is in financial distress it is likely to fail anyway and the additional downside risk due to speculation will be negligible, however, the firm's upside potential will be enhanced leading to an increase in the probability of survival. Second, firms that are less likely for financial distress can engage in more risk taking activities such as using excessive amounts of derivatives, as they are less susceptible to the negative outcomes of such use. Third, risk managers could engage in selective hedging when their compensation is structured in a way that encourages risk taking. Finally, some managers may engage in selective hedging because they erroneously believe that they have a comparative advantage in hedging selectively, which in turn might lead them to overestimate their ability to beat the market. Stulz (1996) suggests that firms that can afford to be wrong are more likely to selectively hedge. Stulz (1996) also argues that only firms with an informational advantage should selectively hedge. However, Stulz (1996) links the widely-reported problems with derivatives use with selective hedging.[21]

Several previous studies relied on survey analysis to identify the motives behind the use of derivatives by firms, as it is difficult to identify motives behind derivative use from annual reports. Below we discuss few of the studies that investigate motives behind derivatives use using survey analysis. Using a survey data of 244 firms, Dolde (1993) reports that almost 90% of the responded firms said that at least some times they changed the size of their derivatives contract based on the future market views. This shows that a large number of firms use derivatives in a way that is not consistent with modern risk management theories. When companies have taken their market views to hedge their FX and IR exposures, smaller companies have significantly overtaken larger firms. Stulz (1996) argue that shareholders of a firm whose managers have private information benefits from the selective hedging. However, managers of small firms may not have this information

[20] *Geczy et al. (2007, p. 2410)*
[21] *See Stulz (1996) for more details.*

advantage which seems to suggest that the responded small firms in Dolde (1993) sample may be using derivatives for speculative purpose. These survey findings show that majority of firms take their market view into account while dealing with derivatives. These survey results also suggest that firms do not thoroughly hedge their exposures but instead hedges exposure based on their own market view of the future prices.

In a survey of 530 US firms Bodnar, Hayt, Marston and Smithson (1995) find heaviest usage of derivatives for 65% of large firms whereas 30% of medium sized firms reported use of derivatives and only 12% of small firms reported use of derivatives. 80% of respondent firms use derivatives for contractual commitments. They report that 43% of firms use derivatives with a view on the direction of the financial prices but only 9% do so frequently while 57% never use derivatives with a market view. This indicates that larger number of firms follow a strategy which leaves some exposure unhedged or increases exposure. Bodnar et al. (1995) also asked respondents to rank the importance of three different risk management goals: minimise fluctuations in accounting earnings, minimise fluctuations in cash flows and protecting the appearance in the balance sheet. 67% of firms responded that they use derivatives to minimise fluctuations in cash flow while 28% of firms responded that they use derivatives to minimise fluctuations in accounting earning and the rest 5% of firms responded that they use derivatives to protect the appearance in the balance sheet. This indicates that large numbers of firms use derivatives for hedging the firm against the volatility in cash flow.

In the updated survey of 399 firms, Bodnar et al. (1998) find that 49% of firms sometimes alter the timings of their foreign exchange hedges to incorporate their market views while 51% of firms sometimes alter the size of their foreign exchange hedges. 26% of firms also said that they take active positions in foreign exchange market-based on their market view. This seems to suggest speculative use of derivatives based on the definition of speculation by Geczy et al. (2007). The numbers are larger for the same type of situation for IR derivatives. In case of IR derivatives 60% of firms sometimes alter the timings of their IR hedges to incorporate their market view, while 54% of firms sometimes alter the size of their IR hedges. 37% of firms also said that they take active positions in IR market-based on their market view. These show that large number of firms uses derivatives in a way that is not consistent with modern risk-management theories. Bodnar et al. (1998) ask non-financial firms if their market views of future interest rates and exchange rates cause them to actively take positions. 13 firms indicated that they frequently take positions, 66 firms mentioned that they time to time take active positions and for 290 firms the response was they never speculated.

In a comparative study of the responses to the 1995 Wharton school survey of derivative usage among US non-financial firms and 1997 companion survey on German non-financial firms, Bodnar and Gebhardt (1999) find firms in US and Germany are different particularity on issues such as derivatives use, the selection of derivative instruments and the influence of their market views when taking derivative positions. German firms' show considerably less concern regarding issues related to financial derivatives use than the US firms. This could be due to the fact that financial accounting standards in Germany have greater importance than the US and German firms have strict corporate policies of control over risk management activities than US firms. However, Bodnar and Gebhardt (1999) report that compare to US firms, German firms are more likely to allow their own market views on future price movements when taking positions with financial derivatives. Almost 25% of German firms responded that they often change the maturity or the amount of their derivative positions based upon their future market views. In addition to this 50.6% of German firms mentioned that considering their future market views they at least sometimes take active positions on their underlying derivatives contracts compared to 41.2% of US firms. These indicate that large numbers of firms in both countries take positions on derivatives market based on their market views and not necessarily based on their underlying exposure and also suggest that German firms make more speculative use of derivatives than US firms.

Using a survey data of 74 non-financial German firms on financial risk management practices Glaum (2002) finds similar results to those of Bodnar and Gebhardt (1999). The author finds that the most of the sample German firms pursue forecast based, profit oriented financial derivative strategies. This indicates that the German firms' use of derivatives is associated with speculation rather than hedging. However, Glaum (2002) suggests that the benefits arising to shareholders from managers allowing their future market views into firm's financial instruments strategy decision is not clear. Therefore, according to Glaum (2002), the question then arises as to why there is a widespread use of risk management strategies based on future market views of managers. Glaum (2002) provides three potential explanations for this. Firstly, managers think that their forecast of future exchange rates is of a value and based on it firms are able to outperform the financial markets, which helps them to make profit on their gambles. Secondly, managers think that their forecast of future exchange rates is of a value but they are unaware that the firms are not able to outperform the financial market. The author argues that firms managers themselves think that they can successfully forecast future market prices and able to outperform the financial market with the information. Lastly, managers are not aware that they are not able to outperform the financial market but they nonetheless take the bets in the market.

Using a data of 234 large non-financial firms Guay and Kothari (2003) show that firms hedge only a small fraction of their exposure with the help of financial derivatives. They argue that corporate derivatives use is a small part of non-financial firms' risk profile. They provide 3 reasons for an economically small derivatives programme that firms have; one of these reasons is that firms may be using derivatives for purposes other than those expected by modern hedging theories such as speculation.[22] We argue that this indicates that firms might be leaving some of their exposures unhedged and therefore selectively hedging their financial price exposure. Their data also suggest that US firms are less exposed to interest rates, exchange rates and CP changes.

In a study of 133 chemical industry firms, Faulkender (2005) shows that speculation or market timing drives IR risk profile and not the hedging considerations. The author does not find evidence that firms are hedging with derivatives, as when firms' issue of debt is investigated, the author find no link between IR exposure and the choice of debt instrument. However, the author finds that firms use IR derivatives to speculate. The author suggests that firms are trying to lower their short-term cost of capital. These findings are consistent with both short-term earnings management and speculation. In order to reduce their short-term debt service payments, which generates higher quarterly earnings, firms might swap the IR profile of their debt into floating when there is a large difference between fixed and floating rates. On the other hand, firms may be speculating by incorporating their views of anticipated IR movements into their IR exposure decision, resulting in a significant sensitivity to the yield spread, if such views are on average correlated with the shape of the yield curve.

[22] *See for more details Guay and Kothari (2003, p. 425)*

Geczy et al. (2007) study corporations' use of derivatives to *"take a view"* on interest rate and currency movements using response to 1998 Wharton School/CIBC Wood Gundy survey. They show that firms start using derivatives for hedging and once the fixed costs of derivatives use are reached, firms start active trading with derivatives using their market views. "*Firms are motivated to use derivative instruments to hedge. Once the fixed costs of derivatives operation in place, however, some firms extend these operations to include active trading based on market view"* (Geczy et al. (2007, p. 2)). They find that firms that actively take positions in derivatives market do so based on perceived information and cost advantage. They find that firms that take a view in FC derivatives market do not always suggest that firms are also more likely to speculate in IR derivatives market. Their results seem to suggest that firms possess expertise in FC or IR speculation and not in both of them. They argue that firms speculate because firms believe that speculation is a profitable activity and provides upside potential without downside fall. This indicates that speculation is not a random activity but instead an expertise in an underlying derivatives product.

There seems to be strong evidence of selective hedging in the gold mining industry (Adam and Fernando, 2006; Brown et al., 2006; Adam et al., 2008; Adam, 2009). In a survey of 111 gold mining firms, Adam (2009) notes that 62% of surveyed firms mentioned their expectations about movements in future metal prices are very important or fairly important when taking decisions on how much exposure to hedge. For 3 firms out of 13 surveyed firms the primary risk management objective was to increase sales revenue. This may suggest that the motive behind the use of derivatives is speculation and not hedging. Using a sample of 92 North American gold mining firms from 1989 to 1999, Adam and Fernando (2006) find evidence of selective hedging but find no economically significant cash flow gains on average from selective hedging. In an attempt to time the market their sample firms do not yield any positive cash flows gains on average and suggest that this kind of speculation creates no value for shareholders. Furthermore, Adam and Fernando (2006) find that gold mining firms consistently achieve economically significant cash-flow benefits from derivatives use. This may suggest that their sample firms are using derivatives for hedging. They also find that this benefits of derivatives on cash flow increase shareholders value, as they do not observe any pass-through effect on systematic risk.

Brown et al. (2006) examine corporate risk management strategy of 44 companies in the gold mining industry using quarterly data and find that risk management strategies in gold mining industry is affected by the risk managers' view of future movement of gold prices. They find that firms decrease their hedging activities as prices move against them. In line with Adam and Fernando (2006), they report that the potential economic benefit arising because of selective hedging in their sample is fairly small even before allowing for the marginal transaction costs of such hedging. They find no evidence of superior operating or financial performance based on selective hedging activities of the managers.

A study by Chernenko and Faulkender (2011) further investigate the reasons for the IR timing behaviour noted by Faulkender (2005) and find that, to meet consensus earnings estimate and to increase managerial compensation firms primarily use IR swap to determine the choice of IR exposure. This is consistent with speculative motives of derivatives use. Consistent with Froot et al. (1993), their results indicate support for economies of scale hypothesis as they find that large investment firms are the ones that use derivatives to hedge IR exposure that is they match their IR liabilities to the cash flow. This also means that small firms use IR derivatives for speculative motives. In support for speculative motives behind the use of derivatives they find that when managerial compensation contracts are dependent on firms' performance and earnings, firms use IR derivatives to speculate. They argue that if firms IR exposure from their operations is not changing over-time then there should not be any significant variation in the use of IR derivatives over-time and if there is a significant variation then the driver of this change is speculative motive. They find evidence that derivative usage is significantly varying over-time and is consistent with firms using IR derivatives for speculation. Overall, their results suggest that non-financial firms use IR derivatives for both hedging and speculative motives. Interestingly, in a study of selective hedging in the airline industry, Sturm (2009) find that the crude oil futures markets may be vehicles by which the domestic airline industry can create value via selectively cross hedging their exposure to jet fuel price.

In a study of Brazilian firms during the financial crisis of 2007-2009, Júnior (2013) finds that a significant number of Brazilian companies speculated in the derivatives market. The author identified two types of speculators: 1) firms that significantly increased their derivatives use in line with their underlying exposure, positive exchange rate exposure, during these period and 2) firms that have taken positions in derivatives contracts in which they do not have any underlying exposure, negative exchange rate exposure, and hence unadvisable, with a common objective of making a gain through a continuous process of home currency appreciation as evident from their short-term position in the foreign exchange market. They show that firms that have information advantage in FC markets, exporters and firms with foreign debt, are more likely to speculate. Júnior (2013) reports that a substantial number of companies in the sample speculated during the period of study. The author reports 37.8% of firms speculated in the exchange rate market in year 2008 while in year 2009, 21% of sample firms were classified as speculators.

Using a panel of non-financial firms from North America during 1996-2001, Beber and Fabbri (2012) find evidence of selective hedging. They find that managers of their sample firms adjusted their positions in derivatives contracts based on the previous year's exchange rate movements and hence suggest that firms take positions in derivative contracts based on their perspective on the exchange rate trajectory. They analyse the time-series variation of FC derivatives and find selective hedging is a reason for considerable time-series variation they observe in currency derivatives holdings in excess of what can be explained by changes in currency exposure.

2.4. Firm Characteristics that Might Influence Corporate Speculation or Hedging

The literature provides various explanations for firms' use of derivatives for speculation. Several empirical studies below suggest that firm size, corporate governance, firm distress level, manager's skills and private information are related to speculation.

Ljungqvist (1994) argues that firms whose managers have private information about firm's exposure to risk may have an incentive to speculate on future financial price movements. If private information suggested by Ljungqvist (1994) motivates the decision to speculate, then there are chances that financial derivative users could be using them for speculation, if they are presented with these incentives. Therefore, it would seem that the only way to differentiate between hedging and speculating firm is to compare the financial risk characteristics of derivative users and non-users. If derivative using firms display lower levels of financial risk then it could be argued that firms are using financial derivatives for hedging purposes and not to speculate.

Tufano (1996), using a sample of 48 North American gold mining firms for the period 1990 to 1994, finds that as US gold producers increase their use of derivatives to the sensitivity of equity value to gold price falls, which is consistent with the theories of hedging that derivatives are used for hedging purposes. Furthermore, the author also shows that firms with less liquidity manage more gold price exposure. Géczy et al. (1997) mention that they are observing derivatives use by sample firms and not the motive of using derivatives; considering this they mention that derivatives might be used for speculation rather than hedging. They mention that some of the firm characteristic variables, such as firm size, are significant determinants of both optimal speculation and optimal hedging, while other proxy variables such as those related with underinvestment costs are unrelated to optimal speculative motives. However, they find no support for the speculative uses of derivatives. They point out that although a currency derivative is not direct measure of hedging, their results suggest that on an average, their sample firms are not speculating with currency derivatives instruments.

Geczy et al. (2007) show three features of survey respondents to 1998 Wharton School/CIBC Wood Gundy survey. First, they find firms that frequently speculate on FX rates have majority of their revenue coming from foreign operations and majority of costs in foreign currency compared to firms that do not speculate. Second, they show that the firms that speculate have different compensation arrangements. They show that firms where derivatives use is benchmarked against profit instead of risk-management are more likely to speculate. Geczy et al. (2007) also provide evidence of a relationship between corporate governance and use of derivatives for speculation. They witness that firms that have lower levels of corporate governance are more likely to speculate with derivatives. However, the internal control system for use of derivatives can limit the unadvised usage of derivatives. Geczy et al. (2007) also show that frequent speculating firms are larger than sometimes speculating firms and significantly larger than the firms that never speculated. They report that speculating firms have significantly lower long-term debt ratios. They argue that non-speculator firms at a greater extent employ risk-taking activities than speculators do.

Adam, Fernando and Salas (2007) use a sample of 97 North American gold mining firms' data that enables them to identify speculating firms and their extent of speculation. They find that compare to larger firms smaller firms speculate more. This result is surprising, as it is normally believed that small firms are less likely than larger firms to possess the information and financial advantages necessary to beat the market through speculation. Similar to Stulz (1996), the authors also show that firms with the more likelihood of bankruptcy speculate more. This show that at the cost of bondholders, firms close to bankruptcy may have incentives to speculate for the benefit of shareholders. However, Adam et al. (2007) also provides evidence that firms that have the lowest possible chances of bankruptcy also speculate more. This can be justified as financially stronger firms can take on additional risk exposure associated with speculation. This would seem to suggest that there is a U-shaped relationship between extent of speculation and the likelihood of bankruptcy. However, more importantly, their results indicate that speculative activities of a firm reduce firm value.

A study by Lel (2012) also finds similar results. The author examines the effect of internal and external corporate governance on the use of derivatives using a sample of firms that are exposed to foreign exchange risk from 30 countries across world during the period 1990-1999. The results of the study suggest that firms with lower levels of corporate governments inclined to use derivatives in a way that increases firm risk while firms with high levels of corporate governments are observed to use derivatives to minimize their exposure to foreign exchange and to overcome costly external financing. The author also reports that the use of currency derivatives is higher when the extent of currency exposure and the need for external financing is higher. The author also controls for the endogeneity between a firm’s inside ownership, government structure and hedging using an instrumental variable approach. In a similar type of analysis, Allayannis et al. (2012) examine a broad sample of firms from 39 countries with substantial exchange rate exposure. They argue that managers can use derivatives for their self-interest and derivatives can be used for either hedging or speculation. They hypotheses that investors can control the use of derivatives by managers by appealing to the firm-level and country-level corporate governance, to draw conclusions on a firm’s motives behind the use of derivatives, as firms with good corporate governance are more likely to use derivatives for hedging than speculation. Consistent with their hypothesis the authors find that use of derivatives adds value to the firms that have strong firm-level and country-level corporate governance. The authors also find more noticeable relationship between the use of FC derivatives and firm value when the firm-level and country-level corporate governance is strong. They use instrumental variable approach to control for the endogeneity and use treatment effects model to control for the self-selection bias.

Oliveira and Novaes (2007) examine a database of 25,457 contracts of foreign exchange swaps between Brazilian firms and financial institutions at the end of year 2002. They find that the existence of external debt and firm size affects positively the probability of hedging while the income from exports affects the probability of speculation. The authors also report that during the period of increased volatility in exchange rates, such as in year 2002, the firms demand for FC derivatives is linked to the speculative motives.

Using a survey data of Danish firms, Aabo et al. (2012) find that firms where non-finance departments play role in risk management activities are more likely to use derivative instruments for speculation. The authors argue that the larger the involvement of non-finance department in risk management department, the more the firm speculates in terms of selective hedging and in terms of active speculation. They also suggest that international presence and firm size also increase the probability of speculation. This is in contrast to the findings of Oliveira and Novaes (2007). Beber and Fabbri (2012) find that firms that have inexperienced young CEOs with MBA degree are more likely to speculate. This finding is consistent with the argument that an overconfident manager takes more risk. They also show that managers of large corporations time the foreign exchange market by adjusting currency hedging using past information.

2.5. Derivatives and Asymmetric Information

Private information in foreign exchange market can motivate firms to engage in speculative activities. Theoretical studies on speculation usually look at the role of asymmetric information as a factor that might motivate such activity. Froot, Scharfstein and Stein (1992) study speculators trading horizon and show that speculators can reap profit by focusing on information that bears no relation at all to fundamental information of long-term firm values. Madrigal (1996) illustrates that speculators trade profitably by obtaining superior knowledge about market environment or exploiting the need of other investors. The author also argues that speculators chase trends and lose money after market overreaction.

Standard models of informed speculation suggest that traders in the financial markets try to learn information that others do not have. Similarly, corporate speculation can be done using derivatives if managers hold private information that other market participants do not have. Demarzo and Duffie (1995) examine the relationship between proprietary information and hedge accounting in the decision to use derivatives and show that when managers hold private information on the firms expected payoff, then corporate hedging is optimal despite shareholders’ ability to hedge their own exposures. Their results suggest that firms with greater information asymmetry between managers and shareholders can generate larger profit by using derivatives. They also argue that derivatives use reduces the information asymmetry between managers and shareholders by reducing the cash flow volatility. These suggest that firms with higher information asymmetry are more likely to use derivatives for hedging. Stulz (1996) argues that when a firm believes that they have private information than rest of the firms in the market, and hence are in better position to gain from the market, they are more likely to enter into derivatives market for speculation. This indicates that firms speculate with information that is not available to other market participants and hedge when the information asymmetry is higher between managers and shareholders.

Dadalt, Gay and Nam (2002) examine the effect of information asymmetry on the derivatives use and find evidence that both the use of derivatives and extent of derivatives use are associated with lower information asymmetry. This is consistent with finding of Demarzo and Duffie (1995) who argue that derivatives use reduces information asymmetry between managers and shareholders.

Guay and Kothari (2003) find that although derivative users have private information about the direction of future movements in IR, FX and CP, majority of the derivative positions appear much too small to increase firm value. We can interpret this in one of the two ways, either this implies that corporate speculation with derivatives is not likely to be widespread or that firms are leaving much of their financial price exposures unhedged. Geczy et al. (2007) find that speculators perceived private information and cost advantages lead them to take active positions. They say "*Several individual pieces of evidence taken together suggest that speculators are more likely to believe they have comparative information advantage relative to the market, and hence to view speculation as a positive net present value (NPV), that is, profitable, activity.*" (Geczy et al., 2007, p. 2). Adam et al. (2007) state that when a firm has private information, which is not available to other participants of the market, selective hedging increases firm value. They find that smaller firms speculate more than larger firms do, although they are less likely to possess the information and financial advantages necessary to outperform the market through speculation compared to larger firms. Stulz (1996) concludes that firms should also possess financial strength besides having a genuine information advantage, to support the extra risk that selective hedging involves, to increase shareholders value using selective hedging.

Lin and Lin (2012) examine the effect of information asymmetry on firms incentive to hedge versus speculate or take a view by using FC derivatives. They find nonlinear relationship between information asymmetry and motives behind derivatives use. In particular, the authors find that firms that hedge have medium level of information asymmetry and firms that speculate have high and low levels of information asymmetry. This is in contrast to finding of Demarzo and Duffie (1995).

2.6. Derivatives and Managerial Compensation

The relation between managerial risk taking and compensation is complicated. The decision to use derivatives is made by managers and hence their rational drives the motive behind the use of derivatives. Previous studies in the field consider managers portfolio structure as a determinant of the corporate risk management choice. Smith and Stulz (1985) state usually the holder of the executive stock options has disadvantage to hedge firm risk. There is a positive relationship between manager option-based compensation and incentives for managers to take on risks as it will increase the stock option values (Smith and Stulz, 1985). Tufano (1996) suggests that corporate risk management policy is mainly determined by managerial risk aversion.

Jensen and Meckling (1976) argue that when risk-averse managers hold an undiversified portfolio of equity and human capital invested in a single firm, then managers are motivated to use derivatives to reduce the risk for personal benefit and at the cost of shareholders. The authors argue that managers may use derivatives to increase the value of their compensation packages, to protect personal wealth invested in equity capital of firm and when managers receive a post-retirement compensation package.

Using a sample of North America gold mining industry, Tufano (1996) finds that firms whose managers hold more options manage less gold price risk, and firms whose managers hold more stock manages more gold price risk which suggest that managerial risk aversion may affect corporate risk management policy. The author finds no evidence of use of derivatives for speculation among these firms. However, it is important to note that this study is carried out on firms in gold mining industry only.

There is a positive relationship among option based compensation policy and incentives for managers to take risk because stock price volatility increases call option value (Smith and Stulz, 1985). Firms are also more likely to use derivatives for speculative purposes when the stock price sensitivity of the CFO's firm related compensation is higher but the convexity of his options is not associated with speculation. Managers might have an incentive to engage in speculation if their remuneration is linked to the profits such strategies produce. Smith and Stulz (1985) demonstrate that when a risk-averse manager owns a large number of firm's shares, his expected utility of wealth is significantly affected by the variance of the firm's expected profits. The manager will direct the firm to hedge when he believes that it is less costly for the firm to hedge the share price risk than it is for him to hedge the risk on his own account. Consequently, Smith and Stulz (1985) predict a positive relation between managerial wealth invested in the firm and the use of derivatives. A study by Beber and Fabbri (2012) using a sample of large US non-financial firms with currency exposure find no significant link between CEO stock price sensitivity (delta) and selective hedging. However, they find a decrease in hedging activity when the sensitivity CEO Vega increases. They also find that CEO education, age, gender and experience can explain speculative behaviour.

Wysocki (1996) examines the relationship between a firm's use of derivatives and its compensation policy, ownership structure and organisational culture using a sample of US firms for the period 1993-1994. The author finds positive relationship between use of derivatives, number of business line and the number of overseas operations. Negative relationship is observed between derivatives use and inside ownership but it is unaffected by the riskiness of CEO compensation, the level of insider wealth invested in to equity or CEO retirement. These results are consistent with the notion that derivatives are used for hedging and not for the opportunistic use of derivatives. Rogers (2002) examines the risk taking incentives of CEOs from stock and option holding compared to derivatives use. The author finds strong negative association between CEO risk taking and derivatives use. This suggests that derivatives are used for hedging: however, it may also suggest that firms are leaving their exposure unhedged. The author measures CEO risk taking as the ratio of Vega-to-delta and uses a sample of 524 US firms.

Using response to a well-known survey Geczy et al. (2007) find that CFO's delta is positively associated with the probability of actively taking positions. However, the equity-based compensation of the CEOs has the negative association with speculation. These results also suggest that the speculating firms have compensation related incentives that encourage speculation, but only if it is expected to be profitable. Geczy et al. (2007) also suggest that managers of derivative using firms are more likely to speculate when derivatives function is benchmarked against profits rather than the effect of derivatives on the firm and when managers have high-powered incentives.

2.7. Effects of Derivatives Use on The Firm Financial Risk

Above, we discussed several of the factors that influence firm's use of derivatives for hedging or speculation. In this section, we discuss the effects of derivatives use on the firms' financial risk. From the above discussion it follows that if firms are using derivative for hedging then it would reduces the firm risk and if firms were using derivatives for speculation then it would increase the firm risk. Copeland and Joshi (1996), Guay (1999), Hentschel and Kothari (2001), Bartram (2006), Nguyen and Faff (2010), Bartram et al. (2011), Boyer and Marin (2013), Magee (2013) and Marin (2013) have investigated the relationship between derivatives use and firm financial risk. These studies examine the effects of derivatives directly on firm financial risk measures. Besides these studies, there are some other studies that indirectly investigated the effects of derivatives on firm risk.

Using a sample of 254 non-financial US firms that started using derivatives, Guay (1999) provides evidence that firm risks (total risk, market risk, idiosyncratic risk, IR exposure and exchange rate exposure) decline in the period following the initiation of a derivatives program. These results are consistent with the theories that firms are using derivatives to hedge and not to increase firm risk. The author compares sample of derivative user firms that started using derivatives with a controlled sample of non-derivative user firms and finds 5% reduction in stock volatility, 22% reduction in IR exposure and 11% reduction in exchange rate exposure for firms that have started using IR and FC derivatives. These show that firms are using derivatives for hedging and are receiving significant benefits of derivatives in terms of lower firm risks. On the contrary, a study by Hentschel and Kothari (2001) fail to find any significant effect of derivatives use on the firm financial risk. The authors also look at firm risk characteristics by investigating whether firms' use of derivatives is significantly related to their overall stock return risk and fail to find any significant effect of derivatives use. Using data from annual reports of 425 large US firms, they focus on firms with an average level of derivative usage and also intensive users of derivatives, they do not detect any economical or statistically significant relationship between firms' risk characteristics and the extent of their participation in derivatives market. They also do not find evidence consistent with the hypothesis that firms use derivatives to speculate on a large scale. However, their results do not provide any evidence suggesting that firms' use of financial derivatives helps in reducing firm risk. They report that compare to non-user firms, derivative users firms display few, if any, measurable differences in risk that are associated with the use of derivatives. They find similar result when they control for endogeneity using an instrumental variable methodology.

Marshall (2000) in a survey of 179 MNCs from US, UK and Asia in year 1998 find that majority of the respondents state that foreign exchange risk management is equally or significantly important in relation to business risk management. With regards to UK MNCs, 45% and 21% of respondent firms, respectively, stated that foreign exchange risk management is equally or significantly important in relation to business risk management. This result is not surprising as given UK geographic location, majority of UK MNCs are highly dependent on business from overseas. The author also finds statistically significant regional differences in the importance and objectives of risk management particularly for translation and economic exposures, internal/external techniques used in managing foreign exchange risk and the policies in dealing with economic exposure. The author also shows that derivative usage does not decrease the variation in the firm value but they show that the usage of certain techniques is related with an increase in the variability of certain financial measures. In a survey of 173 UK firms in year 2001, El-Masry (2006) finds that 37% of respondent firms use derivatives to manage the volatility of cash flow. 29% of respondent firms use derivatives to manage their market value while 25% and 19% of respondent firms use derivatives for managing volatility in accounting earnings and managing balance sheet accounts respectively. In a study of hedging activities of 119 US oil and gas producers for the period 1998 to 2001, Jin and Jorion (2006) find that risk management activities of oil and gas producers decrease with sensitivity of equity returns to oil and gas prices. These results suggest that there is a negative relation between financial derivative instruments and the level of firm risk, which is consistent with firms using derivatives to hedge rather than speculate.

Using a data from 47 countries Bartram (2006) examines whether firms use derivatives for hedging or speculation and finds strong results showing that firms use derivatives for hedging. The author shows that derivative users are exposed to exchange rate risk (higher foreign sales, foreign income, foreign assets, foreign debt) and interest risk (higher leverage and lower quick ratio). Moreover, the author finds that derivative users have lower levels of post-hedging measures of risk such as stock return volatility and market betas than non-users. In terms of economic significance, the results suggest that derivative users have 20-30% lower stock return volatility than non-users. In multivariate analysis, the author finds that both stock return volatility and market betas have significant negative association with derivatives for the whole sample. The author finds qualitatively similar results for IR and CP derivatives use. However, when the author examines the effects of FC derivatives, the author find significant negative effect of FC derivatives on market risk but fail to find any effect of FC derivatives on the stock return volatility. The author also repeats the analysis for UK firms separately. The results of this analysis show that the author fails to find any significant effect of derivatives use on the stock return volatility and market betas.

Purnanandam (2008) examines the effect of risk management in the presence of financial distress costs for a sample of US firms. The author finds nonlinear relationship between leverage and derivatives. In particular, the author finds that derivatives is positively related to leverage for moderate level of leverage and negatively related to leverage for highly leveraged firms. This is consistent with hedging theory that firms with more debt (risky firms) have more incentive to use derivatives. The author reports that hedging incentives disappear with a very high leverage. The author also finds that firms with higher financial distress in concentrated industries hedge more.

Using a large sample of Australian firms for two years period Nguyen and Faff (2010) find that the use of derivatives does not lead to an absolute reduction in the firm risk for their whole sample but they find that the effect of derivatives use on firm risk is nonlinear as they find that the extent of derivatives use of less that 40% is associated with a reduction in firm risk. With regards to extensive derivative users they find that such firms seemed to be associated with an increase in firm risk and suggest that extensive usage of derivatives us associated with speculative use. This finding highlights that not all the levels of derivatives use are associated with a reduction in firm risk. They report that 56.9% of their sample firms experienced a reduction in risk as result of derivative use (198 firms out of 348 derivative user firms). For the remaining firms though they find no evidence of risk reduction. Nguyen and Faff (2010) find that FC derivatives are used for hedging but it has little impact on the overall risk portfolio of the firm. This finding is in line with the Stulz (1996) argument that the use of FC derivatives is primarily to hedge short-term exposure that arises as a result of short-term currency contracts. In respect to IR derivatives, consistent with theories, Nguyen and Faff (2010) find that firm use IR derivatives to hedge long-term exposure. For FC derivative users they find significant reduction in idiosyncratic risk and for IR derivative users they find significant reduction in total risk. They argue that the relationship between derivatives use and firm risk is nonlinear. Guay (1999) also notices nonlinearity in his work. They find that the nature of relationship between firm risk and derivative usage is conditional on the extent of derivative usage.

A recent study conducted by Bartram et al. (2011) using a large dataset of non-financial firms from 47 countries with a sample of 6,888 non-financial firms find significant evidence that the use of financial derivatives reduces both total risk and systematic risk. They also find hedging with derivatives is associated with significantly higher firm value, abnormal returns and larger profits suggesting firms are hedging downside risk. Their results suggest that financial risk management with the help of derivatives significantly reduces firm's cash flow risk, total risk and systematic risk. The effect of derivative use on firm value is positive but sensitive to endogeneity and omitted variables concerned. The authors use a propensity score matching method to match derivative user firms with non-user firms based on their likelihood of using derivatives. They show that derivative users have 7%-8% lower cash flow volatility, 5%-10% lower stock return volatility and 15% to 31% lower market beats compare to matched non-user firms.

Campello et al. (2011) examine the effects of hedging on the loan spread of a sample of US firms. In particular, the authors examine the effects of hedging on the costs of raising external finance and investment spending. For this analysis, the authors use extensive manually collected data on firms hedging activities. The authors focus on private credit agreements in the syndicated loan market. They find that firms hedging activities reduces the cost of external financing. In economic significance their results show that a 1 standard deviation increase in the hedging intensity lowers the loan spread by 54 basis points, which represents 29% reduction in loan spread compared to average loan spread of 189 basis points. Their results also suggest that firms that hedge have less loan covenants in contract than non-hedger firms. The authors also find that hedging lowers the chances of negative outcomes and hence reduces the costs of financial distress. The results highlight the importance of hedging in reducing borrowing costs resulted because of reduced probability of default from hedging. They also find that hedging helps lower the true cost of debt and that hedging is more beneficial to firms that have higher distress risk. Hedging firms also benefits from less capital expenditure constraints in loan agreements. In particular, the authors find that the average IR/FX hedger is 20% less probable to have capital expenditure restriction clause in future credit arrangements.

Using a pair-matched sample of 344 US bankrupt and non-bankrupt firms for the period of 1998 to 2005, Marin (2013) finds, consistent with hedging motives, that the probability of filing for bankruptcy are approximately 96% lower for firms that manages their risk compare to the firms that do not manage their risk. The author uses two alternate measure of risk 1) Distance to default calculated using Black-Scholes-Merton option pricing framework, which measures how far is firm's asset values from its default point in terms of the number of standard deviation and 2) Accounting-based model of equity implied asset volatility. For the first measure of risk, the author finds that firms that use risk management are further away from their distance to default point. The author shows that the distance to default of a firm that uses risk management increases by 3.2 units. For the accounting-based model the author finds that firms that manage risk with derivatives have significantly lower asset volatility. The author shows that when firms manage their risk their asset volatility reduces by 64%. The author also separately examines the effects of IR derivatives and FC derivatives on asset volatility and finds negative association between them. The author also finds significant positive relationship between changes in distance to default and changes in IR risk management as well as between changes in distance to default and changes in FC risk management. These results are suggestive of hedging motives of derivatives use. With regards to the CP exposure, the author finds that the distance to default reduces for the firms that use CP derivatives to manage their low IR and exchange rate exposures.

Magee (2013) looks at the relationship between FC derivative use and the probability of financial distress for a sample of US firms for the period of 1996-2000. The author uses distance to default as a measure of firm financial distress and uses two measures of FC derivatives 1) a continuous measure of derivatives and 2) a dummy measure of derivatives use. The author finds that firms with an extensive use of FC derivatives exhibit a lower probability of financial distress after controlling for the endogeneity problem between hedging and leverage. In economic significance the results suggest that a 1 standard deviation increase in the extent of FC derivatives increases the distance to default by 0.870. This is consistent with FC derivatives being used for hedging rather than speculation. However, the author fails to find any significant effect of the decision to use derivatives on the proxy for the probability of default. A recent study by Boyer and Marin (2013) find that firms that use FC derivatives to manage foreign exchange exposure are less prone to financial distress risk. As a measure of firm financial risk, the author use distance to default, equity implied volatility of assets and moneyness of the debt calculated using the Black-Scholes-Merton option-pricing model. The authors use a dummy measure for a firm's use/non-use of FC derivatives. The authors also investigate the effect of foreign operation and FC debt on financial distress risks and find similar results. Similar to Magee (2013), the authors do not investigate the effect of IR derivatives use on the measures of financial distress. It is not clear why Boyer and Marin (2013) and Magee (2013) focus on FC derivatives only and not IR derivatives since the latter would be expected to have a stronger impact on the risk of financial distress. Furthermore, there is evidence that US firms are timing the market with respect to their use of IR derivatives.[23]

2.8. Effect of Foreign Currency Derivatives on FX Exposure

There are many studies that looked at the relationship between FC derivatives use and firms' FX exposure and reported mixed results (Copeland and Joshi, 1996; Allayannis, Ihrig and Weston, 2001; Allayannis and Ofek, 2001; Carter, Pantzalis and Simkins, 2003; Kim, Mathur and Nam, 2006). Below, we discuss these studies.

In a study of 198 firms with the highest sales in year 1994, Copeland and Joshi (1996) examine the effect of currency derivatives use on the volatility of cash flow as a result of changes in exchange rate. The authors argue that if, after the use of FC derivative, there were a substantial reduction in the cash flow volatility then it would suggest significant benefit of using FC derivatives; whereas small reduction in cash flow volatility would indicate low potential benefits. The authors find that the most superbly designed and executed FX management programmes seem not to reduce cash flow volatility for majority of their sample firms. The authors also argue that management time and substantial capital sums invested in FC derivatives use destroys firm value instead of protecting it. The authors indicate that the reason for the failure of the currency derivatives programme is that many economic factors also change while FX rates change, which are not considered while employing FC derivatives programme. This indicates that the FC derivatives are not

[23] *See Faulkender (2005) for more details.*

suitable to manage FX exposure if they cannot control for other factors that also changes simultaneously with FX rates.

Géczy et al. (1997) show that firms are more likely to use FC derivatives when they have high cost of financial distress and volatility of cash flow, which suggest that their sample firms are using derivatives to protect themselves from unanticipated changes in FX rates that are capable of moving firms into financial distress zone. However, they find no direct evidence that the use of FC derivatives reduced the exposure to FX risk and hence it may be possible that the use is related to expected gain from speculative use of derivatives.

In a study of 171 Japanese MNCs, He and Ng (1998) show that 25% of their sample firms experienced a significant exposure to exchange rate changes and when they examine the relationship between variables that were assumed to reflect derivatives usage and FX exposure for their firms they find that firms that are more likely to use derivatives had lower FX exposure than firms that are less likely to use derivatives. In their sample, they find that large MNCs in machinery industries were not significantly exposed to FX exposure. They argue that the reason why these MNCs were not significantly exposed to FX exposure is that those firms might be using derivatives and other hedging instruments to immunise themselves from unanticipated changes in exchange rates. These suggest that the use of derivative instruments can reduce the sensitivity of a firm's stock to the movement in exchange rates. They provide a survey example conducted by Nippon Life Insurance in 1996 that finds larger Japanese companies making extensive use of derivative instruments. The survey notes that companies use derivatives not only for hedging but also for speculative purposes.[24]

In a study of East Asian non-financial firms for the period 1996 to 1998 Allayannis, Brown and Klapper (2001) examine the effect of FC derivatives on FX exposure. The authors find no evidence that the use of FC derivatives by East Asian firms reduce their FX exposures. Their results indicate that East Asian firms that were using derivatives prior to the 1997 East Asian crisis performed similar to that of non-derivative user firms during the crisis. This may suggest that derivatives were not effective during the period of crisis. The authors also find that firms use foreign earnings as a substitute of hedging with derivatives.

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[24] *See for more details He and Ng (1998, p. 745)*

Allayannis and Ofek (2001) using a data of 378 US non-financial S&P 500 firms for the period 1993 find evidence that firms' use of FC derivatives significantly reduces FX exposure firms' face. The authors use a continuous measure of FC derivatives. They also find that derivative user firms have lower estimated values of firm risk, which suggest that firms use derivatives for hedging financial risk and not for speculation in the FX market. The authors also provide evidence that firms' exposure through foreign sales and foreign trade is a very important factor in deciding what exposure to hedge, the size of hedge and the maturity of contract. This suggests that firms are not taking decisions on FC derivatives use using market views but instead examine the source of their foreign exchange exposure and then firms hedge that exposure. The authors argue that the FC debt is a substitute for FC derivatives and suggest that firms can use FC debt to protect themselves from FX exposure. However, the authors do not examine the effects of FC debt on FX exposure.

Allayannis and Weston (2001) examine a sample of firms that are exposed to FX risk through foreign sales and investigate whether firms that have similar FX exposure differs in firm value based on whether they use FC derivatives or not. They find that FC derivative user firms have higher firm value than non-users firm among the sample of firms that are exposed to FX. This indicates that firms that use FC derivatives have higher market value despite the similar level of FX exposure. A study by Carter et al. (2003) use a dataset of 208 MNCs from the US provide evidence that both operational hedging, such as production in other country, and financial hedging, such as financial derivatives, lowers the firms' FX exposure. In a sample of 424 US MNCs Kim et al. (2006) find both operational and financial hedging strategies are effective in reducing FX exposure. They find higher usage of FC derivatives by non-operationally hedged firms compare to their level of FX exposure. They also find that lower FC derivatives usage by operationally hedged firms that have more FX exposure. This suggests that operational hedging is substitute of FC hedging.

Nydahl (1999) studies a sample of 47 Swedish firms using a cross-section differences in exposure and find that foreign sales is positively related to the estimated FX exposure while use of FC derivatives has negative effect on the FX exposure. This is also consistent with hedging theories and the findings of Allayannis and Ofek (2001). In a study of firms during the year 1995 to 1999 that disclose the use of derivatives to hedge, Nelson, Moffitt and Affleck-Graves (2005) find evidence that firms that use derivatives for hedging consistently out-performed other firms by 4.3% per year on average on the stock return.

However, they note that this gain of stock market performance is observed only for those firms that are using FC derivatives. They report 21.6% of their sample firm disclosing use of derivatives and consistent with other studies majority of derivative users firms are larger. In support for theories on economies of scale and transaction cost they find evidence on relative valuation that suggests that only larger firms are getting benefits of hedging. Their results on use of IR derivative or CP derivatives suggest no abnormal returns for the user firms.

For a sample of 144 Australian firms with average foreign sales of 40% of total sales for the year 1990, Nguyen and Faff (2003) examine the role of FC derivatives in reducing FX exposure. They find that the use of FC derivatives by Australian non-financial firms reduces the short-term FX exposure. They also find that FC derivatives are used to hedge an existing FX exposure and not to speculate in the derivatives market. Their results suggest that Australian firms use derivatives for hedging as its use reduces exposure to exchange rate. Jong, Ligterink and Macrae (2006) study Dutch firms over a period of 1994-1998 using a questionnaire data and find that over 50% of the sample firms are significantly exposed to FX exposure. They find no significant effects of off-balancing hedging with derivatives on exposure. However, they find that exposure is significantly reduced by using natural hedge such as employing FC debt or producing in foreign countries. They also show that Dutch firms use derivatives to reduce the transaction risk where as economic exposure remains largely exposed to exchange rate movements[25].

Muller and Verschoor (2008), using a sample of 471 European non-financial firms, examine the effects of derivatives use on firms' FX exposure. They find firms' decision to use FC derivatives is negatively related to exchange rate sensitivity. This evidence suggests that non-financial firms use FC derivatives primarily for hedging purpose. However, the results they find are statistically and economically weak. The authors argue that the reason for these weak results is either 1) Managers are hedging a very small portion of exposure that they are facing or 2) while assessing the link between FC derivatives usage and firm's risk exposures, investors make systematic errors. Allayannis et al. (2012) find positive and significant relationship between firms' use of derivatives and the value of their sample firms. The authors suggest that the use of FC derivatives by firms

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[25] *Bodnar, Jong and Macrae (2003) find similar results*

with foreign exchange exposure increases the firm value. They report that firms that use FC derivatives have 10.7% higher firm value than the firms that do not use FC derivatives.

Using a sample of 148 UK non-financial firms for the year 1999, Zhou and Wang (2013) test the relation between the use of FC derivatives and firm's FX exposure. As opposed to others studies, this study uses fair values of FC derivatives instead of notional values. The authors calculate FX exposure using weekly data, similar to Allayannis and Ofek (2001). The authors find negative sign on the FC derivatives variable but the associated p-value is larger than the critical value of 0.10. The coefficient for which the associated p-value is closets to 0.10 is 0.1235 when the exposure variable includes both positive and negative exposures and suggests that the findings of the study are weak. However, it is hard to interpret the coefficient on FX exposure when FX exposure variable contains both positive and negative values as it creates problem in interpreting the effect of FC derivatives on FX exposure.

2.9. The Effect of Foreign Debt on FX Exposure

Majority of previous studies that looked at the risk management and FX exposure relationship focused mainly on the financial derivatives usage of the firms. To manage FX exposure a firm can create natural hedge by issuing debt in a currency in which it has exposure, to match foreign assets with foreign liabilities.[26] There are other benefits of issuing FC debt such as borrowing in FC debt may have low cost of interest than borrowing in domestic currency.[27] However, there are circumstances where the use of FC debt can increase FX exposure.[28] Firms can also use other methods of natural hedging such as production in other countries, known as operational hedging. However, operational hedging is more costly as it requires a large cash outlay and a long-term commitment, which may not be feasible and economical for many firms. There is also a cost benefit of using FC debt to manage FX exposure as issuing FC debt is not costly and also it is not as complex as financial derivative instrument (Nandy, 2010).

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[26] *Allayannis and Ofek (2001) and Kedia and Mozumdar (2003) argue that by issuing FC debt a firm can create cash outflow and can match it with cash inflow from foreign sales and hence can mange FX exposure.*

[27] *Keloharju and Niskanen (2001) show three reasons for firms to issue debt. 1) FC debt provided hedging for FX exposure, 2) borrowing in FC may cost less than borrowing in the domestic currency and 3) speculative reasons may make FC debt an attractive alternative. For detailed discusses of these reasons see Keloharju and Niskanen (2001)*

[28] *Géczy et al. (1997) ague that FC debt can increase firms FX exposure if the cash-outflow associated with FC debt is negatively correlated with cash-inflows from foreign operations.*

FC debt is also considered as natural hedge that may either complement of substitute FC derivatives. Allayannis and Ofek (2001) suggest that firms can use FC debt to protect themselves from FX exposure. They argue that firms can match their cash inflow (revenue denominated in FC) with cash outflow (expense denominated in FC) by issuing FC debt. Allayannis and Ofek (2001) confirm the role FC debt as a tool for hedging, however the authors do not further investigate the role of FC debt as an alternative of FC derivatives in FX risk management. Natural hedge is more suitable than derivatives during the periods of uncertainty for FX risk management (Chowdhry and Howe, 1999). Empirically, very few studies examine the relation of FC debt and/or FC derivatives on FX exposure (Elliott, Huffman and Makar, 2003; Hagelin and Pramborg, 2004; Nguyen and Faff, 2006) while other studies incorporated natural hedge in the examination of FC derivatives (Géczy et al., 1997; Allayannis and Ofek, 2001).

Keloharju and Niskanen (2001) investigate the role of FC debt by using a unique data set of 44 Finnish firms that have raised private and public debt between 1985 and 1991. The authors suggest that firms use FC debt for hedging as they find that firms with significant portion of foreign sales are more likely to use FC debt. This shows that Finnish firms are creating foreign liabilities to match with their foreign assets. The authors also find that firms use FC debt for speculation as firms borrow in certain currency when the rate of interest for borrowing in that currency is lower than usual compared to the rates in other currencies. They report that 54.9% of their sample firms use FC debt.

Doukas, Hall and Lang (2003) in a study of 1079 Japanese firms traded on Tokyo stock exchange over 1975-1995 period examine role of FC debt as a hedging instrument. The authors use debt to asset ratio as a proxy for firms FC debt usage as most Japanese firms do not report consolidated accounting information and hence the data on FC debt is not available. The authors find that FX exposure of Japanese firms declines with increase in FC debt. The authors use 2 sub-sample 1) pre-plaza accord period Jan 1975- Sep 1985 and 2) post-plaza accord period Oct 1985- Dec 1995 and find that the coefficient on debt to asset ratio is negative in both period and more significant in pre-plaza period during which derivatives and risk management strategies were not widely developed. This indicates that FC debt work as derivative substitute.

Kedia and Mozumdar (2003) examine issuance of debt in 10 major currencies by sample of 523 large US firms for the year 1996 to investigate the role of FC debt in hedging currency exposure. The authors find strong negative relationship linking FC debt and exposure to individual currencies as well as at aggregate level and suggest that firms use FC debt to hedge. They also find some support that firms issue FC debt in a currency where the information asymmetry between domestic and foreign investors is low. They find strong evidence that the location of foreign operations increase the probability of FC debt issuance supporting the notion of natural hedge benefit of FC debt. Kedia and Mozumdar (2003) show reasons other than hedging for the use of FC debt. They argue that differences in cost of borrowing in different currencies, due to the capital market imperfection, decide firms' choice of FC debt. The authors also provide evidence that the presence of information asymmetry between foreign and domestic investors affects the choice of MNCs in FC debt.

Chiang and Lin (2005) using a monthly data for Taiwanese non-financial firms for the period 1998-2002 examine the use of FC derivatives and FC debt. They calculate FX exposure using two-factor model as in Allayannis and Ofek (2001). The authors use binary variables as a proxy for both FC derivatives and FC debt. Consistent with hedging motive, they find that the use of FC derivatives is associated with a reduction in absolute values of the FX exposure. In respect of FC debt, they find that the use of FC debt increases FX exposure. This indicates that for Taiwanese firms, FC debt does not work as a natural hedge. They also find that for a given FX exposure an increase in the revenue from foreign sales increases the FX exposure. The authors find significant negative coefficient on firm size suggesting that firm size is significantly associated with lower FX exposure. This is consistent with the notion that larger firms have more geographical dispersed operations that leads to lower FX exposure.

Nandy (2010) examines the determinants of decision to raise the loan in FC for the UK and Canadian firms. The author finds significant positive relationship between foreign sales and borrowing in FC. They find that firms that have high sales in US are more likely to hedge their FX exposure by borrowing in USDs. This shows that firms are matching their foreign assets with foreign liabilities. The author reports that a 1% increase in the ratio of foreign sales to US increases the probability of borrowing in USDs by 23%. The author argues that as firms can match foreign income with foreign liabilities by issuing FC debt, it works as low cost and less complicated hedging instrument compared to complex derivative instrument. Aabo, Hansen and Muradoglu (2013) examine foreign debt usage of Danish non-financial firms with international operations. The authors find that FC debt is used to hedge foreign assets and subsidiaries as opposed to foreign sales. This indicates that FC debt is used to hedge accounting exposure and not the operating exposure. The authors have used questionnaire to collect the data on firms' foreign debt usage.

2.10. Effect of Foreign Currency Derivatives and Foreign Debt on FX Exposure

Majority of the studies discussed above find that that FC derivatives and FC debt have risk reducing effect as the use of either of the financial instrument results in lower FX exposure (Nydahl, 1999; Allayannis and Ofek, 2001; Kedia and Mozumdar, 2003; Nguyen and Faff, 2003; Chiang and Lin, 2005; Nelson et al., 2005; Gharghori, Chan and Faff, 2006; Jong et al., 2006; Muller and Verschoor, 2008; Nandy, 2010). Theses suggest that if firms use both of these instruments then it may get more benefits in terms of larger reduction in the FX exposure.

Allayannis, Ihrig, et al. (2001) investigate the impact of financial and operation exchange rate risk management strategies on monthly FX exposure for a sample of US MNCs firms. In financial risk management, they consider firms that use either FC derivatives and/or FC debt and create a dummy variable based on this. Consistent with hedging motive for using FC derivatives and FC debt, the authors find significant negative relationship between FX exposure and financial risk management. The authors find that firms that are geographically dispersed have relatively higher FX exposure. Their results suggest that operational hedging is not a substitute for financial hedging. They find that geographically dispersed firms are more likely to use financial hedging to manage FX exposure.

Hagelin and Pramborg (2004) investigate the effects of FX exposure hedging using a survey data for Swedish firms during a period of 1997 – 2001 and examine the risk reducing effects of FC derivatives and FC debt. The authors find a significant reduction in FX exposure from the use of both FC derivatives and FC debt. Moreover, the authors find that the independent use of FC derivatives and FC debt is associated with a significant reduction in the FX exposure. Their findings suggest that the translation and transaction exposure hedges also reduce the exposure. However, translation exposure is nothing but a cosmetic change in the appearance of the balance sheet and hence does not require hedging. They argue that translation exposure approximates the exposed value of future cash flow from operations in foreign subsidiaries and hence, hedging translation exposure, economic exposure is reduced. They also find that natural hedge also plays important role in reducing FX exposure as for the sample of large firms they find lower FX exposure as they have operational hedges.

Chiang and Lin (2005) investigate the effects of combined use of FC derivatives and FC debt besides investigating the relationship separately. In a cross-sectional framework, they model both FC derivatives and FC debt against FX exposure. They find opposite signs on proxies for FC derivatives and FC debt suggesting that the combined use is not effective in lessening the FX exposure. In particular, the authors find that use of FC derivatives lower the FX exposure whereas the use of FC debt increases the FX exposure suggesting that the use of FC derivatives reduces FX exposure while the use of FC debt increases FX exposure.

For a sample of Australian firms Nguyen and Faff (2006) examine the effects of FC debt, as a natural hedging instrument, and FC derivatives on FX exposure. They find that the likelihood of issuing FC debt is highly associated with the extent of foreign operations. However, the authors fail to find any significant evidence at aggregate level that the use of FC debt is directly associated with a reduction in FX exposure. In further analysis the authors find that the use of FC debt by firms in industrial sector is associated with a reduction in FX exposure confirming that FC debt is used for hedging. The authors fail to find any significant evidence of risk reducing effect of FC debt on FX exposure for firms in resource sector. They report that the primary goal behind issuing FC debt is the cheaper cost of borrowing for firms in resource sector.

2.11. Foreign Currency Derivatives and Foreign Debt: Complement or Substitute

The review of literatures above showed that there is evidence that the use of FC derivatives on its own, FC debt on its own and the combined use of FC derivatives and FC debt are associated with alleviating the FX exposure. In this section, we discuss literatures that focus on the relationship between FC derivatives and FC debt. Previous studies that investigate this relationship have presented mixed results. Some researchers find that the use of FC debt complements the use of FC derivatives in reducing the FX exposure (Chiang and Lin, 2005; Bartram et al., 2009; Aabo, Hansen and Muradoglu, 2011). On the other hand, some researchers find that use of FC debt substitutes the use of FC derivatives in reducing FX exposure (Géczy et al., 1997; Elliott et al., 2003; Aabo, 2006).

Géczy et al. (1997) examine why firms use currency derivatives for a sample of 372 US corporations in 1990. They provide indirect evidence suggesting that firms use FC debt as a substitute for FC derivatives. They find that firms with greater growth opportunities and tighter financial constraints are more likely to use currency derivatives but for a sub-sample of naturally hedged firms, firms with foreign operation and FC debt, they find that research and development (R&D) expenses and short-term liquidity are not significant determinants of FC derivatives use. However, the authors find R&D expenses and short-term liquidity significant determinants of FC derivatives when they use a sub-sample that has only foreign operations and not FC debt.

Allayannis and Ofek (2001) fail to find any significant evidence that US MNCs prefer to use FC derivatives or FC debt to hedge FX exposure. However, the authors find significant evidence that firms with more export prefer to use FC derivatives than FC debt. This suggests that exporting firms are more interested in relatively short-term and customisable financial instruments such as FC derivatives rather than long-term FC debt. Allayannis and Ofek (2001) find positive but insignificant relationship between FC debt and FC derivatives.

Elliott et al. (2003) examine the relationship between FC derivatives, FC debt and FX exposure using a unique dataset for US MNCs corporations for the period 1994-1997. The authors find significant negative relationship between FC debt and FX exposure and show that FC debt may be used as hedging. They also find negative relation between FC debt and FC derivatives indicating that FC debt is substitute for FC derivatives and hence again suggest that FC debt is a hedging tool. The authors use ratio of foreign sales to total sales as a measure of FX risk whereas majority of other studies that examine the effect of FC derivatives or FC debt on FX exposure used sensitivity of stock return volatility to changes in exchange rate as a measure of FX exposure (Allayannis and Ofek, 2001; Nguyen and Faff, 2003; Hagelin and Pramborg, 2004; Jong et al., 2006; Nguyen and Faff, 2006; Muller and Verschoor, 2008).

Chiang and Lin (2005) investigate whether FC derivatives and FC debt are used as substitute or complement. Using logit regression estimation the authors regress FC derivatives on FC debt and other control variables and find significant positive relationship between FC derivatives and FC debt suggesting that the use of FC derivatives and FC debt is complement. However, when they regress FC debt on FC derivatives and other control variables they find positive but insignificant coefficient on FC derivatives. This suggests that the relation they observed between FC derivatives and FC debt is weak. Aabo (2006) shows, using public information and data collected using questionnaire for Danish firms, that FC debt is a very important alternative to the use of FC derivatives in actual decision making in non-financial firms. They show that relative importance of FC debt is positively associated with 1) the number of countries in which the firm has subsidiaries, 2) the extent to which firms' value is associated with the foreign assets in place and 3) the debt ratio.

Using a sample of 7292 firms from 48 countries, Bartram et al. (2009) find positive and significant relationship between FC derivatives and FC debt. The authors argue that they add FC debt dummy variable in regression analysis as it may work as a hedging tool, that is a complement to FC derivatives, if they have cash inflow from the country of the debt or as a source of exposure, in case the firm issue FC debt in a country from where they have no cash inflow, which require hedging through the use of FC derivatives. Their positive relationship between FC derivatives and FC debt confirm that FC debt is either a complement to FC derivatives or may be increasing FX exposure for which FC derivatives is needed to lower the FX exposure. However, if FC derivatives and FC debt both are targeted to manage different source of FX exposure, the observed positive relationship will still hold.

Using survey data for medium sized non-financial Danish firms Aabo et al. (2011) find that FC debt is not a substitute but the complement of FC derivatives. They find that the use of FC derivatives is associated with flow measures such as revenue from foreign sales and the use of FC debt is important for hedging FX exposure arising from stock measures such as foreign assets and foreign subsidiaries. The authors also find that the use of FC debt is not important to hedge revenues from foreign operations. This suggests that FC derivatives and FC debt are not applied similarly to manage FX exposure. This supports Bartram et al. (2009) finding that FC derivatives and FC debt are complements and both are used to manage different source of FX exposure.

2.12. Conclusion

In this chapter we review existing literature that investigate the motives behind the use of derivatives and the effect of derivatives use on the firm financial risk measures. This chapter discusses main theories of risk management with derivatives along with empirical findings. This chapter also highlights the lack of empirical studies that utilised UK firms' data to examine the derivatives use on firm risk, despite the fact that UK firms provide unique setting for this type of examination.

This chapter shows that many existing studies that investigate the effect of derivatives on firm risk use measures such as total risk, market risk and idiosyncratic risk and show whether firms use derivatives for hedging or speculation (Guay, 1999; Hentschel and Kothari, 2001; Nguyen and Faff, 2010; Bartram et al., 2011) whereas recent empirical studies use market-based measure of firm risk such as distance to default, equity implied volatility of assets to examine the effects of derivatives (Boyer and Marin, 2013; Magee, 2013; Marin, 2013). These suggest that there is no consensus in empirical literature on a good measure of firm risk. However, review of existing studies provides firm risk variables to be employed in the current study.

Chapter 3. Data and Methodology

This chapter outlines the relevant data and research methodologies to be used in the following empirical chapters. The objective behind this chapter is to offer a clear logical reason behind the variables and the research methods used in this thesis. This chapter is organised as follow: Section 3.1 describes the sample selection procedure and sample period. Section 3.2 focuses on the sources of data collection and the measurement of proposed variables. Section 3.3 discusses the research methods employed in empirical chapters and Section 3.6 concludes this chapter.

3.1. Sample Selection and Sample Period

This section describes the sample selection procedure and sample period. This section is organised as follow: Section 3.1.1 describes the sample of this thesis and Section 3.1.2 describes the sample period.

3.1.1. Sample

This study uses a large sample of UK non-financial firms listed on London Stock Exchange for investigating the effects of derivatives on firm risk. Following existing literature[29], financial firms such as banks, financial institutions, insurance firms and other financial service sector firms are excluded from our sample, as these types of firms may have different motives for using financial derivatives product than non-financial firms. Financial firms may use derivative products for trading purposes and hence inclusion of such firms in the analysis will bias the result and the real effects of derivatives use on non-financial firms will be misjudged. We have different number of firms each year as a firm can exit the database due to the prevalence of merger, delisting, and acquisition or if no financial information is available. Overall, we have 4264 firm year observations.

3.1.2. Sample Period

The variables subject to the examinations are taken for a period of 12 years. The exact period for the study started in year 1999 and finished in year 2010. The selection of the initial year for our sample period is driven by the availability of the data on firms' use of

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[29] *(Guay, 1999; Allayannis and Weston, 2001; Hentschel and Kothari, 2001; Glaum, 2002; Faulkender, 2005; Judge, 2006b, 2006a; Chernenko, Faulkender and Jenkins, 2007; Purnanandam, 2008; Nguyen and Faff, 2010; Magee, 2013)*

derivatives. Financial Reporting Standard (FRS) 13 was introduced in year 1999, which required firms to disclose the use of derivatives. The period 1999 to 2010 examined in this study exhibits significant variation in macroeconomic and more importantly credit risk conditions. The study period covers the global recession of 2000 and 2001 and the recent financial crisis of 2007 to 2009. Both of these periods witnessed elevated levels of both macroeconomic uncertainty and corporate financial distress, with these distress levels reaching new heights during the most recent financial crisis. Between these two episodes of financial and economic crisis, macroeconomic conditions in the UK were relatively benign with gross domestic product (GDP) growth at around 2 per cent per annum. Our sample period provides a unique opportunity to investigate the impact of derivatives use on the firm risk during a time when one would expect such activity to be most beneficial.

3.2. Sources of Data Collection

The data for this study are collected from several sources. We source data for this study mainly from annual reports and DataStream. Few other data are collected from different sources, which are discussed along with the data in variable measurement section. Below we discuss the two main sources of data collection: Annual Reports and DataStream.

3.2.1. Data from Annual Reports

We use annual reports to collect data on derivatives use, foreign sales, foreign assets and foreign debt.

One of the difficulties with research on the corporate use of derivatives is the availability of data on firms' derivative usage. Due to the lack of disclosure in annual reports, prior studies heavily relied on surveys to collect data[30]. However, after the successive implementation of international financial reporting standard, the disclosures of derivatives use in annual reports are improved. In the UK several accounting standards relating to the reporting of derivatives in financial statements have been enacted during 1990's. The first of these and the most relevant in the context of this study was FRS 13, which came into force in March 1999. FRS 13 required non-financial firms to provide both narrative and numerical disclosure on their derivative activities in their financial statements. The standard suggests that narrative disclosures should describe the role that financial

[30] *Bodnar et al. (1996), Bodnar et al. (1998), Faff and Marshall (2005) and Judge (2006b)*

derivatives have in creating or changing the risks that the firm faces, including the firm's objectives and policies in using financial derivatives to manage these risks. The numerical disclosures in annual reports should explain how these objectives and policies are implemented and provide supplementary information for evaluating significant financial exposures. This disclosure requirement of narrative and numerical information is in response to the escalating use of derivative by corporations over last 20 years. FRS 13 was followed by FRS 26, which implemented the recognition, measurement and hedge accounting requirements of the international standard IAS 39 and came into operation on the 1st January 2005. FRS 26 permitted the use of hedge accounting for financial instruments such as derivatives.[31] Finally, FRS 29 'Financial Instruments: Disclosure' was adopted on the 1st January 2007. FRS 29 requires firms to disclose information about their exposure to risks arising from financial instruments, such a credit, liquidity and market risks together with descriptions of management's objectives, policies and processes for managing those risks. Quantitative disclosures are also required to provide information about the extent to which the entity is exposed to risk, based on information provided internally to the entity's key management. FRS 13 was withdrawn on implementation of the disclosure requirements of FRS 29. Prior to FRS 13 it was hard to distinguish between firms that do not use derivatives and firms that uses derivative but did not disclose the use of derivatives. This resulted in the non-disclosure bias for studies prior to 1999. The disclosure requirement of FRS 13 benefited various stakeholders in valuing their investments and in analyzing the risk they are facing. It has also helped researchers in examining the effects of derivative use on various measures of firm risk.

However, this disclosure requirement did not provide a standard reporting format. In the absence of a uniform reporting format, for the use of derivative instruments, firms disclose this information in different ways. As a result, some firms provide detailed information about the derivative instruments they use, the notional amount of derivative instruments and purpose of using derivative instruments where as other firms just disclose that they use derivative instruments but do not provide information on type of derivative instrument, notional amount and the purpose of using it.

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[31] *Hedge accounting involves deferring the recognition in the profit and loss accont of gains and losses that would otherwise be recognized there immediately.*

The data on firms' use of financial derivative instruments are manually collected from annual reports of respective firms. We read the financial review section of the annual reports and the notes to the accounts relating to the firms' use of risk management instruments to identify which firms use derivatives, the type of derivative instrument and to collect the quantitative data on the use of derivative instruments, notional values of derivatives. A qualitative discussion of corporate risk management policy will usually be found in the 'Operating and Financial Review' section of the annual report under the heading 'Finance Directors Review'. In this section it is usually possible to determine if a firm is using FC and/or IR and/or CP derivatives, More specific data on the types of derivatives used and in some instances data on the notional amounts of FC, IR and CP derivatives outstanding at yearend are disclosed in the 'Notes to the Financial Statements' section of the annual report under the heading 'Financial Instruments'. If there is no mention of the use of derivatives in the annual report we classify the firm as a non-derivative user firm. Two types of variables are created based on the derivatives usage 1) a binary variable based on a firms' decision to use derivative instrument and 2) An extent of derivatives based on a firms' disclosure of notional values of derivatives. Earlier studies that used derivatives data also collect it from annual reports (Guay, 1999; Hentschel and Kothari, 2001; Bartram et al., 2011; Boyer and Marin, 2013; Magee, 2013).

We also read the segmental reporting section of the annual reports to collect data on firms' foreign sales and foreign assets. Firms report their sales and assets data, based on their geographical segments, under segmental reporting section. We collect these data and record it for UK, US, EU and Rest of the World (ROW). Data on firms debt denominated in foreign currencies are also collected from annual reports. This information is normally reported in the liabilities section. Firms disclose this information based on the currency of the debt. We also collect and record these data for UK, US, EU and ROW. This bifurcation of debt allows us further examination.

3.2.2. Data from DataStream

The firm level financial data are collected from DataStream. We collect raw data from DataStream and then calculate total risk, market risk, idiosyncratic risk, foreign exchange exposure, Z-score, leverage, firm size, profitability, liquidity, equity volatility, excess return, market to book, dividend yield and instrumental variables. These variables are discussed in more detail in following sections.

3.3. Variable Measurement

This section discusses the measurement of firm risks, control and credit risks variables that we use in our empirical analysis.

3.3.1. Dependent Variables[32]

In this section, we discuss the risk variables (total risk, market risk, idiosyncratic risk, EDF, FX exposure and Z-score) that we use in empirical chapters and the methods used to calculate these variables.

3.3.1.1. Dependent Variables in Chapter 4

In Chapter 4 we examine the effects of derivative use on the total risk, market risk and idiosyncratic risk. These firm risk measures are calculated as follow:

3.3.1.1.1. Total Risk

Total risk is calculated as annualised standard deviation of weekly stock returns over two years multiplied by $52^{1/2}$. This is a measure of aggregate firm risk. Bartram (2006) argues that total risk is a summary measure of the different financial risk. The data on sample firms share price are collected from DataStream. Total risk is further separated into market risk (systematic risk) and idiosyncratic risk (non-systematic risk). This break down of total risk into market risk and idiosyncratic risk allows us additional examination regarding the effects of derivatives use on the type of risk.

3.3.1.1.2. Market Risk

This is a measure of the extent to which a firm's equity return moves with that of the stock market as a whole. This variable is calculated using a regression of firm's weekly stock return against weekly return of FTSE all share price index over two years period. The data on FTSE all share price index is collected from DataStream. To calculate market risk following regression equation is estimated.

$$R_{it} = \beta_0 + \beta_1 R_{mt} + \varepsilon_{it} \qquad [1]$$

$\therefore$Where R_{it} is the rate of return on the *i*th firm's common stock in period *t* and R_{mt} is the rate of return on the market portfolio in period *t*.

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[32] *To mitigate the effect of extreme values we winsorize each variable in the top and bottom 1 percentile.*

The beta from this model measures a firm's systematic or market risk. In equation [1], β_1 represents the systematic or market risk and measures the percentage change in the rate of return on a firm's common stock against a 1% change in the market return.

3.3.1.1.3. Idiosyncratic Risk

Idiosyncratic risk measures the variability in a firm's equity return that arises due to the specific and unique circumstance of a firm as opposed to overall movements in the stock market. This variable is calculated as the annualised standard deviation of the idiosyncratic component of stock returns calculated using equation [1][33].

Several previous studies examine the effects of derivatives use on the above discussed measures of firm risk (Guay, 1999; Hentschel and Kothari, 2001; Bartram, 2006; Nguyen and Faff, 2010; Bartram et al., 2011). However, none of these studies specifically examine the effects of derivatives use on risk of UK non-financial firms. Bartram (2006) and Bartram et al. (2011) investigate this analysis for a sample of firms from 47 countries including UK. Bartram (2006) examines separately the effects of derivatives use on total risk, market risk, net foreign exchange exposure, net IR exposure and net CP exposure for UK non-financial firms. However, the author fails to find any significant effect of derivatives use on these measures of risk for UK non-financial firms. Bartram et al. (2011) do not investigate the effects of derivatives use separately for UK firms. As discussed in section 1.2, the UK is an interesting setting to examine the effects of derivatives use and the discussion above shows that not much is known about the effects of derivatives use on UK non-financial firms risk measures as majority of the earlier studies examine the research question using data from other countries.

3.3.1.2. Dependent Variables in Chapter 5

3.3.1.2.1. EDF1YEAR and EDF5YEAR

In Chapter 5 we examine the effect of derivatives use on the expected default frequency (EDF). EDF measurers the probability that the market value of firm's assets will be less than the book value of the firm's liabilities by the time the debt matures. This measures the uncertainty surrounding a firm's ability to payoff its debt and obligations (Bohn and Crosbie, 2003). In EDF default is defined as the non-payment of any scheduled payment,

[33] *Annualised by multiplying with $52^{1/2}$*

interest or principal (Bohn and Crosbie, 2003). EDF is advanced version of distance to default, which is also a measure of financial distress estimated using Merton's (1974) option pricing model. EDF data is sourced from Moody's. Moody's has provided EDF data covering two time horizons: 1) 1-year EDF (Short-term: EDF1YEAR) and 2) 5-year EDF (Long-term: EDF5YEAR).

Few of the recent studies examine the effects of derivatives on the measure of firm financial risk calculated using option-pricing model (Boyer and Marin, 2013; Magee, 2013; Marin, 2013). Boyer and Marin (2013), Magee (2013) and Marin (2013) use distance to default as a measure of firm risk besides other measures and use data for US firms.

3.3.1.2.2. EDF Model

EDF is calculated for each firm at any point in time using the KMV-Merton model. Moody's KMV used Vasicek-Kealhofer (VK) model to calculate EDF. VK model is the extension of Black-Scholes-Merton framework to calculate probability of default and assume the firms' equity is a perpetual option and default point acts as the absorbing barrier for the firm's asset value. In VK model a firm can continuously borrow and repay their debt unlike under Merton model. In this model, the default is defined as the non-payment of any scheduled payment, interest or principal. When firm's asset value reaches to its point of default, a firm is assumed to default. All different types of liabilities such as short-term liabilities, long-term liabilities and convertible and preferred equity are modelled to calculate default point. The default for a firm can occur on or before the date of maturity (Bohn and Crosbie, 2003).

This model needs equity prices and certain financial items, such as total debt, from annual report to calculate default probabilities. To calculate the default point the model takes the difference between face value of firm's debt and an estimate of market value of the firm, divided by an estimated volatility of firm. The result of above procedure is known as distance to default and it is substituted into a cumulative density function to calculate the probability that the value of the firm will be less than the face value of its debt at the forecasting horizon (Bohn and Crosbie, 2003).

KMV model uses two important equations from Merton model to calculate probability of default from value and volatility of firm's assets. Only two types of liabilities Black-Scholes model allow a single class of equity and a single class of debt. If D is the face value of debt that is due at time T then the market value of equity and the market value of assets are linked by the following equation;

$$E = V\mathcal{N}(d1) - e^{-rT}D\mathcal{N}(d2) \qquad [2]$$

Where E is the market value of firm's equity, V is the market value of firm's assets, D is the face value of firm's debt which is due at time T, r is the risk free interest rate, $\mathcal{N}$ is the cumulative distribution function, $d1$ is given by

$$d1 = \frac{ln(V/D) + (r + 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}} \qquad [3]$$

Where σ_V is a standard deviation of the market value of firm's assets and

$$d2 = d1 - \sigma_V\sqrt{T}$$

The second Merton equation that KMV uses relates the volatility of the firm's value to the volatility of its equity,σ_E, and it is known as optimal hedge equation. Under the Merton model volatilities of firm and its value are related as follow;

$$\sigma_E = \left(\frac{V}{E}\right)\mathcal{N}(d1)\sigma_V \qquad [4]$$

Nonlinear equations [2] and [4] are used by KMV-Merton model to estimate value of firm and its volatility. In KMV-Merton model the value of option is observed as the total value of firm's equity while the value of underlying asset is not directly observable. So, value of a firm can be calculated by multiplying the price of shares with number of shares outstanding.

To implement KMV-Merton model, first σ_E is estimated using historical stock return data or from option implied volatility data. In the second step a time horizon and a measure of the face value of firm's debt is chosen. In the third step, data is collected for risk free rate and market equity of the firm. In the last step equation [2] and [4] are simultaneously solved to get V and σ_V. However, KMV does not use the above equations simultaneously arguing that they provide bad results and instead uses another nontrivial iterative solution technique to estimate V and σ_V. After obtaining the value for V and σ_V the distance to default is calculated as follow;

$$Distance\ to\ Default = \frac{ln(V/D) + (\mu - 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}} \qquad [5]$$

Where μ is an estimate of the expected return on firm's assets. Distance to default efficiently distinguish firms likely to bankrupt from those less likely to default (Sun, Munves and Hamilton, 2013). Distance to default measures the number of standard deviation a firm is away from its default point at given time.

Distance to default measures a normalised distance of a firm's asset value from its default point (Caouette, Altman and Narayanan, 1998). However, Bohn and Crosbie (2003) point out that in reality the assumption of normal distribution results in an underestimation of the calculated distance to default. To control for this underestimation problem, the KMV model goes one step forward and converts the distance to default estimation into an EDF. This is done by linking the distance to default with observed default rates based on 30 years of default history data collected by KMV. Moody's construct a calibration sample for which Moody's has the most reliable default data. This database includes over 250,000 company-years of data and more than 4700 incidents or bankruptcy (Bohn and Crosbie, 2003). This step provides much wider tail for the normal distribution. The corresponding EDF is:

$$\pi_{KMV} = \mathcal{N}\left(-\left(\frac{ln(V/D) + (\mu - 0.5\sigma_V^2)}{\sigma_V\sqrt{T}}\right)\right) = \mathcal{N}(-Distance\ to\ Default) \qquad [6]$$

3.3.1.2.3. Market-based Vs. Accounting-based Measures of Default

Market-based models of probability of default overcomes the problems of accounting-based default models by estimating the distress risk by utilising the market price of firms assets with firms liability. The main assumption under the market-based default models is that the information provided by market contains all the available information for the particular firm. In 1974, Merton introduced the first market-based model. However, market models became popular among investors after the introduction of KMV in 1990 and the development of reduced models in year 2000.

Hillegeist, Keating, Cram and Lundstedt (2004) and Gharghori et al. (2006) investigate the performance of accounting-based and market-based probability of default models. They find that market-based models are superior to accounting-based models and also provide rich information. They argue that probability of default estimates the likelihood of future events while accounting-based models suffer from backward looking information and hence accounting information may not be very much relevant about the future prospect of the firm (Hillegeist et al., 2004; Gharghori et al., 2006). Financial statements are formulated under the assumption that firm will not go bankrupt and hence they are limited by design to accurately predict probability of default (Hillegeist et al., 2004; Gharghori et al., 2006). Accounting-based models use ratios, which are calculated using delayed and infrequently updated information. As the accounting information is published infrequently, accounting based measures of default cannot be calculated at any point in time while market-based default models can be calculated at any time for any publicly-traded firm regardless of time and industry (Hillegeist et al., 2004). The other problem with items in accounting statement is reporting of assets in conservative principle that understates value of item than its market value and hence overstates the accounting-based leverage (Hillegeist et al., 2004; Gharghori et al., 2006). This method of reporting items in accounts also affects the calculated distress measure. Market-based models are derived from theory, which provides the theoretical determinants of default risk and how to extract the default related information from the market prices, and they are economically justifiable (Hillegeist et al., 2004). Market-based models can also be easily modified to calculate the probability of default for any time horizon by changing the time parameter. On the other hand, accounting-based measures are based on coefficients estimated in a first stage regression that are specific to a model's prediction horizon and also depends on the characteristics of the first stage sample (Hillegeist et al., 2004).

The other important weakness of accounting-based model of distress risk is that they do not use volatility of assets while calculating probability of default. However, volatility of asset is very vital determinant of probability of default. Volatility of assets captures the possibility of the firm value decline to the degree that the firm will not be able to service its debt (Hillegeist et al., 2004). Hillegeist et al. (2004) argue that two firms with identical leverage ratios can have different default probabilities based on their asset volatility and suggest that volatility is an important omitted variable from Altman Z-score and Ohlson O-Score models of default probabilities.

The main benefits of using option pricing models in prediction default probabilities are that they help in calculating default probabilities by supplying the necessary structure to extract information related to bankruptcy and they also provide theoretical determinants of default risk (Hillegeist et al., 2004). Market-based models provide timely warnings of credit risk and up-to-date view of firm's value as they use market information.

The main assumption under market-based models is that the markets are efficient but if they are not then market prices may not reflect all the available information about the firm. However, if the markets are not efficient then the market-based models may not be perfect and may lead to potential bias in estimated default probabilities. There are 3 main elements that determine the probability of default of a firm: 1) The market value of firm's assets 2) volatility of assets and 3) leverage. Two of these determinants, 1 and 2, are not directly observable and should be estimated. The other problem with market-based model is that they collect information from market prices of companies and hence requires companies to be listed on stock markets. This limits the calculation of default probabilities to only listed companies. However, market-based distress models provide rich information and are more flexible than accounting-based models. Hillegeist et al. (2004) show that market-based model of default provides significant more information than accounting based Z-score and O-score.

3.3.1.3. Dependent Variables in Chapter 6

3.3.1.3.1. Foreign Exchange Exposure

In Chapter 6, we examine the effects of FC derivatives use and FC debt on FX exposure. In the first step we calculate FX exposure as the sensitivity of the value of the firm, proxy by the return on firm's equity, to an unanticipated change in exchange rate using time-series data consistent with Jorion (1990), Allayannis and Ofek (2001) and Nguyen and Faff (2003). We calculate FX exposure using weekly and monthly data.[34] Majority of the previous studies also use weekly and monthly data to calculate FX exposure (Jorion, 1990; He and Ng, 1998; Guay, 1999; Nydahl, 1999; Allayannis and Weston, 2001; Hagelin and Pramborg, 2004; Dominguez and Tesar, 2006; Muller and Verschoor, 2008). Using equation [7] we estimate FX exposure for our sample firms for the period 1999 to 2010.

$$R_{it} = \beta_{0i} + \beta_{1i}R_{mt} + \beta_{2i}STR_t + \varepsilon_{it} \qquad [7]$$

Where R_{it} is the rate of return on the i_{th} firm's common stock in period t; R_{mt} is the rate of return on the market portfolio in period t; STR_t is the rate of return on a moving, trade-weighted exchange rate index, measured in pounds per unit of basket of foreign currencies

[34]We use three years return data surrounding the particular year to calculate monthly FX exposure. For example to calculate the FX exposure for year 2010, we used monthly return starting in 2009:01 to 2011:12.

in period t; β_{2i} is the coefficient of exchange rate sensitivity of the i_{th} firm. We expect a net exporter firm to be hurt by appreciation of pound suggesting a positive FX exposure and a net importer firm should benefit from appreciation of pound suggesting a negative FX exposure.

In the model above, the coefficient β_{2i} represents FX exposure for the i_{th} firm and measures the percentage change in the rate of return on an individual firm's stock return given a 1% change in the exchange rate. We use Bank of England's effective exchange rate index, which measures the strength of Sterling against a basket of 21 currencies that includes Britain's major trading partners. The trade-weighted exchange rate is appropriate in calculating FX exposure, as it is expected that a firm's exposure to international currencies would be similar to that of national trade with foreign countries. Moreover, majority of previous studies use trade-weighted index (Jorion, 1990; Allayannis and Ofek, 2001; Nguyen and Faff, 2003; Yip and Nguyen, 2012).

3.3.1.3.2. Other Measures of FX Exposures

To check for the robustness of our results, we also calculate FX exposure using Sterling/Euro and Sterling/USD bilateral exchange rates. We do this by replacing return on trade-weighted effective exchange in equation [7] with return on Sterling/Euro and Sterling/USD exchange rates. We also calculate lagged FX exposure using lagged values of trade-weighted effective exchange rate. The data on exchange rates and exchange rate index are collected from Bank of England's website.

3.3.1.3.3. Z-score

Z-score is a single measure returned from a number of appropriately chosen financial ratios, weighted and added together (Agarwal and Taffler, 2007). Altman (1968) applies a multivariate discriminant analysis to develop a model that can "Best" differentiate between distress firms and non-distressed firms. Altman (1968) uses a sample of 66 manufacturing industry firms out of which 33 firms have filed for bankruptcy and the other 33 firms are financially healthy and are similar to the firms that have filed bankruptcy in terms of size for the period 1946 to 1965. From the sample, Altman (1968) uses firms that have assets more than $1 million. Altman (1968) groups 22 ratios into five categories: profitability, liquidity, leverage, solvency and activity. After many statistical tests, Altman (1968) finally specified five ratios that are significant to determine financial distress risk. These five ratios are also given weights to calculate Z-score. Following is the model to calculate general Z-score:

$$Z\ Score = 1.2 * \frac{Working\ Capital}{Total\ Assets} + 1.4 * \frac{Retained\ Earnings}{Total\ Assets} + 3.3 * \frac{EBIT}{Total\ Assets} + 0.6 * \frac{Avg\ Market\ Cap}{Total\ Liabilities} + 1 * \frac{Total\ Sales}{Total\ Assets} \quad [8]$$

where $Z\ Score$ is over all score. If the calculated Z-score is above the cut off rate, 2.675, then the firm is classified as healthy firm and if Z-score is below the cut off rate, 2.675, then the firm is considered as risky firm[35].

After the introduction of the model, many researchers tested the accuracy of Altman's Z-score. Begley, Ming and Watts (1996) find Z-score unreliable during the period of different economic environment. They provide example of changes in bankruptcy laws and buyout activities in 1980s that changed the probabilities of bankruptcy and hence Z-score model which was introduced before these changes may increase the number of classification errors. A study by Grice and Ingram (2001) find considerably lower accuracy of original model in recent years.

Accounting-based techniques to predict financial distress for firms are greatly improved by Altman's Z-score. This measure of financial distress combines the ratios and weights them to discriminate between financial distress firm and financially healthy firm. Taffler introduced UK based Z score model in 1977 which is used to calculate the accounting based financial distress for UK based firms[36]. The model was developed explicitly for the analysis of UK based manufacturing and construction companies. This Z-score requires four financial ratios, which measures a distinct feature of a company's performance, as input. Using a stepwise linear discriminant package for many times the following model is resulted:

$$Z\ Score = 3.20 + 12.18 * Profitability + 2.50 * Working\ Capital - 10.68 * Financial\ Risk + 0.029 * Liquidity \quad [9]$$

∴Where

Profitability = profit before tax/current liabilities (53%)

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[35] *Altman (1968)*

[36] *(Agarwal and Taffler, 2007)*

Working Capital = Current assets/Total liabilities (13%)

Financial Risk = Current liabilities/Total assets (18%)

Liquidity = Quick assets - current liabilities/ (Sales- profit before tax – depreciation)/365 days (16%)[37]

We use UK based measure of Z-score in our analysis.

In Chapter 6 we also use EDF1YEAR and EDF5YEAR as dependent variables.

3.3.2. Main Explanatory Variables

The main explanatory variables of interest in this study are the use of financial derivatives by our sample firms. Majority of the earlier studies use a binary variable and/or a continuous variable (notional amount of financial derivatives) to proxy for the use of financial derivatives. We follow this norm and employ two measures to capture the use of derivative instruments by UK non-financial firms. The first measure is a dummy variable and the second measure is the continuous measure of derivatives use. In Chapter 6, FC debt is an important explanatory variable besides financial derivatives. Majority of the previous studies use a binary variable for the use of foreign debt. We use a binary and a continuous measure as a proxy for foreign debt usage. Below we provide the measurement of these variables.

3.3.2.1. Dummy Measure of Derivatives Use

After carefully reviewing annual report of a firm, we assign ‘1’ to a firm if it discloses the use of derivatives and ‘0’ otherwise. The binary measure of derivative usage has been employed by many of previous studies (Géczy et al., 1997; Allayannis and Ofek, 2001; Allayannis and Weston, 2001; Graham and Rogers, 2002; Purnanandam, 2008; Bartram et al., 2011; Campello et al., 2011; Boyer and Marin, 2013). We follow this norm and use multiple proxies for derivatives use. We classify derivative users based on the underlying asset: 1) All derivative users is a dummy variable set equal to ‘1’ if a firm uses FC and/or IR derivatives and ‘0’ for non-users 2) FC derivative users (B) is a dummy variable set

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[37] *The percentages in brackets after the variable descriptors represent the Mosteller-Wallace contributions of the ratios to the power of the model (Agarwal and Taffler, 2007).*

equal to '1' if a firm uses FC derivatives and '0' for non-FC users 3) IR derivative users (B) is a dummy variable set equal to '1' if a firm uses IR derivatives and '0' for non- IR users. We argue that the inclusion of firms referred to as "other" derivative users in the non-user firms' sample might potentially bias the results against finding particular hypothesized relationships. The majority of "other" derivative users in the non-FC users sample are IR derivative only users and in non-IR users sample are FC derivative only users. Hence, an analysis where "other" derivative users are included in non- users sample could make it difficult to detect a meaningful relationship between FC derivative users & firm risk and IR derivative users & firm risk. To control for this bias, we create 2 additional dummy variables by removing "other" derivative users from non-users sample: 1) FC derivative users (UB) is a dummy variable set equal to '1' if a firm uses FC derivatives and '0' for non-users 2) IR derivative users (UB) is a dummy variable set equal to '1' if a firm uses IR derivatives and '0' for non- users.[38,39]

3.3.2.2. Continuous Measure of Derivatives Use

Using dummy variables as a proxy for derivatives use has its limitation; they do not distinguish between firms that have high intensity derivative usage and those that have low intensity derivative usage. In order to overcome this problem, data is collected on the notional amount of derivatives use. We scale the notional values of derivatives by total assets to arrive at a proxy for the extent of derivatives use. This measure of derivatives use can distinguish between a firm with a low extent of derivatives use and a firm with high extent of derivatives use. In the absence of uniform reporting standard not all the UK firms report the notional amounts of their derivatives contract. This results in many missing values for the continuous measure of derivatives variable. We have also created several proxies for this measure: 1) an extent of all derivatives variable for the total notional values of FC derivatives, IR derivatives and CP derivatives contract scaled by total assets, 2) an extent of FC derivatives variable for the total notional values of FC derivatives contract scaled by total assets and 3) an extent of IR derivatives variable for the total notional

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[38] In empirical Chapter 5 we create additional categories of derivatives by combining all various derivatives dummy and then reclassifying firms based on the use of number of derivative instruments used and the combination of derivative used. See section 0 for more details.

[39] In Chapter 6 we create additional dummy variables to identify firms that use both FC derivatives and FC debt. See section 0 for more details.

values of IR derivatives contract scaled by total assets[40]. Some studies have used these continuous measures to proxy for the extent of derivatives (Allayannis and Weston, 2001; Carter et al., 2003; Purnanandam, 2008; Nguyen and Faff, 2010; Campello et al., 2011; Magee, 2013).

3.3.2.3. Continuous Measure of Foreign Currency Debt

In Chapter 6, we examine the effect of FC debt on the FX exposure, EDF1YEAR, EDF5YEAR and Z-score besides FC derivatives. We collect data on firms debt denominated in foreign currency to calculate FC debt. Annual reports of the sample firms are searched for a list of keywords.[41] We read the surrounding text of the searched keyword and if available collect the data on debt. We collect data on debt denominated in Sterling, Euro, USD and ROW. Once we have data on firm's debt structure, we calculate the percentage of debt in 4 categories: 1) Sterling debt 2) Euro debt 3) USD debt and 4) ROW debt. We calculate FC debt by aggregating Euro debt, USD debt and ROW debt percentages. This gives us the measure of firms' extent of FC debt. Few of the previous studies use continuous measure of foreign debt (Elliott et al., 2003; Kedia and Mozumdar, 2003; Nguyen and Faff, 2006; Aabo et al., 2013).

3.3.2.4. Dummy Measure of Foreign Debt

From the continuous data on FC debt, we also create a binary measure of FC debt use. In particular, we create: 1) FC Debt dummy which is set equal to '1' if a firm uses Euro and/or US and/or ROW debt and '0' otherwise 2) EU debt dummy which is set equal to '1' if a firm uses Euro debt and '0' otherwise 3) US debt dummy which is set equal to '1' if a firm uses US debt and '0' otherwise and 4) ROW debt dummy which is set equal to '1' if a firm uses ROW debt and '0' otherwise. Few of the previous studies used a dummy measure of FC debt in their analysis (Allayannis, Ihrig, et al., 2001; Allayannis and Ofek, 2001; Keloharju and Niskanen, 2001; Kim et al., 2006; Aabo et al., 2013).

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[40] We do not investigate the independent effect of CP derivatives use on firm financial risk measures as very small percentage of our sample firms use CP only derivatives.

[41] We search annual reports for: Sterling, Euro, US dollar, liabilities, debt, foreign, interest rate, fixed, floating, borrowings and other combination of these keywords.

3.3.3. Control Variables[42]

In order to examine the effects of derivatives use on various firm risks, it is vital to separate other factors that may also contribute to firms' level of risk. We use previous literature to determine the control variables that we can employ in our multivariate analysis (Mainly Guay, 1999; Hentschel and Kothari, 2001; Shumway, 2001; Chava and Jarrow, 2004; Campbell, Hilscher and Szilagyi, 2008; Nguyen and Faff, 2010; Bartram, Brown and Stulz, 2012; Magee, 2013). Reviews of these literatures suggest that firm financial risk measures are shown to be associated with the following firm characteristics.

3.3.3.1. Leverage

The relationship between leverage and firm risk is well established in the literature. Hedging theory suggests that firms with higher leverage have a higher probability of default and therefore higher expected costs of financial distress (Smith and Stulz, 1985). Guay (1999) uses leverage to explain variation in firm financial risk of new derivative users. Hentschel and Kothari (2001) find a positive and significant association between leverage and the standard deviation of daily stock return volatility. They measure leverage as the ratio of book values of liabilities to the market value of equity. Shumway (2001) and Chava and Jarrow (2004) find a strong positive association between leverage and bankruptcy. Both of these studies measure leverage as the ratio of total liabilities to total assets. Bartram (2006) measures leverage as the ratio of total debt to size and shows that derivative user firms are more exposed to various measures of risks due to higher leverage before considering the potential effects of hedging. This suggests positive relationship between leverage and firm financial risk. Campbell et al. (2008) show that a 1 standard deviation increase in leverage increases the probability of failure by 156%. They calculate leverage as the ratio of total liabilities to total assets. Nguyen and Faff (2010) use leverage as a control to explain the variation in total risk, market risk and in idiosyncratic risk. They measure leverage similar to Shumway (2001). Bartram et al. (2011) calculate leverage as the ratio of total debt to size and show that firms with more financial leverage have higher total and systematic risk. Bartram et al. (2012) show that leverage is an important

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[42] *In this section we discuss all the control varaibles that we have used in this thesis. In Chapter 4 we use leverage, firm size, profitability, market to book, dividend yield and liquidity as control variables. In Chapter 5 we use leverage, firm size, profitability, excess return, equity volatility and liquidity as control variables. In Chapter 6 we use foreign sales, leverage, firm size, market to book and liquidity as control variables.*

determinant of both total risk and market risk and find positive relationship between leverage & total risk and leverage & market risk. Marin (2013) shows that leverage is associated with higher chances of filing for bankruptcy, higher asset volatility and higher probability of default. Marin (2013) also finds that leverage is associated with significantly smaller distance to default. Marin (2013) also shows that highly levered firms are more likely to fail. Magee (2013) finds that leverage is negatively associated with distance to default. Magee (2013) shows that a one standard deviation increase in leverage decreases the distance to default by 3.99%. In this study, we calculate leverage as the ratio of total debt to book value of assets minus book value of equity plus market value of equity.

3.3.3.2. Firm Size

Larger firms are more likely to produce and sell a diversified range of goods and services as well as operate in many geographical markets. This product and geographical diversification may lead to lower firm risk. It follows then that large firms may exhibit lower levels of financial risk. Empirical literature also supports this hypothesis. Hentschel and Kothari (2001) find a negative relationship between total risk and firm size. Chava and Jarrow (2004) find that size is negatively associated with bankruptcy risk. In contrast to this, Guay (1999) find positive effect of firm size on the total risk. Similarly, Campbell et al. (2008) find that the failure probability of their sample firms increases by 17% due to a one standard deviation increase in market capitalisation, their measure of firm size. Bartram (2006) also uses firm size in the model and reports mixed effects of firm size on firm risk.[43] Nguyen and Faff (2010) find that firm size is negatively associated with firm risk measures. Bartram et al. (2012) find that firm size is an important determinant of both total and market risk and it is negatively related to both measures of risk. Marin (2013) provides evidence that suggest that firm size is negatively associated with probability of default and asset volatility. Similarly, Magee (2013) finds that firm size is directly associated with distance to default. We use natural log of total assets as a measure for firm size.[44]

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[43] Bartram (2006) finds that firm size is negatively associated with standardised equity volatilty, net FX exposure, net IR exposure and net CP exposure and positively associated with marke risk.
[44] In unreported regression results we use logarithm of total sales as a measure of firm size and find that our results are qualitatively similar.

3.3.3.3. Profitability

Firms that are more profitable possess a greater ability to service their debt commitments and therefore are less likely to face the threat of bankruptcy. In addition, highly profitable firms are able to make greater use of internal funds to finance themselves rather than going through banks or capital markets and borrowing funds at increased cost. Using more of internal funds and relying less on external finance will result in a lower likelihood of default. Several previous studies establish a strong link between profitability and the firm risk. Guay (1999) uses profitability as a control to explain variation in total risk. Chava and Jarrow (2004) also use a measure of profitability in their model to determine bankruptcy. Campbell et al. (2008) find that profitability is negatively associated with the probability of firm failure. They show that a one standard deviation increase in profitability reduces the probability of failure by 44% of its initial value. Profitable firms are expected to have lower financial distress costs because they are less risky (Bartram et al., 2009). Bartram et al. (2011) and Bartram et al. (2012)find that profitability is negatively associated with various risk measures. Campello et al. (2011) show that profitable firms have lower cost of borrowing. Magee (2013) finds that profitability is associated with a greater distance to default. This shows that profitability plays an important role in predicting firm risk. These findings suggest that firms with higher profitability have lower financial risks and in particular lower credit risk. Therefore, in this study it is expected that more profitable firms are likely to have a lower firm risk than less profitable firms. We use the return on invested capital as a measure for profitability.

3.3.3.4. Liquidity

Hedging theories suggest that firms with an abundance of cash or liquidity on the balance sheet are faced with a lower level of financial risk (Nance et al., 1993). Firms possessing large holdings of cash can use it to manage their short-term liabilities, to pay interest on their borrowings and need to rely less on costly external debt finance for the purposes of financing investment expenditure. Copeland and Joshi (1996) argue that firms possessing fewer liquid assets are likely to face a higher probability of financial distress. Consistent with this Marin (2013) and Magee (2013) find that firm liquidity is positively associated with a firm's distance to default. Bartram (2006) and Bartram et al. (2012) show that firms are more exposed to IR risk if they have lower liquidity. Campbell et al. (2008) argue that a firm with sufficient liquid assets to make interest payments may postpone default with the likelihood of avoiding it all together if macroeconomic and firm-specific conditions improve. They also find a negative association between liquidity and bankruptcy. Nguyen and Faff (2010) suggest that liquidity is associated with low underinvestment risk and hence low overall risk. Bartram et al. (2011) report a negative association between liquidity and IR risk. Bartram et al. (2012) show that liquidity is a determinant of various firm financial risks. We measure liquidity as ratio of total current assets minus total stock and work in progress over total current liabilities.[45]

3.3.3.5. Equity Volatility

It is expected that firms with greater equity return volatility should have a higher probability of default. Shumway (2001) uses the standard deviation of a firm's stock returns as a measure of equity volatility and finds a strong positive relation between equity volatility and bankruptcy. Chava and Jarrow (2004) and Campbell et al. (2008) also find that equity volatility is positively associated with bankruptcy. The latter find an increase of one standard deviation in equity volatility increases the probability of bankruptcy by 64% of its initial value. Magee (2013) finds a negative association between equity volatility and the distance to default. We follow these studies and calculate equity volatility as the standard deviation of each firm's daily stock return over the entire fiscal year.

3.3.3.6. Excess Return

If equity markets discount the equity of the firms that are very close to their default point then a firm's past excess return could predict firm's bankruptcy (Shumway, 2001). Shumway (2001) finds statistically negative impact of excess return on bankruptcy. Chava and Jarrow (2004) also observe negative association between excess return and bankruptcy. Campbell et al. (2008) find a negative association between failure probability and excess return. They show that a one standard deviation increases in excess return reduces the probability of failure by 28%. Magee (2013) finds positive association between excess return and distance to default. We calculate excess return as annual equity return minus the value weighted FTSE all shares index annual return over the entire fiscal year. Each firm's annual return is calculated by cumulating its monthly return.

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[45] *We also use the current ratio and cash holdings over the market value of assets as a measure of liquidity in unreported regressions and find similar results.*

3.3.3.7. Market to Book

Theoretically, firms with more growth options are considered risky due to the underinvestment problem. Froot et al. (1993) show firms' that are underinvested are costly as they cannot maximise the shareholders value and hence are risky. Hentschel and Kothari (2001) and Bartram (2006) use book to market ratio as a control to investigate the effect of derivatives on firm risk measures. Nguyen and Faff (2010) find positive and significant relationship between market to book ratio and total risk and between market to book ratio and idiosyncratic risk. Bartram et al. (2012) find positive and significant relation between market risk and market to book and fail to find any significant relation between total risk and market to book. We calculate market to book as the ratio of market value of assets to book value of assets.

3.3.3.8. Dividend Yield

Earlier studies suggest that firms that pay dividends are less likely to be financially constrained and may thus have lower level of risk (Allayannis and Weston, 2001; Allayannis et al., 2012). Bartram (2006) controls for dividend yield while examining the effects of derivatives on firm risk. Nguyen and Faff (2010) find negative relationship between dividend yield and measures of risk. Bartram et al. (2011) argue that firms that pays higher dividend should have stable cash flow and hence are less likely to be financially constrained. We measure dividend yield as dividend per share divided by the share price.

3.3.3.9. Foreign Sales

A foreign sale is a measure of firm's foreign operations and also measures firm's exposure to foreign exchange. Majority of the previous studies that investigated the effects of derivatives use on foreign exchange exposure incorporated foreign sales in their model (Allayannis, Brown, et al., 2001; Allayannis and Ofek, 2001; Keloharju and Niskanen, 2001; Nguyen and Faff, 2003; Muller and Verschoor, 2008; Zhou and Wang, 2013). We calculate this measure as foreign sales divided by total sales.

3.3.3.10. Other Variables

We also use several other variables such as measures of pre-derivatives exposure. We discuss these variables prior to their use in respective chapters.

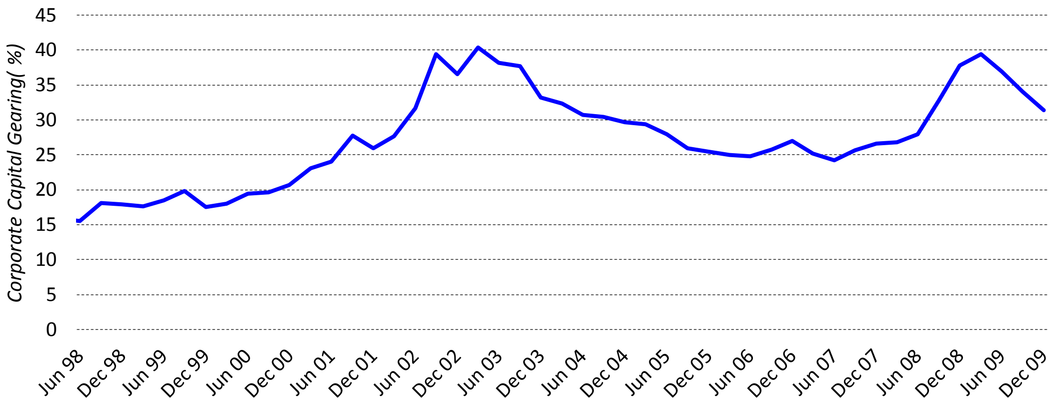
3.3.4. Credit Market Proxies

In Chapter 5 we examine the effect of derivatives use on the probability of default during the period of heightened credit risk conditions. For this analysis we use several measures of aggregate credit risk and interact them with our derivative dummies[46]. These aggregate credit risk proxies are measured as follows:

3.3.4.1. Corporate Capital Gearing[47]

For our first proxy, we employ aggregate corporate capital gearing data for UK firms. Corporate capital gearing is defined as debt net of liquid assets relative to the market value of capital. Figure 3-1 shows UK corporate capital gearing for the period 1998 to 2009. Figure 3-1 shows that there are two noticeable peaks in capital gearing these being around 2002-2003 and 2008-2009. In June 1998 the capital gearing is around 15%. The capital gearing increased sharply from 26% at the end of 2001 to 40% around 2002-2003. This is the period of global economic slowdown. The capital gearing again peaked during recent financial crisis of 2008-2009. The lending rates to business were declining since recent financial crisis of 2008-2009 (Bank of England, 2010b). However, if there is an increase in the interest rate then many firms will face increased interest payment burden as firms are exposed to interest rate changes due to higher capital gearing.

Figure 3-1: Corporate Capital Gearing for UK firms



Source: Bank of England

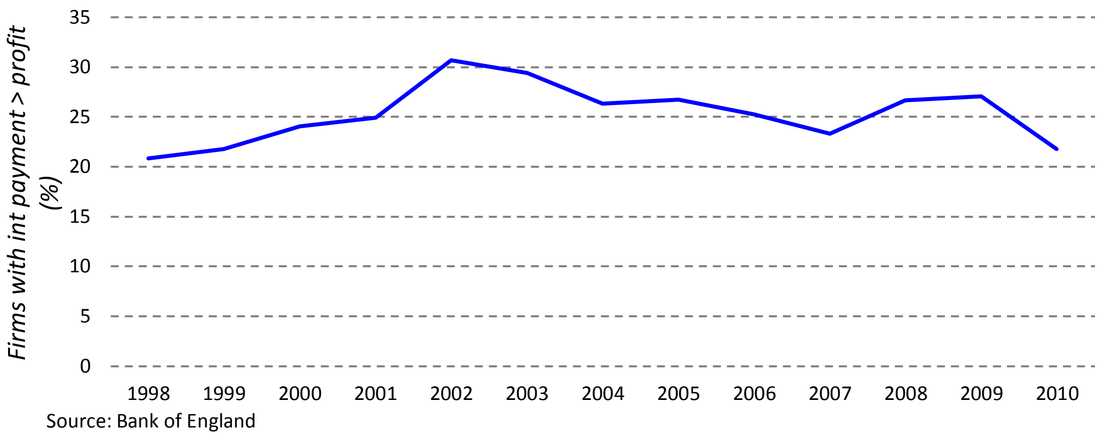
[46] *See section 5.4.3 for more details.*

[47] *This data is collected from Bank of England (2010a). Data for this variable is available only up to year 2009.*

3.3.4.2. Interest Payment[48]

Our second proxy for credit risk condition is interest payment. Interest payment is defined as the percentage of UK firms with interest payments greater than their profits for firms with turnover greater than £1 million. Similar to Figure 3-1 in Figure 3-2 we observe two peaks in this measure of corporate credit risk in years 2002-03 and 2008-09. These peaks coincide with those seen with aggregate capital gearing.

Figure 3-2: Percentage of Firms with Interest payment greater than profits for companies with turnover greater than £1m



The percentage of companies with interest payment greater than their profits were slightly above 20 per cent in 1998 and increased sharply between 2001 and 2002 peaking at just over 30 per cent in 2002 and then was on a downward trend during the 2003-2007 pre-crisis periods but then went up again in 2008 and 2009 at the peak of the crisis. The aim of macroeconomic policies advanced by public policy makers during the financial crisis was to keep businesses going through an exceptionally difficult period and so to keep corporate insolvencies as low as possible. During the 2007-2009 financial crisis loss making companies have been able to survive in part due to low interest rates and in part due to a more tolerant attitude to corporate borrowers from the banks. This most probably explains why the increase in the percentage of firms for whom interest payments exceed profits is less during this financial crisis than the crisis in the early part of the decade, despite the fact that the recent crisis is of much greater severity than the one earlier in the decade. However, according to the Bank of England firms' financial positions are still relatively fragile since they say "*Data from companies' accounts indicate that a fall in revenues of*

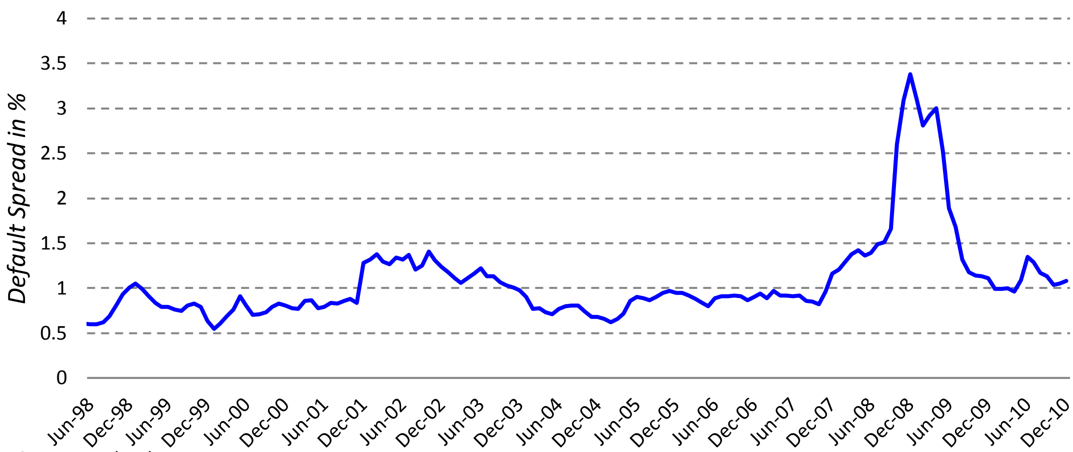
[48] *Source: Bank of England (2011a)*

only 2% would be sufficient to take the percentage of companies unable to service their debt out of profits above the levels seen in the early 1990s" (Bank of England, 2011a, Pg no. 25)

3.3.4.3. Default Spread

Default spread is defined as the difference between Moody's yield on seasoned AAA and BBB Corporate Bond. Figure 3-3 shows the corporate default spread for the period 1998 to 2010.

Figure 3-3: Corporate Default Spread



Source: Federal Reserve

From Figure 3-3 it is clear that the spread between BAA and AAA corporate bonds increases during adverse economic conditions. Figure 3-3 shows a substantial increase in spread during 2001 to 2002 and 2007 to 2009 period. During favourable aggregate risk conditions the spread is smaller. The cost for BAA rated firm increases at least by 1% on their bonds compare to AAA rated firms. During the recent financial crisis of year 2007 to 2009 BAA rated firms paid at least 1.5% more to their bondholders than AAA rated firms. This increase in the bond yield for BAA rated firms went up by almost 3 to 4 times to their yields in year 1998 and 1999.

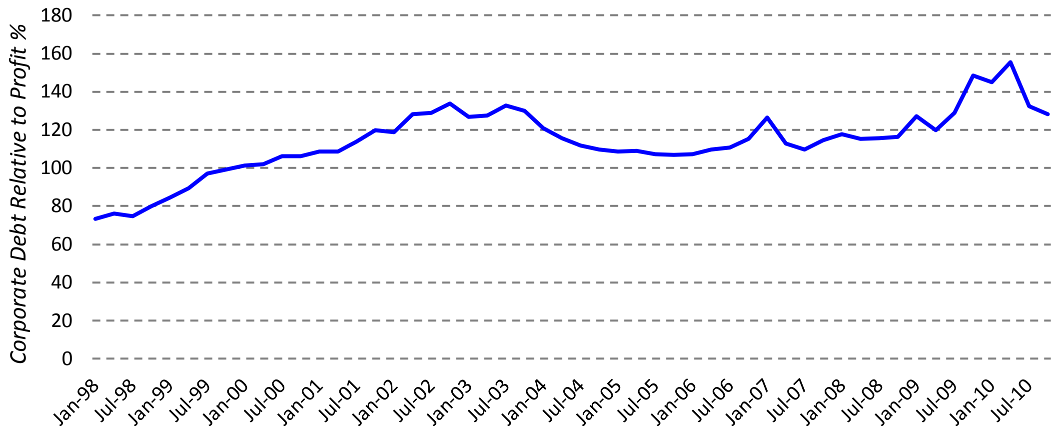
3.3.4.4. Debt Relative to Profit[49]

Debt relative to profit is our fourth proxy and defined as debt net of an estimate of liquid assets, relative to a four-quarter moving sum of gross operating surplus. Figure 3-4 shows

[49] *Source: Bank of England (2011b)*

that the debt is normally higher than the profit and during the adverse economic condition of 2001 to 2002 and 2007 to 2009 debt is comparatively higher. This also increases the probability of default during this period.

Figure 3-4: UK Corporate Debt Relative to Profit



Source: Bank of England

3.3.4.5. Deloitte Financial Stress Index[50]

Our sixth proxy is the Deloitte Financial Stress Index, which purports to measure stress in financial markets by aggregating measures of volatility, investor risk aversion and the health of major financial market participants such as banks. More specifically, the Deloitte Financial Stress Index is an arithmetic average of the ratio of the three-month LIBOR to base rates, the ratio of yield on high yield bonds to yield on government bonds, the VIX index[51], the ratio of total market return to banking stocks return and the ratio of yield on long-term government bonds to yield on short-term bonds. The index normalizes daily data points from each of these series against a long-run average (01/01/98 to 31/12/10) and then averages the normalized values for the five series.

Figure 3-5 shows that there was a small peak in the Deloitte Financial Stress Index in 2002 followed by a very large peak in 2008. This shows that financial stress is at very high levels during the recent financial crisis. The stress level in 2007-2009 is more than the average of stress index from 1998-2007.

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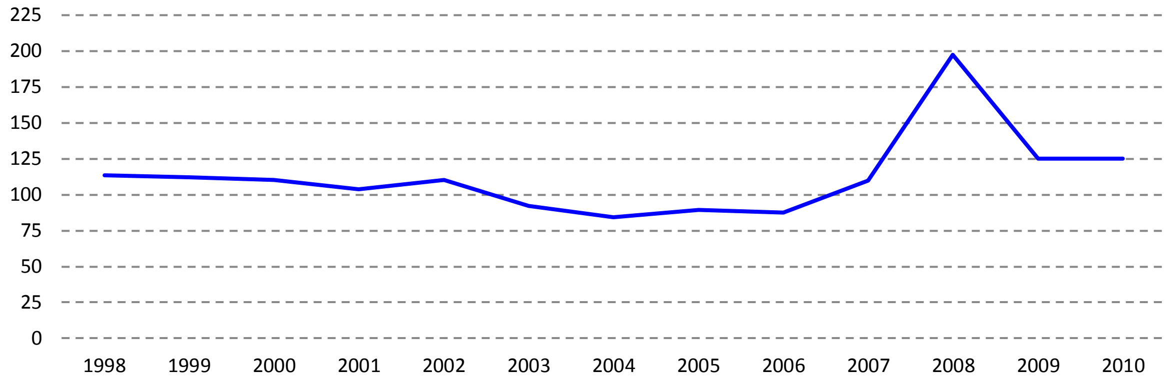
[50] *Source Deloitte (2012)*

[51] *VIX is a ticker symbole for Chicago Board Options Exchange Volatility Index.*

Figure 3-5: Deloitte Financial Stress Index



Source: Deloitte

3.4. Methods of Estimation

In this thesis, we use an unbalanced panel of UK non-financial firms for the period of 1998-2010. We remove firms from our sample if they are merged, delisted, acquired or do not provide any financial information. Thus resulted in an unbalanced panel data set for our empirical work. The unbalanced panel data used for analysis contains two dimensions; a cross-sectional dimension and a time-series dimension. Contrast to time-series data and cross-section data, unbalanced panel data controls for the unobserved individual heterogeneity. For example, sample firms are similar in factors like economical & financial development, government rules and regulations but they still have differences in managing their risk, managerial skills and expertise. This difference in sample firms cannot be controlled by time-series and cross-section data and may produce results that are biased. Panel data can be used where time-series and cross-section data fails that is the problem of omitted variable. Other benefit of using panel data format is that it provides data with more information and variability, less collinearity and more degree of freedom and efficiency (Baltagi, 2005). Time-series studies are also affected by multicollinearity problem; for example there could be a high collinearity between size and use of derivatives for an individual firm. In contrast, this multicollinearity is less likely with a panel data across a large sample of firms as this will add variability and information to the data.

Additionally, studies that use panel data can produce results that are not detected using time-series and cross-section data. Determination of whether use of derivative instruments reduces financial risk or increases cannot be answered efficiently using either time-series data or cross-section data. This question can better be examined using panel data where firms are examined on many variables across number of years. Holding the firm's characteristics constant, panel data models are better equipped to determine whether use of derivative affect firm risk and by how much.

3.4.1. Estimation Framework

We use a range of statistical and econometric techniques for data analysis. Previous studies suggest that there are substantive differences, on an average, in the characteristics of the firms that use derivatives and those that do not.[52] In order to examine whether such differences in characteristics exist in our sample firms, we employ univariate tests for difference in means and medians. However, univariate tests cannot reveal significant differences in firm characters, holding other firm attributes constant. To overcome this problem, we also employ empirical analysis within a multivariate framework.

3.4.1.1. Estimation Framework in Chapter 4

Multivariate analysis is used to establish the relationship between firm risk measures and derivatives use. To examine the effects of the use of derivatives on various measures of firm risk we estimate the following regression model:

$$\begin{aligned} Total\ Risk_{it} or\ Market\ Risk_{it}\ or\ Idiosyncratic\ Risk_{it} \\ = \alpha_{it} + \beta_1 Derivatives\ Dummy_{it} + \beta_2 Leverage_{it} \\ + \beta_3 Firm\ Size_{it} + \beta_4 Profitability_{it} + \beta_5 Market\ to\ Book_{it} \\ + \beta_6 Dividend\ Yield_{it} + \beta_7 Quick\ Ratio_{it} + \varepsilon_{it} \end{aligned} \qquad [10]$$

Equation [10] examines the effects of derivatives on the various measures of risk. We use dummy variables for derivatives use based on the disclosure in annual reports. We perform this analysis for all derivative users, FC derivative users and IR Derivatives users. We also repeat this analysis for FC derivative users and IR derivative users after removing “other” users from non-users sample.

To test for the linear relationship between the use of derivatives and various measures of firm risk we estimate the following regression models:

$$\begin{aligned} Total\ Risk_{it} or\ Market\ Risk_{it}\ or\ Idiosyncratic\ Risk_{it} \\ = \alpha_{it} + \beta_1 Extent\ of\ All\ Derivatives\ Use_{it} + \beta_2 Leverage_{it} \\ + \beta_3 Firm\ Size_{it} + \beta_4 Profitability_{it} + \beta_5 Market\ to\ Book_{it} \\ + \beta_6 Dividend\ Yield_{it} + \beta_7 Quick\ Ratio_{it} + \varepsilon_{it} \end{aligned} \qquad [11]$$

Equation [11] examines the effects of an extent of all derivative use on various firm financial risk measures. Extent of all derivative use is calculated using the cumulative notional amount of FC, IR and CP derivatives disclosed by firms and scaled by total assets.

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[52] *Gay and Nam (1998); Guay (1999); Allayannis and Weston (2001); Bartram et al. (2009)*

The extent of derivative use captures firms total notional derivatives use and helps in distinguishing between firms with different levels of derivatives use. We repeat equation [11] for extent of FC derivatives and IR derivatives separately. The empirical methods used in this chapter follows that used in previous studies (Allayannis and Weston, 2001; Bartram, 2006; Nguyen and Faff, 2010).

We examine whether macroeconomic conditions are important in influencing the impact of derivatives use on a firm financial risk by interacting our derivatives variables with the year dummies (see Equation [12]). This allows us to examine the effect of derivatives coefficient over our sample period in a manner consistent with the changing economic circumstances witnessed during this period. This analysis will show whether there is any variation in the impact of derivatives use on the firm financial risk measures over-time and if so, whether this variation is consistent with changes in macroeconomic circumstances or not. We estimate the following model:

$$\begin{aligned} Total\ Risk_{it} or\ Market\ Risk_{it}\ or\ Idiosyncratic\ Risk_{it} \\ = \alpha_{it} + \beta_1 Derivatives\ Dummy_{it} + \beta_2 Leverage_{it} \\ + \beta_3 Firm\ Size_{it} + \beta_4 Profitability_{it} + \beta_5 Market\ to\ Book_{it} \\ + \beta_6 Dividend\ Yield_{it} + \beta_7 Quick\ Ratio_{it} + \beta_8 GDP_t \\ + \sum_{t=9}^{19} \beta_t Year_t * Derivatives\ Dummy_{it} + \varepsilon_{it} \end{aligned} \qquad [12]$$

Where all the variables are defined as above and *GDPt* is macroeconomic variable rate to control for time period effects that may influence the firm financial risk measures. In all the models in this chapter, we include year dummies to control for common shocks and industry dummies to control for industry effects.

3.4.1.2. Estimation Framework in Chapter 5

We use regression analysis to examine the effects of derivatives use on the probability of default. We largely follow the empirical work of Shumway (2001), Chava and Jarrow (2004) and Campbell et al. (2008) to arrive at a model that contains a list of drivers of the probability of default to which we add our derivatives use variable. Our regression model generally takes the following specification:

$$\begin{aligned} EDF1YEAR_{it} or EDF5YEAR_{it} \\ = \beta_0 + \beta_1 Derivatives_{it} + \beta_2 Leverage_{it} + \beta_3 Profitability_{it} \\ + \beta_4 FirmSize_{it} + \beta_5 EquityVolatility_{it} + \beta_6 ExcessReturn_{it} \\ + \beta_7 Profitability_{it} + \varepsilon_{it} \end{aligned} \qquad [13]$$

We create many different derivatives variable and repeat equation [13] with new derivatives variables. In our model, we include year dummies to control for common shocks to the probability of default for all firms and industry dummies to control for industry effects in the model. Standard errors are corrected for within-firm correlation (clustering) and heteroskedasticity using the White-Huber estimator.

There are some important challenges in empirically testing the equation [13]. The first problem is of self-selection bias where firms self-select to use derivatives based on their benefits. The second challenge is that the independent variables leverage and derivative use are likely to be defined jointly by firms, which creates the problem of endogeneity. Theories based on ex-ante incentives show that by using derivatives, firms could increase their debt capacity as a result of a reduction in the likelihood of financial distress. This creates a reverse causation problem between these variables. We use a heckman treatment effects to control for self-selection bias and an instrumental variable model, PSM method and CEM method to address the issue of endogeneity.

In Chapter 5, we examine whether the difference in the probability of default between derivative users and non-users depends on the level of aggregate credit risk using the following models:

$$\begin{aligned} EDF1YEAR_{it}\, or\, EDF5YEAR_{it} \\ &= \beta_0 + \beta_1 Derivatives_{it} + \beta_2 Credit\ Market\ Proxy_{it} \\ &+ \beta_3 Derivatives * Credit\ Market\ Proxy_{it} + \beta_3 Leverage_{it} \\ &+ \beta_4 Profitability_{it} + \beta_5 FirmSize_{it} + \beta_6 EquityVolatility_{it} \\ &+ \beta_7 ExcessReturn_{it} + \beta_8 Profitability_{it} + \beta_8 GDP\ Growth_t \\ &+ \varepsilon_{it} \end{aligned} \qquad [14]$$

In equation [14] we use several measures of credit market conditions.[53] In particular, we use corporate capital gearing, interest payment, default spread, debt relative to profit, income gearing and Deloitte stress index. We include GDP growth rate to control for macroeconomic conditions. All of the credit market condition proxies are standardised.[54] This facilitates an easy interpretation of the coefficients and suggests percentage change in EDF1YEAR and EDF5YEAR for a one standard deviation change in the credit market proxies. Definitions and sources of these proxies are defined in section 3.3.4.

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[53] *All the variables are winsorised at 1% from both tails to control for the outliers.*

[54] *We subtract sample mean from actual values and divide it by standard deviation for each variable*

In Chapter 5, we also examine time-varying effect of derivatives use on the probability of default. To examine whether the impact of derivatives on the probability of default varies over our sample period we estimate the following model:

$$\begin{aligned} EDF1YEAR_{it}\, or\, EDF5YEAR_{it} \\ &= \alpha_{it} + \beta_1 Derivatives\ Dummy_{it} + \beta_2 Leverage_{it} \\ &+ \beta_3 Firm\ Size_{it} + \beta_4 Profitability_{it} + \beta_5 Equity\ Volatility_{it} \\ &+ \beta_6 Excess\ Return_{it} + \beta_7 Quick\ Ratio_{it} + \beta_8 GDP\ Growth_t \\ &+ \sum_{t=9}^{19} \beta_t Year_t * Derivatives\ Dummy_{it} + \varepsilon_{it} \end{aligned} \quad [15]$$

We include the annual GDP growth rate to control for time period effects that may influence the probability of default. We estimate equation [25] using pooled OLS, RE and FE model and present the results of only best model.

To examine whether derivatives use by firms with higher pre-derivative firm-specific credit risk, as measured by a firm's Z-score, has a greater impact on default probabilities than derivative use by firms with lower pre-derivative firm-specific credit risk, we use following equation:

$$\begin{aligned} EDF1YEAR_{it} or EDF5YEAR_{it} \\ &= \beta_0 + \beta_1 Derivatives_{it} + \beta_2 Derivatives * Z\ Score_{it} \\ &+ \beta_3 Z\ Score_{it} + \beta_3 Leverage_{it} + \beta_4 Profitability_{it} \\ &+ \beta_5 FirmSiz_{it} + \beta_6 Equity\ Volatility_{it} + \beta_7 Excess\ Return_{it} \\ &+ \beta_8 Profitability_{it} + \beta_8 GDP_{it} + \varepsilon_{it} \end{aligned} \quad [16]$$

3.4.1.3. Estimation Framework in Chapter 6

We use the FX exposure calculated in equation [7] as a dependent variable and use it in our regression analysis where FX exposure is simultaneously determined by ratio of foreign sales to total sales, foreign operations, and notional values of FC derivatives to total assets, financial operations. The second stage regression equation takes following form:

$$\hat{\beta}_{2it} = \alpha_1 + \alpha_2 FC\ Derivatives_{it} + \alpha_3 Foreign\ Sales_{it} + \mu_{it} \quad [17]$$

Where $\hat{\beta}_{2i}$ is a firm's FX exposure estimated in equation [7]; *FC derivatives* is a firm's ratio of FC derivatives to total assets; *foreign sales* is a firm's ratio of foreign sales to total sales.

Next, we follow He and Ng (1998) and Chow and Chen (1998) to include a set of control variables that proxy for the incentives of FC derivatives use namely: leverage, liquidity, firm size and market to book ratio. Moreover, we also include FC derivatives variable in the regression specification following Nguyen and Faff (2003) and Muller and Verschoor (2008). The regression model has following form;

$$\hat{\beta}_{2i} = \alpha_1 + \alpha_2 FC\ Derivatives_{it} + \alpha_3 Foreign\ Sales_{it} + \alpha_4 Leverage_{it} + \alpha_4 Firm\ Size_{it} + \alpha_5 Liquidity_{it} + \alpha_6 Market\ to\ Book_{it} + \mu_{it} \qquad [18]$$

Where $\hat{\beta}_{2i}$is a firm's FX exposure estimated in equation [7][55]; FC Derivatives is the notional value of FC derivatives use scaled by the firm's total assets; Foreign Sales is a ratio of foreign sales to total sales; Leverage is the ratio of total debt to book value of assets minus book value of equity plus market value of equity; Firm Size is the natural log of total assets; Liquidity is measured as the as ratio of total current assets minus total stock and work in progress over total current liabilities and Market to Book is calculated as the ratio of market value of assets to book value of assets.

Furthermore, We also calculate FX exposure of UK non-financial firms using lagged changes in exchange rates following He and Ng (1998), Hagelin and Pramborg (2004) and Jong et al. (2006). He and Ng (1998) argue that as financial information is published with a time lag, the exchange rate changes also take longer time to affect the firms' cash flow. Jong et al. (2006) argue that changes in FX rates do not incorporated directly into stock prices and it may take some time before the stock prices react to these changes that suggest market inefficiency. Therefore, we calculate lagged FX exposure of UK non-financial firms to examine for the presence of such effect. We calculate the lagged FX exposure as follow:

$$R_{it} = \beta_{0i} + \beta_{1i} R_{mt} + \beta_{2i} STR_t + \beta_{3i} STR_{t-1} + \varepsilon_{it} \qquad [19]$$

Where $\beta_{3i} STR_{t-1}$measures the effect of lagged exchange rate changes on stock return.

Moreover, we investigate the impact of FC debt on FX exposure. As we discussed earlier firms can use financial and operation hedging techniques to manage exchange rate-exposure. To examine the effects of FC debt we employ following models;

$$\hat{\beta}_{2i} = \alpha_1 + \alpha_2 FC\ Derivatives\ and\ FC\ Debt\ Dummy_{it} + \alpha_3 FC\ Derivatives\ Only\ Dummy_{it} + \alpha_4 FC\ Debt\ Only\ Dummy_{it} + \alpha_5 Foreign\ Sales_{it} + \mu_{it} \qquad [20]$$

$$\hat{\beta}_{2i} = \alpha_1 + \alpha_2 FC\ Derivatives\ and\ FC\ Debt\ Dummy_{it} + \alpha_3 FC\ Derivatives\ Only\ Dummy_{it} + \alpha_4 FC\ Debt\ Only\ Dummy_{it} + \alpha_5 Foreign\ Sales_{it} + \alpha_6 Leverage_{it} + \alpha_7 Liquidity_{it} + \alpha_8 Firm\ Size_{it} + \alpha_9 Market\ to\ Book_{it} + \mu_{it} \qquad [21]$$

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[55] *In later analysis we use equation [7] but change the dependent variable to other measures of FX exposure that we calculate such as Sterling/Euro exposure, Sterling/USD exposure and Lagged FX exposure.*

These models examine risk-reducing effect of different financial instruments. We create three dummy variables to capture the use of different financial derivative instruments. *FC derivatives and FC debt dummy* is set equal to '1' if a firm uses both FC derivatives and FC debt and '0' otherwise; *FC Derivatives only dummy* is set equal to '1' if a firm uses FC derivatives but not FC debt and '0' otherwise; *FC Debt only dummy* is set equal to '1' if a firm uses FC debt but not FC derivatives and '0' otherwise; $\hat{\beta}_{2i}$ is the absolute value of monthly FX exposure calculated using equation [7][56]; all other explanatory variables are measured as discussed above.

We have also collected data on percentage of debt denominated in FC and use it to examine the effect of extent of FC debt use on FX exposure. We use equations [22] and [23] to investigate the impact of percentage of FC debt on exchange rate exposure.

$$\hat{\beta}_{2i} = \alpha_1 + \alpha_2 FC\ Derivatives\ Dummy_{it} + \alpha_3 FC\ Debt_{it} + \alpha_4 Foreign\ Sales_{it} + \mu_{it} \qquad [22]$$

$$\begin{aligned}\hat{\beta}_{2i} = \alpha_1 &+ \alpha_2 FC\ Derivatives\ Dummy_{it} + \alpha_3 FC\ Debt_{it} + \alpha_4 Foreign\ Sales_{it} \\ &+ \alpha_5 Leverage_{it} + \alpha_6 Quick\ Ratio_{it} + \alpha_7 Firm\ Size_{it} \\ &+ \alpha_8 Market\ to\ Book_{it} + \mu_{it}\end{aligned} \qquad [23]$$

We expect a negative relationship between FC debt and FX exposure. We use dummy variable for FC derivatives use to control for other interpretation of coefficient on FC debt.

To investigate the effects of FC debt on probability of default we use the following equation.

$$\begin{aligned}EDF1YEAR_{it}\, or\, EDF5YEAR_{it}\, or\ Z\ score_{it} &= \alpha_1 + \alpha_2 FC\ Derivatives\ and\ FC\ Debt\ Dummy_{it} \\ &+ \alpha_3 FC\ Derivatives\ Only\ Dummy_{it} \\ &+ \alpha_4 FC\ Debt\ Only\ Dummy_{it} + \alpha_5 Leverage_{it} \\ &+ \alpha_6 Profitability_{it} + \alpha_7 Firm\ Size_{it} + \alpha_8 Equity\ Volatility_{it} \\ &+ \alpha_9 Excess\ Return_{it} + \alpha_{10} Quick\ Ratio_{it} + \mu_{it}\end{aligned} \qquad [24]$$

3.5. Estimation Methods

In this thesis, we use following econometric methods to examine the relationship between firms' use of derivatives and firm financial risk measures:

- *Ordinary Least Square*

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[56] *In unreported regression results we repeat the regression analysis presented in Table 6-7 using absolute values of weekly FX exposures. The regressions results are slightly weaker and the coefficients on FC debt are insignificant with mixed signs.*

- *Random Effects*
- *Fixed Effects*
- *First Difference Estimator*
- *Weighted Least Square*
- *Instrumental Variable Approach*
    a. *Two Stage Least Squares*
    b. *Generalised Methods of Moments*
- *Treatment Effects Model*
- *Matching Methods*
    a. *Propensity Score Matching*
    b. *Coarsened Exact Matching*

3.5.1. Ordinary Least Squares

We start our analysis using ordinary least squares (OLS) methodology. A pooled OLS model uses data on different firms pooled together without controlling for individual differences. The pooled panel data model used in the empirical chapters has following general model:

$$Firm\ Risk\ Measures_{it} = \alpha_i + \beta_1 Main\ Explanatory\ Variable_{it} + \beta_2 Control\ Variables_{it} + \varepsilon_{it} \quad [25]$$

Where $Firm\ Risk\ Measures_{it}$ is a dependent variable. We use different firm risk measure in our empirical chapters. In Chapter 4 we use total risk, market risk and idiosyncratic risk as measures of firm risk. In Chapter 5 we use EDF1YEAR and EDF5YEAR as measures of firm risk. In Chapter 6 we use exchange rate exposure as a measure of firm risk.[57] $Main\ Explanatory\ Variable_{it}$ is a proxy for firm’s derivative use or foreign debt use as discussed in section 3.3.2. We use different control variables in our empirical chapters. In Chapter 4, we use leverage, firm size, profitability, market to book, dividend yield and liquidity as control variables. In Chapter 5, we use leverage, firm size, profitability, equity volatility, liquidity and excess return as control variables. In Chapter 6, we use foreign

[57] *In Chapter 6 we also use Z-score, EDF1YEAR and EDF5YEAR as dependent variables when we examine the risk reducing effect of foreign currency debt.*

sales, leverage, firm size, market to book and liquidity as control variables. In equation [25] index *i* refers to the unit of observation, firm, and the index *t* refers to the time. ε_{it} is a disturbance term assumed to satisfy the regression model assumptions. The model also includes time and industry dummies.

OLS model has several assumptions such as linearity in parameters, normality of data, no heteroskedasticity, no multicollinearity and no serial correlation. Further analyses on the data were carried out to determine that the data satisfies the assumptions. These analyses include descriptive statistics of variables and correlation analysis. The unobservable heterogeneity is captured by disturbance term, ε_{it}, from the obtained pooled OLS estimator. ε_{it} can be expressed as;

$$\varepsilon_{it} = \mu_i + v_{it} \qquad [26]$$

Where μ_i refers to unobservable individual firm-specific effect and v_{it} denotes the remainder disturbance. t in equation [26] represents different times for the same firm. The unobserved effect is often interpreted as capturing features of a firm such as business practices, management skills and expertise in risk management that are constant over-time and which are not explicitly represented in the model and hence are included in μ_i (Wooldridge, 2002). v_{it} varies with firms and time and hence considered as usual disturbance in the regression. The pooled OLS estimates are consistent if the explanatory variables, derivative instrument and other control variables, are not correlated with the disturbance term, ε_{it}. However, if there were a correlation between the disturbance term and the explanatory variables, then the OLS estimates would be biased.

Two different techniques are available to control for the unobserved individual specific effects; 1) Fixed Effects (FE) Estimation Method and 2) Random Effects (RE) Estimation Method.

3.5.2. FE Model

If μ_i in equation [26] is considered as fixed, then FE estimation method can be used to control for the unobservable individual firm-specific effects. FE model examines the impact of variables that changes over-time and drops the variables that do not change over-time such as business practices, management skills and expertise in risk management. The assumption is that the unobserved effects such as business practices, management skills and expertise in risk management affects the explanatory variable in OLS model and hence bias the results and to control for that FE model is used.

Equation [25] can be written as follow with the help of equation [26] as follow:

$$Firm\ Risk\ Measures_{it} = \alpha_i + \beta_1 Main\ Explanatory\ Variable_{it} + \beta_2 Control\ Variables_{it} + \mu_i + v_{it} \qquad [27]$$

Averaging equation [27] over the time gives:

$$\overline{Firm\ Risk\ Measures_i} = \alpha_i + \beta_1 \overline{Main\ Explanatory\ Variables_i} + \beta_2 \overline{Control\ Variables_i} + \mu_i + \overline{v}_i \qquad [28]$$

Therefore, subtracting equation [27] from [28] gives:

$$Firm\ Risk\ Measures_{it} - \overline{Firm\ Risk\ Measures_i} = \beta_1\left(Main\ Explanatory\ Variables_{it} - \overline{Main\ Explanatory\ Variables_i}\right) + \beta_2\left(Control\ Variables_{it} - \overline{Control\ Variables_i}\right) + (v_{it} - \overline{v}_i) \qquad [29]$$

In equation [29] the unobserved cross-section FE, μ_i, and intercept, α_i, has now disappeared. The process of change expressed in equation [29] is known as "within effects" as it explains the variation of the mean of dependent variable in terms of the variations in the means of independent variables relating to a given firm. FE model does not suffer from heterogeneity bias as they only estimate "within estimates" (Dougherty, 2011).

Dougherty (2011) argues that the use of FE is costly as the intercept, α_i, and any other variable that is not changing over the time for each firm will disappear from the model. Although, the intercept may not be of much importance but the removal of unvarying independent variables could be problematic. For example, this study investigates the effects of derivatives use on firms' risk for a large sample of UK non-financial firms. Derivatives dummy for individual firm *i* in period *t* is D_{it}. Now if firms do not change their risk management activity during the period of study, i.e. they either use derivative instrument throughout the sample period or they do not, D_{it} will remain unchanged for all *t* for that firm and $D_{it} = \overline{D}_i$ for all time period, *t*. Therefore, the difference $(D_{it} = \overline{D}_i)$ is zero for all the time periods and hence, the firm will not be included in the analysis. If all the firms in sample have not changed their risk management policy during the sample period, then D_{it} will be zero for all *i* and *t* and hence, D_{it} cannot be included in regression analysis. However, FE model provides robust results while controlling for unobserved heterogeneity.

3.5.3. Random Effects Model

In the RE model the assumption is that all the firm differences are captured by the intercept parameter and as the firms in sample are selected randomly, the firm-specific effects are considered as a random variable and uncorrelated with the explanatory variables included in the model. If μ_i, in equation [27], is considered as RE instead of FE, then RE estimation method can be used (Hill, Griffiths and Lim, 2011). By allowing different intercepts RE model controls the shortcomings of FE model. RE model provides different intercepts for each firm similar to FE model. However, RE model assumes the different firm-specific terms as a random component and deviations from the random component are treated as a part of error term. Baltagi (2005) suggests random effects specification if a sample is randomly selected from a large population.

In the RE model the error has two factors: the individual firm-specific error and the error term showing how far the intercept of each firm is compared to the overall intercept. As discussed above in RE model μ_i is considered as random element instead of fixed and with a mean value of $\overline{\mu}$. In this instance, the firm-specific intercept can be expressed as;

$$\mu_i = \overline{\mu} + e_i \qquad [30]$$

Where $e_i$is an i.i.d error term with a zero mean value and constant variance of σ_e^2. Now by substituting equation [30] into equation [27], we have;

$$\begin{aligned} &Firm\ Risk\ Measures_{it} \\ &\quad = \alpha_i + \beta_1 Main\ Explanatory\ Variables_{it} \\ &\quad + \beta_2 Control\ Variables_{it} + \overline{\mu} + \omega_{it} \end{aligned} \qquad [31]$$

where:

$$\omega_{it} = v_{it} + e_i \qquad [32]$$

The combined error term ω_{it}includes two error elements, v_{it}, which is a panel error term, and e_i, which is a firm-specific error term. It is assumed that firm-specific error term is not correlated with each other and also not auto-correlated across both cross-section and time-series units. RE model assumes that the firm-specific error term is not correlated with the explanatory variables, which allows the time-invariant variables to be included as explanatory variables, and shows advantage of RE model over FE model. RE model produces more estimators than FE model as observed characteristics that remain constant for each firm are retained in the regression analysis while they have to be dropped in FE model (Dougherty, 2011). Also, the degrees of freedom are more with random effects model than with FE model (Dougherty, 2011).

3.5.4. Tests to Choose Between OLS, RE and FE Models

In our empirical analysis, we use OLS, RE and FE models but do not provide results for all these models. We employ several tests to select the best model among OLS, RE and FE and report the results of the best model in the empirical analysis. Below, we discuss these tests.

3.5.4.1. F-Test

First, OLS model is tested for the presence of heterogeneity using F-test as suggested by Greene (2002). This test compares the results of pooled OLS with the results of FE model. The pooled OLS is the restricted model and the rejection of H_0 indicates the presence of FE. The F-test has following form:

$$F = \frac{(RSS - URSS)/(N-1)}{URSS/(NT_i - N - K)} \sim F_{N-1, N(T_i-1)-K} \qquad [33]$$

In equation [33] *RSS* is restricted sum of squares from OLS model; *URSS* is unrestricted sum of squares from FE model. The rejection of the null hypothesis suggests that the FE model is better suited than pooled OLS model.

3.5.4.2. Breusch and Pagan Lagrange Multiplier Test

Second, Breusch and Pagan LM test is used to test for the presence of random effects model based on the OLS residuals (Greene, 2002). This test compares the results of pooled OLS with the results of RE model. The LM test takes following form:

$$LM = \frac{nT_i}{2(T_i - 1)} \left[\frac{\sum_{i=1}^{n} \left[\sum_{t=1}^{T_i} e_{it} \right]^2}{\sum_{i=1}^{n} \sum_{t=1}^{T_i} e_{it}^2} - 1 \right]^2 \qquad [34]$$

The rejection of null hypothesis indicates presence of RE and suggests that RE model is suitable than pooled OLS model.

3.5.4.3. RE vs. FE Test

Third, a test for over identifying restrictions between FE and RE model is employed[58]. The FE estimator uses the orthogonality conditions that the regressors are uncorrelated with the idiosyncratic error while random effects estimator uses the additional orthogonality conditions that the regressors are uncorrelated with the group-specific error. The null

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[58] We use xtoverid command in stata created by Schaffer and Stillman (2006) to select between fixed effects and random effects model. The standard Hausman test for fixed effects and random effects cannot be calculated with robust standard errors and hence this command is used.

hypothesis for the test is that individual effects are uncorrelated with the other regressors in the model. The rejection of null hypothesis suggests that the individual effects are correlated with regressors and FE model is best suited than random effects in such a scenario.

3.5.5. First Difference Model

We also analyse data using a second version of FE model called first difference (FD) model. In this model the unobserved effect is removed by taking the difference of observation for the previous time from observation with current time and this is repeated for all the periods Dougherty (2011). For a firm *i* in time period *t* the model is [27]. For the previous year, the relationship is as follow:

$$\begin{aligned} &Firm\ Risk\ Measures_{it-1} \\ &\quad = \alpha_i + \beta_1 Main\ Explanatory\ Variable_{it-1} \\ &\quad + \beta_2 Control\ Variables_{it-1} + \mu_i + v_{it-1} \end{aligned} \qquad [35]$$

Now subtracting equation [35] from equation [27] gives:

$$\begin{aligned} &\Delta Firm\ Risk\ Measures_{it} \\ &\quad = \beta_1 \Delta Main\ Explanatory\ Variable_{it} + \beta_2 \Delta Control\ Variables_{it} \\ &\quad + \Delta v_{it} \end{aligned} \qquad [36]$$

In equation [36] the unobserved heterogeneity has disappeared. "Δ" represents simple change from t to $t-1$. Under the assumption of presence of unobserved heterogeneity, the coefficient on β_1 and β_2 provides better estimate when changes in probability of default are regressed on change in main explanatory variable and changes in other control variables. FD model will yield consistent estimates as Δv_{it} is uncorrelated with $\Delta Main\ Explanatory\ Variables_{it}$ and $\Delta Control\ Variables_{it}$ and satisfies the assumption that $E(v_{it} | Main\ Explanatory\ Variables_{it}, Control\ Variables_{it}) = 0$.

3.5.6. Weighted Least Square

In Chapter 6, we use weighted least squares (WLS) methodology to control for the heteroskedasticity. We assign more weights to more precise estimates and less weight to less precise estimates. In un-weighted regression, the model prefers observations with larger values to observations with smaller values. Hence, generated regression curves fit points at higher levels than at lower levels ("NIST/SEMATECH E-Handbook of Statistical Methods," 2012). We use t-statistics of the FX exposure coefficients calculated using equation [7] as a weighting factor. WLS enables us to assign more weights to more precise FX exposure estimates and therefore can increase the accuracy of our second stage regression estimation. Allayannis and Ofek (2001) and Muller and Verschoor (2008) also use the WLS estimation method. Allayannis and Ofek (2001) use inverse of standard errors estimated from equation that they used to calculate FX exposure whereas Muller and Verschoor (2008) use t-statistics from the exposure coefficients calculated from first stage model as a weighting factor. The benefit of WLS is that the estimates obtained from it have better efficiency properties than OLS.

3.5.7. Instrumental Variable Approach

The above discussed methods of panel data tries to control for the problem of unobserved heterogeneity in data but still the estimate derived from the above models may not be completely reliable under the possible problem of endogeneity. Endogeneity arises because of simultaneous causality in this study. This occurs when the causality runs in both directions, that is, from the regressor(s) to the dependent variable and from the dependent variable to the regressor(s). In our case, the relationship between derivative use and the firm risk measures is affected by a feedback loop such that derivative use affects the firm risk but firm risk also affects the decision to use derivatives. In effect, derivative usage lowers the firm risk but it is also the case that firms with a high firm risk are more likely to use derivatives. Hence it becomes important to address this problem and to account for this bias. When there is simultaneous causality, the endogenous variables and the error term are correlated and OLS estimation picks up both forwards and backwards effects, thereby leading to bias and inconsistent coefficients.

To better understand it, suppose main explanatory variable (v_{it}) is the only explanatory variable available to explain the variation in firm financial risk (y_{it}). To estimate the mean structure of a model following OLS ($\hat{\beta}_{OLS}$) model can be used:

$$y_{it} = \beta v_{it} + \varepsilon_{it} \qquad [37]$$

In the above equation, [37], β is consistent and unbiased when explanatory variable (v), derivatives use, and error term (ε) are uncorrelated, $Cov(v, \varepsilon) = 0$, However the estimated coefficient is biased and inconsistent when ε contains any omitted variable that is correlated with main explanatory variable v, $Cov(v, \varepsilon) \neq 0$. This problem can be controlled using an instrumental variable (IV) approach and the equation [37] can be used.

To obtain unbiased and consistent estimates for β, when v and ε are correlated, instrumental variables needed. A good instrumental variable affects dependent variable through its effect via endogenous variable and not directly (Hill et al., 2011). In this study a good instrumental variable must affect firm risk trough its effect on derivatives use and not directly. These instrumental variables provide additional information. A good instrumental variable, z, must satisfy the following two conditions:

- *z is uncorrelated with ε that is,*

$$Cov(z, \varepsilon) = 0 \qquad [38]$$

In equation [38] z is considered as exogenous and it mean that z should not have any partial effect on other control variables and also it should not be correlated with other factors that affect control variables. This equation is also called "Instrument Exogeneity" (Wooldridge, 2009).

- *z is correlated with v that is,*

$$Cov(z, v) \neq 0 \qquad [39]$$

In the above equation z must be either positively or negatively correlated with endogenous explanatory variable v. This condition is known as "Instrument Relevance" (Wooldridge, 2009).

If the instrumental variable satisfies the above two conditions only then it can be used as an instrumental variable for v. However, it is very hard to test the covariance between z and unobservable error ε, equation [38]. Generally, this assumption cannot be tested and in majority of cases researchers maintain $Cov(z, \varepsilon) = 0$ by intuition (Wooldridge, 2009). The second condition [39] can be tested given a random sample of population. A simple regression analysis between z and v can test the second condition (Wooldridge, 2009).

If the selected instrumental variable satisfies the above-discussed conditions then it can be considered as valid instrumental variable and can be used to estimate y using following equation:

$$y_{it} = \beta \hat{v}_{it} + \varepsilon_{it} \qquad [40]$$

In equation [40] $\hat{v}$ is the predicted value of v from the simple regression of v on z. This equation will provide unbiased and consistent estimate for β.

3.5.7.1. Two Stage Least Square Approach

2SLS is used to control the problem of endogeneity by implementing instrumental variable regression analysis.[59] This model combines multiple instruments into one instrument in first stage and then the predicted values of the endogenous variable can be used in second stage model. We use this analysis in section 5.4.7 where we use extent of derivatives variable as our main explanatory variable. We consider extent of derivatives use and leverage as endogenous variables and use instrumental variables to control for endogeneity. In the first stage, endogenous, extent of derivative use and leverage, variables are regressed using instrumental variables[60]. The extent of derivative use and leverage are regressed on all valid instruments and all other exogenous variables in the first stage. The instruments capture the variation in the extent of derivative usage and leverage. As the instrumental variables are uncorrelated with error term, the estimated endogenous variables, extent of derivative use and leverage, will not be correlated with the error term. In the second stage regression, the probability of default is estimated using the predicted values of extent of derivative use and leverage from the first stage regression and all other exogenous variables.

In determining our choice of instrumental variables, we follow the literature (Géczy et al., 1997; Allayannis and Ofek, 2001; Graham and Rogers, 2002; Purnanandam, 2008; Magee, 2013). The first instrumental variable is the ratio of R&D expenditure to sales. Géczy et al. (1997) and Allayannis and Ofek (2001) find a positive and significant relationship between this variable and the use of currency derivatives, which is consistent with the theory that firms use derivatives to reduce underinvestment costs. Magee (2013) also use R&D expenditure as an instrument for hedging. Our second instrumental variable is ratio of foreign sales to total sales. This variable measures the foreign exposure and hedging theories suggest that firms with more FX exposure are more likely to use derivatives (Allayannis and Ofek, 2001). This variable also measures firms' real foreign operations. The third instrumental variable that we used is depreciation and amortisation scaled by the total assets of the firm as a measure of firms non-debt tax shield (Purnanandam, 2008).

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[59] Boyer and Marin (2013) and Magee (2013) uses 2SLS approach in their examination.

[60] The first stage instrumental variables estimation is to estimate the endogenous variables as a function of the exogenous variables in the second stage plus additional instruments.

Finally, we use property, plant and equipment scaled by total assets to control for the collateral available for borrowing (Purnanandam, 2008).

The first stage regression form is as follow:

$$Extent\ of\ Derivative\ Use_{it} = \pi_i + \pi_1 Instrumental\ Variables_{it} + \pi_2 Control\ Variables_{it} + \omega_{it} \quad [41]$$

$$Levarage_{it} = \pi_i + \pi_1 Instrumental\ Variables_{it} + \pi_2 Control\ Variables_{it} + \omega_{it} \quad [42]$$

The second stage regression form is as follow:

$$EDF1YEAR_{it} = \alpha_i + \beta_1 Extent\ of\ \widehat{Derivatives}\ Use_{it} + \beta_2 \widehat{Leverage}_{it} + \beta_3 Control\ Variables_{it} + \varepsilon_{it} \quad [43]$$

In equation [43], $Extent\ of\ \widehat{Derivatives}\ Use_{it}$ is the predicted value of extent of derivatives use from equation [41] and $\widehat{Levrage}_{it}$ is the predicted value of leverage from equation [42].

2SLS provides consistent IV estimates; but it is suboptimal in the presence of heteroskedasticity (Magee, 2013). Due to the problem of omitted variables, the individual firm effects may change over-time. This means that individual firms may responds to the changing unobservable variables in different ways. The panel data model can be rewritten as follow to include the effects of time-varying unobservable variables.

$$EDF1YEAR_{it} = \alpha_i + \beta_1 Extent\ of\ Derivatives\ Use_{it} + \beta_2 Control\ Variables_{it} + \xi_{it} \quad [44]$$

Where $\xi_{it} = \theta_t \propto_i + \varepsilon_{it}$. Because of this the variance of error term is no longer constant, $\theta_t^2 \sigma_{\propto_{ij}}^2 + \sigma_{\varepsilon_{ij}}^2$, and leads to the problem of heteroskedasticity. This problem can be partially addressed using heteroskedasticity consistent or "Robust" standard errors and statistics. However, 2SLS-IV is suboptimal in the presence of heteroskedasticity.

3.5.7.2. Generalized Methods of Moments Approach

As 2SLS is suboptimal, in the presence of heteroskedasticity, a GMM instrumental variables approach can be used. GMM, introduced by Hansen (1982), is the standard method when unknown form of heteroskedasticity is present (Baum, Schaffer and Stillman, 2003). This method uses the orthogonality conditions to allow for efficient estimation under the presence of unknown heteroskedasticity (Baum et al., 2003). Complete distribution knowledge of data is not required for GMM. GMM estimates need only specified moments derived from an underlying model. GMM will work in a similar way as IV estimate if the moments are more than equations. It estimates the parameter vector by minimizing the sum of squares of the differences between the population moments and the sample moments, using the variance of the moments as a metric. The adjustment to the covariance matrix accounts not only the moving average aspect of disturbances but also for heteroskedasticity aspect of the disturbance conditional on the explanatory variables. This is how GMM ensures efficient estimate in the presence of unknown heteroskedasticity. Under the problem of heteroskedasticity GMM estimator is more efficient than the standard IV estimator. However, if heteroskedasticity is not present the GMM estimator is no worse asymptotically than the IV estimator (Baum et al., 2003).

We perform several checks of instrument validity on our instruments. In particular, we use Sargan-Hansen Test, Under-Identification test and Crag-Donald F-Stat.

3.5.8. Selection Bias: Treatment Effects Model

In Chapter 5, we use treatment effects model to correct for the possibility of self-selection bias. Self-selection occurs when firms self-select themselves into certain behaviours or programmes and hence participation is not randomly determined (Wooldridge, 2009). If derivative user firms are systematically different from the firms that do not use derivatives, then the problem of self-selection bias arises. If derivatives are used by firms with high firm financial risks for reasons other than risk management and if our control variables cannot capture this information, then it is best to use treatment effect model as it will correct the problem of self-selection bias and produces consistent results.

In treatment effects model, we use predicted probabilities of firms using derivative instruments as an explanatory variable in the risk equation. Treatment effects model considers derivatives as endogenous and includes it on the right side of the first regression equation. The inverse mills ratio statistics from the treatment effects model shows whether a bias exists or not. To examine the effect of derivatives on firms' probability of default, following treatment effect model is estimated:

3.5.8.1. Treatment Effects: Two-Step

Heckman's two-step treatment effects model involves 2 equations: 1) the selection equation, where we model the firm's decision to use derivatives, and 2) the regression equation considering mechanisms determining the outcome variable, using the predicted values of derivatives use from the selection equation. In our case, we assume that the probability of default of a firm is a function of derivatives use, leverage, firm size, profitability, liquidity, equity volatility and its excess return; whereas the probability of derivatives use is a function of foreign sales, capital expenditure and interest coverage. We first estimate our selection equation model as follow:

$$Derivatives_{it}^{*} = \pi_0 + \pi_1 Instrumental\ Variables_{it} + \pi_2 Control\ Variables_{it} + \mu_{it} \qquad [45]$$

$$Derivatives_{it} = 1\ if\ Derivatives_{it}^{*} > 0, and\ Derivativesi_{it} = 0\ otherwise$$

Where $\mathrm{Derivatives}_{\mathrm{it}}^{*}$ is a latent variable. $\mathrm{Instrumental\ Variables}_{\mathrm{it}}$ are instrumental variables. $\mathrm{Control\ Variables}_{\mathrm{it}}$ are set of observed variables that affect firms' use of derivatives. $\mu_{it}$is an error term.

We use the predicted value of $\mathrm{Derivatives}_{\mathrm{it}}^{*}$ in following outcome equation:

$$EDF1YEAR_{it} = \beta_0 + \delta Derivatives_{it}^{*} + \beta_1 Leverage_{it} + \beta_2 Firm\ Size_{it} + \beta_3 Profitability_{it} + \beta_4 Liquidity_{it} + \beta_5 Excess\ Return_{it} + \beta_5 Equity\ Volatility_{it} + \varepsilon_{it} \qquad [46]$$

Where $EDF1YEAR_{it}$ is the probability of default, $\mathrm{Derivatives}_{it}$ is a predicted value for derivatives variable from equation [45] and $\varepsilon_{\mathrm{it}}$is an error term. In all the equations, we also include industry dummies and year dummies. The coefficient of interest is δ, which measures the average effect of derivative use on the probability of default. By using a treatment effects model, we can estimate the regression coefficients δ on our endogenous derivatives variable by using the observed variables.

3.5.9. Matching Methods

There are several problems that affect the results of studies that use observational data. The first problem is the distribution on observed characteristics between treatment and control group. Majority of the studies that examine the effects of derivatives uses on firm risk use a regression model where they regress measure of risk on a dummy or a continuous measure for derivatives and other control variables (Bartram, 2006; Boyer and Marin, 2013; Magee, 2013). Researchers then examine the coefficient on derivatives by saying ceteris paribus and hence assume the value of coefficient as the casual effect of the derivatives. However, the problem with simple regression analysis is that they cannot identify whether the observed characteristics used have any comparable overlap. Li (2013) argues that the findings of studies that use regression model with observational data could be misleading as they do not control for the overlap between treated and control group. Endogeneity is other econometric issue that affects the result of studies that uses observational data. Endogeneity arises when the explanatory variable is correlated with the error term. Many previous studies have raised the issue and tried to correct for it[61]. Endogeneity arises from three sources, measurement error, simultaneity and omitted variables[62]. If present, these problems results in biased estimation of the causal effects. In this study, we also use matching methods to control for the above-discussed problem of endogeneity.

Assessing the impact of derivatives use is complex because of incomplete information. With observational data one can identify whether a firm uses derivatives or not and the firm financial risk conditional on derivatives use. However, the problem with making causal inference is how to identify the outcomes that are not observed. This means that if firm *i* used derivatives at time *t*, what would have happened if it had not used derivatives. Hence, the fundamental problem in estimating unbiased causal effects is constructing the unobserved counterfactuals for treated (derivative users) observations.

In observational studies, the researcher has no control on observations. The treated and control groups may have substantial difference on the observed covariates and these differences can lead to biased estimates of treatment effects if not controlled. We show in our univariate results in Chapter 4 and Chapter 5 that treated and control firms have large differences on the observed covariates and that there is a possibility of endogeneity. To control for these problems, majority of the studies use instrumental variable approach where they use instruments to control for endogeneity (Boyer and Marin, 2013; Magee, 2013). However, instrumental variable approach for dealing with endogeneity requires finding instruments that are uncorrelated with error term and explain variation in dependent variable only through the endogenous variables. Finding good instruments is hard and researchers rely on economic intuition to justify the conditions of instrument validity. To examine the effect of a “Treatment” one could use two firms that have similar characteristics for all the variables except that one gets the treatment (uses derivatives) and the other does not (non-user). This examination will provide unbiased estimation effects of treatment on the outcome variable. However, in observed data, this is very hard to achieve and hence statistical method should be used which can create such a matching. In this

[61] *Hentschel and Kothari (2001); Purnanandam (2008); Magee (2013)*
[62] *Li (2013)*

thesis, we use propensity score and coarsen exact matching methods to examine the impact of derivatives use (treatment effect) on firm risk measures (outcome variable).

Matching methods control for the covariate imbalance before matching and prune observations that are out of balance for which a matching is not available (Blackwell, Iacus, King and Porro, 2009). This ensures comparison of treated & control firms and allows examination of causal effect of treatment on the outcome variables.

3.5.9.1. Propensity Score Matching

In this study, we examine the effect of derivatives use on the firm financial risk measures using regression analysis. However, the results of analysis could be biased due to the potential problem of endogeneity. We use propensity score matching (PSM) method, which is one of the econometric models that are used to calculate causal effects while controlling the endogeneity problem. PSM method matches the treated and control firms first on their propensity score and then calculate the mean difference for outcome variable. This makes sure that only comparable firms are used to calculate the mean difference and hence removes the bias. The optimal setting for this comparison could be one where firms are randomly allocated to use derivatives and to not. The random allocation of firms would control irrelevant influences by equating them in two groups. However, randomised experiments are difficult and costly to achieve in observational studies and hence, the advantage of PSM method is that it provides randomised experiment by matching firms on the observed covariates. This method matches derivative user firms with non-user firms and control for endogeneity. Li (2013) argues that if PSM technique is used appropriately then it can increase researchers' ability to draw causal inferences with observational data. Researchers can use observational data and reconstruct the counterfactuals using PSM method. Li (2013) shows that PSM reconstructs counter factual by adjusting covariates between treated and control group using observational data.

In this study, we use matching on propensity score method to match derivative user and non-users on various covariates. PSM is specifically designed to achieve balance on observed covariates between the treatment and control groups (Rosenbaum and Rubin, 1983). PSM calculates conditional probability of receiving treatment based on observed covariates. In this thesis, the propensity score is the conditional probability of using derivatives. Propensity score is calculated using a logistic regression model where a dependent binary variable (use of derivatives) is regressed on covariates that are expected to be related to both dependent variable and outcome variable (firm financial risk measures). PSM reduces the selection bias in results by matching on a single index propensity score and make derivative user firms and non-user firms as comparable as possible on covariates.

We use propensity score estimation method to identity firms that have similar characteristics to use derivatives but differ only on their choice of using derivatives and then match the derivative user and non-user firms on the propensity score. Few studies earlier used a PSM method developed by Rosenbaum and Rubin (1983) to examine the effects of a treatment on the outcome variable in finance field[63].

3.5.9.1.1. Propensity Score Estimation

We calculate each firm's propensity score (the estimated likelihood that firm will use derivatives) based on covariates that are expected to affect firm's choice of whether to use derivatives. We use the following model to calculate the propensity score;

$$\begin{aligned} Derivatives\ Use_i &= \alpha_1 + \alpha_2 Z\ score_i + \alpha_3 Interest\ Coverage_i + \alpha_4 Leverage_i \\ &+ \alpha_5 Quick\ Ratio_i + \alpha_6 Firm\ Size_i + \alpha_7 Market\ to\ Book_i \\ &+ \alpha_8 FC\ Debt\ Dummy_i + \alpha_9 Foreign\ Sales_i + u_i \end{aligned} \qquad [47]$$

Where Derivatives Use_i is a dummy variable. Z-score, interest coverage, leverage, liquidity, firm size, market to book, FC debt dummy and foreign sales are the firm characteristics that are expected to affect firms' choice of whether to use derivatives.

We estimate the propensity score using a logit model on determinants of derivatives use[64]. Once the propensity score is calculated, we match a treated firm with a control firm without replacement using various methods. We also use a caliper value to create a tolerance level on the maximum propensity score distance to be matched against. This matching is done on the individual propensity score of using derivatives.

3.5.9.1.2. Matching Methods

There are number of matching methods available to match treated firms with control firms on estimated propensity score. We use following matching methods to match treated firm with control firm based on their propensity score.

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[63] Campello, Graham and Harvey (2010); Bartram et al. (2011)

[64] We use psmatch2 Stata module created by Edwin and Barbara (2003) to calculate propensity score and to match derivative users and users.

3.5.9.1.2.1. One-to-One Matching Without Replacement

This matching method is one of the most common and frequently used methods (Austin, 2011). In this matching method a firm from derivative user group is matched one by one with a firm from non-derivative user group, without replacement, that is closets on the estimated propensity score. The firm from control group is used only once to match with a firm from treated group. We also impose a common support that drops treatment observations whose propensity score is higher than the maximum or less than the minimum from control group. As a result of this, a firm from treatment group is matched with a firm from control group whose propensity score difference is lowest. This matching method ensures that the difference between matched treated and control firm is minimum.

3.5.9.1.2.2. One-to-One Matching Without Replacement with Caliper

This method of matching is similar to one-to-one matching but creates a good match by imposing the tolerance level on the maximum propensity score distance defined by caliper[65]. Once the caliper value is assigned, a treated firm is matched against the control firm whose propensity score is within the $\pm$ of caliper value from the treated firm. This matching is better than the matching without caliper, as a treated firm is more likely to be matched with a control firm that has a similar propensity score due to caliper; whereas in nearest neighbour matching the match could be bad if the closest matching is far away. Caliendo and Kopeinig (2008) argue that caliper and replacement work in similar way, reduces bad matching and increases the quality of matches.

3.5.9.1.2.3. Kernel Matching

The one-to-one matching discussed above uses only one observation from control group to match against treated group and because of this only few observations from control group are used. This limits the number of firms that are matched with control group and reduces the number of observations. Kernel method uses weighted averages of all the firms in the comparison group to calculate the counterfactual (Caliendo and Kopeinig, 2008). The benefit of kernel matching over one-to-one matching is that it uses more information and reduces the variance. However, the method can use bad matches as it takes weighted averages.

[65] *Caliendo and Kopeinig (2008)*

3.5.9.1.3. Balancing Test

To ensure the balance of the strata for the covariates the *t-test* and the standardized bias (SB) are two extensively used techniques (Rosenbaum and Rubin, 1985). The *t-test* simply compares the mean difference between treated and control groups both before and after matching. The insignificant value of *t-test* indicates the mean difference is not statistically important. We would expect insignificant mean difference after matching as we want the mean for covariates to be similar after matching for treated and control firms. This ensures good comparison for outcome variable.

The main reason that we use PSM is to remove the bias from the data and calculate the unbiased causal effects. Therefore, it is important to know how successful is PSM method in removing the selection bias on observed covariates for treated and control firms. We calculate the SB for all the observed covariates as follow.

$$SB_{Match} = 100 \frac{|\bar{X}_T - \bar{X}_C|}{\sqrt{0.5(\sigma_T^2 + \sigma_C^2)}} \qquad [48]$$

Where $\bar{X}_T$ and $\bar{X}_C$ are sample means and σ_T^2 and σ_T^2 are the variance for treated and the matched control group. The SB is calculated as the difference of sample means for treated and control firm as a percentage of the square root of the average sample variance for the two groups.

3.5.9.1.4. Sensitivity Analysis

Compare to a standard regression model the propensity score model provides more reliable and unbiased results by comparing treated firms with control firms that have similar propensity score. However, Rosenbaum (1991) argues that there are two situations under which groups are not comparable for studies that use observational data. First situation is of overt bias where groups differ on observable characteristics. For example, treated firms are generally larger than control firms. This situation can be solved with different matching algorithms where a treated firm is matched with control firm that has similar size. Second situation is of hidden bias where groups differ on unobserved characteristics that are not measured. This situation is hard to resolve as the hidden or unobserved variables are difficult to measure. If there are unobserved or hidden variables that affect treatment assignment (the decision to use derivatives) or outcome variable, then there is a problem of endogenous selection and under such circumstances the estimates obtained from PSM are inconsistent and the results are no longer unbiased. These unobserved variables may compromise the validity of inferring causality from observational data.

PSM allows sensitivity analysis on this selection bias and also estimates the extent to which this hidden bias may affect the inference about the effects of derivatives use. We perform a sensitivity analysis by looking at Rosenbaum bounds and hidden bias equivalents (Diprete and Gangl, 2004). This method determines the extent to which selection on unobserved variables needed in order to change the inferences calculated by the PSM. Using Rosenbaum bound this sensitivity of observed effects can be calculated for number of scenarios with various levels of gamma, Γ. Gamma represents assumptions about unmeasured heterogeneity or endogeneity in treatment assignment expressed in terms of odds ratio of differential treatment assignment due to an unobserved covariate. A scenario of bound estimate $\Gamma=1$ suggests absence of hidden bias and shows that 2 firms have identical observable characteristics and no other unobserved variables affects it. Similarly, a gamma of 1.4 indicates that the unobserved variable that would increase the odds of using derivatives for the firm that actually is a user by 40% than a firm that is a non-user. We calculate the Rosenbaum bounds for our treatment variable at different levels of gamma that allows us to measure the strength of unobserved variables would require in order to overturn our inferences from PSM method.

3.5.9.2. Coarsened Exact Matching[66]

Coarsened Exact Matching (CEM) is an exact matching method and hence does not require balance checking after matching (Blackwell et al., 2009). Similar to PSM, CEM is a member of the Monotonic Imbalance Bounding matching method which in our case matches derivative users (treated group) with non-users (control group) and improves the estimation of the treatment effect by reducing the covariates imbalance between treated and control groups and makes them more comparable (Blackwell et al., 2009). In this method, the covariates are first coarsened and then treated firms (derivative users) are exactly matched with control firms (non-users) on the coarsened data. Once the matching is done then the effect of treatment on outcome variable can be investigated using uncoarsened data.Blackwell et al. (2009) argue that in PSM user is required to set the size

[66] *We use cem command in stata to perfrom Coarsened Exact Matching. See Blackwell et al. (2009) for more details.*

of the matching solution pre-matching and then they have to check the balance for matched variables after matching. This process needs to be repeated until the balance is achieved. These suggest that PSM method is slow and complicated to apply. Wells et al. (2013) show that a causal effect estimated from CEM produces a lower variance and bias for any given sample size compared with PSM. They also show that CEM retains more observations and achieves a better balance between matched samples. In contrast to PSM, CEM matches directly on the covariates and not on any intermediate score. *"We discover a serious problem with PSM (and especially PSM with calipers) that causes it to approximate random matching in common situations. Moreover, and contrary to conventional wisdom, random matching is not benign; on average, it increases imbalance (and variance) compared to not matching.*" Gay, Lin and Smith (2011, p. 1). King et al. (2011) did not find this problem with CEM. The above discussion shows that CEM is efficient than PSM.

3.6. Conclusion

In this chapter, we discuss the sample and sample period that we use in empirical chapters. We provide the definitions, measurements and the sources of our firm risk, main explanatory, control and credit risk variables. This chapter also provides the theoretical and empirical reasoning behind the use of control variables. Furthermore, this chapter outlines the estimation methods that we use in the following empirical chapters.

This chapter provides insight into the various econometrics issues, such as heterogeneity, endogeneity, self-selection bias and omitted variable bias, that we encounter in our data and also discusses the methods, such as random effects, fixed effects, first difference, instrumental variable, treatment effects and matching methods, that we employ to control for the econometric issues.

Chapter 4. The Effects of Derivatives Use on Equity Implied Risk

4.1. Introduction

In the last twenty years, there is a sharp increase of risk management activities with the use of financial derivatives instruments across the world. However, there are group of people , financial regulators, shareholders and employees, who become more and more concerned regarding how corporations use these financial derivatives in the wake of recent financial crisis. This group of people are worried about how the use of derivatives by corporations affects firm financial risk.

Most UK non-financial firms disclose the use of derivatives and risk management activities in their annual reports. Unfortunately, the quality of derivatives disclosure in UK annual reports varies and in many instances, it is difficult to quantitatively assess the impact of derivatives use on firm risk. This has stimulated a debate among investors, creditors, regulators and dealers about the appropriate level of derivatives disclosure. This discussion has largely occurred in the absence of systematic empirical evidence about the effects of derivatives use on firms' risk and value. The aim of this study is to contribute to this debate by examining the impact of UK non-financial firms' use of derivatives on the firm financial risk.

Figure 4-1: Notional Amounts of Outstanding OTC Derivatives of Non-Financial Users

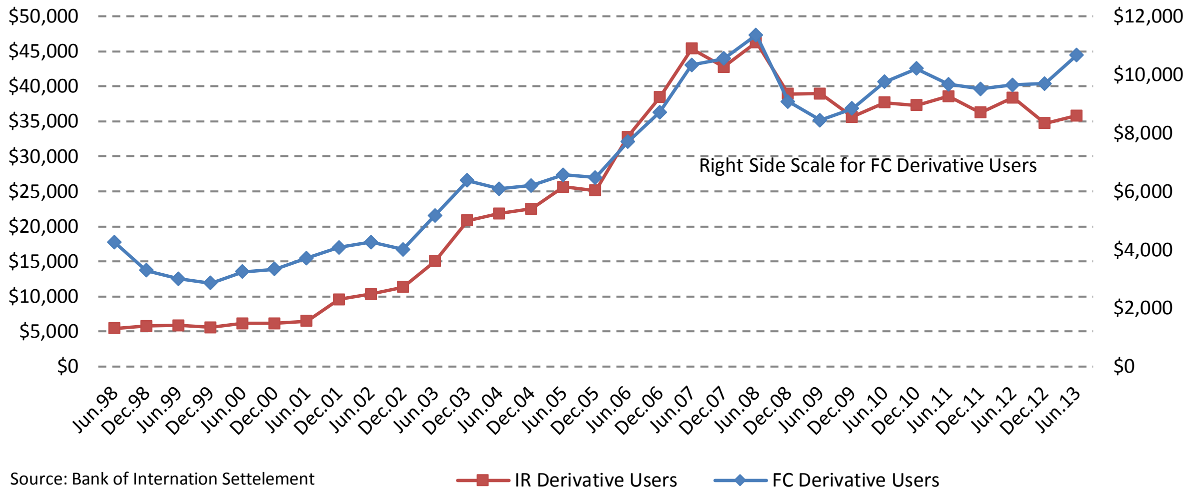

Figure 4-1 shows the usage of OTC FC and IR derivatives for non-financial firms since June 1998 to the first half of 2013. The figure shows that the demand for derivatives is on rise from June 1998 to June 2008 (Period of recent financial crisis). For the few years staring June 1998, the demand for derivative instruments increased very gradually but after year 2001 the demand increased very sharply. The figure also shows that in last 10 years there is huge increase in the use of derivative instruments. During the period, there is a small decline in the usage of FC and IR derivatives. However, in December 2008 the demand for FC and IR derivatives dropped by 20% and 16% respectively. This decrease in demand may suggest that firms may have started to realise the credit constraint. The demand for FC and IR derivatives after this period remains stable over-time. The average growth in FC derivatives during 2009 to June 2013 is 2% and for IR derivatives the average growth is -0.75%.

The aim of this chapter is to examine whether UK non-financial firms are using derivatives for hedging or speculation. This is done empirically by examining the effects of financial derivatives on firm financial risk measures of UK non-financial firms. We use total risk, idiosyncratic risk and market risk as a measure of firm financial risk. In this chapter, we use 3 broad categories derivatives 1) firms that use FC and/or IR and/or CP derivatives 2) firms that use FC derivatives and 3) firms that use IR derivatives. We use a large panel of UK non-financial firms for the period 1999 to 2010 for this analysis. This dataset covers a wide range of derivatives use and firm financial risk measures. We use both dummy and continuous measures of derivatives. The dataset also allows us to investigate the effect of derivatives use on firm financial risk during a period that includes two episodes of a significant increase in business risk, the 2001 and 2007 global recession.

We show that a 1% increase in the extent of all derivatives use results in a reduction of 2.52% of stock return volatility per annum. We also find that a 1% increase in extent of IR derivatives use reduces total risk by 9.74% (represents 22% of mean total risk) suggesting that IR derivatives use have economically large effect on total risk. For market risk, we find that a 1% increase in the extent of all and FC derivatives leads to a reduction of 0.0651 and 0.0945 basis points in market risk. Our results suggest that a 1% increase in the extent of all and IR derivatives leads a 2.23% (represents 5.69% of mean idiosyncratic risk) and 6.82% (represents 17.40 % of mean idiosyncratic risk) reduction in idiosyncratic risk. When we use dummy measure for derivatives use our results suggest that all derivative users, FC derivative users and IR derivative users have both statistically and economically significant 4.16%, 3.62% and 4.82% lower total risk than non-users respectively. For idiosyncratic risk, we find that all and IR derivative users have statistically and economically significant 2.02% and 2.55% lower idiosyncratic risk than non-users respectively.

In this chapter, we also investigate whether the effect of derivatives use on firm financial risk measures is influenced by macroeconomic conditions. Our sample period includes global economic uncertainty around 2002, a period of credit market tightening around 2003, a period of strong economic growth with relatively loose credit market conditions between 2004-2006 and recent financial crisis of 2007. This investigation will highlight how derivatives affect firm financial risk in different economic times. We find that derivative users have significantly lower total risk than non-users during 2002-2010. Derivatives use has largest negative effect on firm financial risk during 2005-2006 of 12% to 13%. This is the period of strong economic growth with relatively loose credit market conditions. During recent financial crisis of 2007-2009, we find that derivative users have 4.85% to 8.85% lower firm financial risk. Our results for year 2000 and 2001 shows that derivatives use has either no effect or it increase the firm financial risk during stable economic times. Overall, our results suggest that UK non-financial firms limiting their derivative activities to the hedging of downside risk and selectively hedging during favourable macroeconomic conditions.

In this chapter, we also control for endogeneity by matching derivative users and non-users on their likelihood of using derivatives using PSM method and then examine the mean difference of firm financial risk between matched firms. The results of these analysis show that derivative users have significantly lower mean values for total risk and idiosyncratic risk.

This chapter is organised as follow: Section 4.2 discusses the data employed in the study. Section 4.3 provides descriptive analysis of data. Section 4.4 presents the empirical results and section 4.5 draws some conclusions.

4.2. Variable Description[67]

This section describes the firm risk variables, main explanatory variables and control variables used in the empirical analysis of this chapter.

[67] *We winsorised all variables in this study by 1% from both tails to remove outliers affecting the analysis.*

4.2.1. Dependent Variables

To examine the effect of derivatives use on firm financial risk for UK non-financial firms, we use following firm risk measures calculated using equity share prices:

- *Total risk*
- *Market Risk*
- *Idiosyncratic Risk*

Total risk measures the aggregate firm risk and hence would show the effect of derivatives use on aggregate level instead of showing the effect on specific risks such as IR or FX e exposures. Next, we separate total risk into market risk and idiosyncratic risk[68]. These firms' financial risk measures are defined in section Chapter 3 on page no 52.

4.2.2. Main Explanatory Variables

The main explanatory variable for our analysis is the coefficient on the derivatives variable. We are interested in knowing the effect of derivatives on firm financial risk. Following measures of derivatives are employed in this chapter:

- *Continuous Measure of Derivatives:*

  We use year-end outstanding notional values of derivatives as a continuous measure of derivatives use. We scale notional values of derivatives by total assets. This gives an extent of derivatives use and can differentiate between a firm with high derivative usage and a firm with low derivative usage. We calculate this for 1) extent of all derivatives 2) extent of FC derivatives and 3) extent of IR derivatives.

- *Dummy Measure of Derivatives*

  We create dummy measures of derivatives based on the firm's decision to use derivatives. Based on firms disclosure in annual reports we assign '1' to a firm that disclose use of derivatives and '0' to a firm that does not report use of derivatives. We create following categories based on this definition 1) All Derivative Users is a dummy variable set equal to 1 if a firm use FC and/or IR and/or CP derivatives and

[68] *Guay (1999), Hentschel and Kothari (2001), Nguyen and Faff (2010) and Bartram et al. (2011) also uses similar firm financial risk measures.*

0 for non-users[69] 2) FC Derivative Users is a dummy variable set equal to '1' if a firm uses FC derivatives and '0' for non-users 3) IR derivative users (B) is a dummy variable set equal to '1' if a firm uses IR derivatives and '0' for non-users.

4.2.3. Control Variables[70]

In multivariate analysis, we control for other factors that also affect the firm financial risk. In particular, we control for following variables:

- *Leverage:* We calculate leverage as the ratio of total debt to book value of assets minus book value of equity plus market value of equity. We expect a positive association between leverage and total risk, market risk and idiosyncratic risk.
- *Firm Size:* We use natural log of total assets as a measure for firm size. We expect that firm size will be negatively associated with total risk, market risk and idiosyncratic risk.
- *Profitability:* We use the return on invested capital as a measure for profitability. We expect a negative association between profitability and total risk, market risk and idiosyncratic risk.
- *Market to Book:* We calculate market to book as the ratio of market value of assets to book value of assets. We expect positive association between market to book and total risk, market risk and idiosyncratic risk.
- *Dividend Yield:* We measure dividend yield as dividend per share divided by the share price. We expect negative association between profitability and total risk, market risk and idiosyncratic risk.
- *Liquidity:* We measure liquidity as ratio of total current assets minus total stock and work in progress over total current liabilities. We expect a negative association between profitability and total risk, market risk and idiosyncratic risk.

[69] *We do not investigate the effects of CP only derivatives as there are very few firms in our sample that use CP only derivatives.*

[70] *See section 3.3.3 for information on the theoretical and empirical reasoning behind using these control variables.*

4.3. Descriptive Analysis

This section provides the summary analysis of our risk, extent of derivatives use and control variables, the frequency distribution of the derivatives variable and the Pearson correlation coefficients for derivatives, firm risk measures and control variables.

4.3.1. Summary Statistics

Table 4-1 presents summary statistics for the firm financial risk measures and the control variables.[71] The table shows the number of observations, minimum and maximum value, means, median and standard deviation for the risk measures and independent or control variables.

Panel A of Table 4-1 shows that the mean (median) total risk for our sample firms is 42.98% (37.06%). This suggests that the average UK firm in our sample has very high total risk. Guay (1999) reports that their sample of US firms have 33.80% of median total risk. Hentschel and Kothari (2001) find the mean total risk for their sample of US firms is 1.81%. Bartram et al. (2011) report 56% of mean total risk for a sample of firms from 47 countries. Bartram et al. (2012) show that the median total risk for UK firm is 33.9% and the median total risk for US firms is 44.8% for US firms. The average estimated value of market risk is 0.63 suggesting that the average firm in our sample have relatively low market risk. Guay (1999) reports 0.97 median market risk. Hentschel and Kothari (2001) report 1.02 mean market risk. Bartram et al. (2011) report 0.70 mean market risk. Bartram et al. (2012) show 0.178 and 0.215 mean market risk for UK and US firms respectively. The average idiosyncratic risk for our sample firm is 39.19%. Guay (1999) reports 32.07% median idiosyncratic risk for their sample firms. Bartram et al. (2012) report 28.3% and 38.5% idiosyncratic risk for UK and US firms respectively. Overall, these summary statistics suggest that UK and US firms have higher total risk and higher idiosyncratic risk but low market risk. In panel B, we present summary statistics of our extent of derivatives use variables. We measure extent of derivatives use by scaling notional amounts of derivatives by firm total assets. Not all the firms in our sample disclose use of derivatives. The table shows that the average all derivatives use by our sample is 23.41% while the average extent of FC derivatives and IR derivatives is 13.87% and 13.81% respectively.[72]

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[71] See section 3.3.3 for variable definitions and justification
[72] We also include firms that specifically mention that they have zero notional values.

Table 4-1: Summary Statistics

*This table provides summary statistics for the variables used in the analysis. **Total Risk** is calculated as the annualised standard deviation of weekly stock returns over two years. **Market Risk** is calculated as the coefficient of the market index from a regression of individual stock returns on returns of the market index. **Idiosyncratic Risk** is calculated as the variance of residuals from the regression used to calculate market risk. **Leverage** is the ratio of total debt to market value of assets. **Firm size** is a natural logarithm of total assets. **Profitability** is calculated as the sum of pre-tax profits and total interest charges divided by invested capital. **Market to Book** is the ratio of market value of assets to book value of assets. **Dividend Yield** is measured as dividend per share divided by the share price. **Liquidity** is the ratio of total current assets minus total stock and work in progress over total current liabilities. **Z-score** is Altman's Z-score for UK firms; **Interest Coverage** is the ratio of Earnings before Interest and Taxes to Interest Expenses on Debt; **FC Debt** is a dummy variable set is equal to '1' if a firm uses Foreign Debt and '0' otherwise. **Foreign Sales** is the ratio of foreign sales to total sales.*

Variables	*N*	*Mean*	*Median*	*Minimum*	*Maximum*	*Standard Deviation*
			Panel A: Firm Financial Risk Measures			
Total Risk	3586	42.9810	37.0662	14.4539	131.1462	23.0683
Market Risk	3586	0.6323	0.5638	-0.3230	2.4849	0.4913
Idiosyncratic Risk	3586	39.1931	33.7480	13.1242	125.473	21.1809
			Panel B: Extent of Derivatives Use			
All Derivatives	1152	0.2341	0.1280	0.0000	2.9237	0.3888
FC Derivatives	845	0.1387	0.0536	0.0000	2.4139	0.2988
IR Derivatives	942	0.1371	0.0789	0.0000	1.1909	0.1810
			Panel C: Control Variables			
Leverage	2995	0.2406	0.2101	0.0000	0.8920	0.1883
Firm Size	2995	13.4688	13.3849	0.0000	17.2529	1.7561
Profitability	2995	0.1031	0.1031	-1.0365	0.7632	0.1777
Market to Book	2995	1.4631	1.0980	0.2781	14.3325	1.3937
Dividend Yield	2995	3.2122	2.7724	0.0000	16.1528	2.6703
Liquidity	2995	0.8824	0.7800	0.0000	8.8000	0.7018
Z-score	2384	3.1501	2.5431	-4.5056	25.1795	3.2535
Interest Coverage	2384	15.8771	5.5872	0.0000	100.0000	26.9284
FC Debt	2384	0.7752	1.0000	0.0000	1.0000	0.4176
Foreign Sales	2384	0.5706	0.5974	0.0000	1.0000	0.3397

The summary statistics for control variables are presented in panel B of Table 4-1. Our sample firms have an average leverage ratio of 24.06%. Hentschel and Kothari (2001) show that the average leverage for their sample firms is 1.72%. Judge (2006b) reports 32.7% of mean leverage ratio for a sample of UK firms. Clark and Judge (2009) report 18.7% of average leverage for UK firms. Bartram et al. (2012) report 14% and 17.1% average leverage ratio for UK and US firms respectively. Moreover, average sample firm have 10.31% profitability, an average market to book ratio of 1.46, an average firm have dividend yield of 3.21% and an average liquidity of 0.8824.

4.3.2. Frequency Distribution of Derivatives Use

Table 4-2 presents a frequency distribution of derivatives dummy employed in empirical examination. Panel A shows that 86.61% of firms in the sample use at least one type of derivatives while 13.39% of sample firms do not use any derivative instruments. Bartram (2006) finds that 60.5% of firms across all countries use at least one type of derivative and Bartram et al. (2011) reports 64.4% of derivative usage for their UK sample firms. Judge (2006c) reports 79.3% of derivative usage for a sample UK firms. For a sample of US firms Graham and Rogers (2002) report 35.7% of derivative usage, Purnanandam (2008) reports 28.60% of derivative usage and Campello et al. (2011) report 50.1 % of sample firms use derivatives. FC derivatives are the most frequently used with 74.01% of sample firms disclosing the use of FC derivatives followed by IR derivative users (70.61%) and CP derivative users (10.01%). Nelson et al. (2005) also find that majority of their sample firms also use FC and IR derivatives and only few uses CP derivatives. Graham and Rogers (2002) report 24.2% of FC derivative usage and 25% of IR derivative usage for US firms. Bartram et al. (2011) report 55% of FC derivative usage, 36.5% of IR derivative usage, 3.8% of CP derivative usage for UK firms and 37.8% of FC derivative usage, 40.4% of IR derivative usage, 16.1% of CP derivative usage for UK firms. Campello et al. (2011) report 27.3% of FC derivative usage and 35.6% of IR derivative usage for US firms. A recent study by Magee (2013) reports 67.3% FC derivative usage for a sample US firms. Clark and Judge (2008) report 74.2% of FC derivative usage for UK firms. These show that UK firms have higher use of derivatives. When we look at those firms that use only one type of derivative instrument, we find that FC derivatives are again most common derivative instruments (17.49%) followed by IR derivatives (13.76%) and CP derivatives (0.19%). 57.11% of our sample uses both FC and IR derivatives, whereas firms that use CP derivatives with either FC or IR derivatives are less than 1% of user firms. 10% of sample derivative user firms use all the three types of derivatives. Overall, Majority of UK firms use FC and IR derivatives and very few firms use CP derivatives.[73]

Table 4-2: Frequency Distribution of Derivatives Use

This table provides data on the use of derivatives by our sample firms. In panel A, we present data for all derivatives usage. In panel B, we present broad categories of derivatives used by our sample. In panel C, we present different combinations of derivative used by our sample firms.

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[73] *We do no investigate the effect of CP derivatives only use on firm financial risk as there are only few firms that use this derivative instrument.*

Panel A: Derivative use	*N*	*%*
Derivative Users	3693	86.61
Non-Users	571	13.39
Total	4264	100.0
Panel B: Types Of Derivative Users[74]	N	%
FC Derivative Users	3156	85.46
IR Derivative Users	3011	81.53
CP Derivative Users	427	11.56
Panel C: Combinations Of Derivative Used[75]	N	%
FC Derivatives Only	646	17.49
IR Derivatives Only	508	13.76
CP Derivatives Only	7	0.19
FC & IR Derivatives Only	2109	57.11
FC & CP Derivatives Only	29	0.79
IR & CP Derivatives Only	22	0.60
FC, IR & CP Derivatives	372	10.07
Total	3693	100.0

4.3.3. Correlation Analysis

Table 4-3 presents the correlation coefficients for derivatives variables, firm risk characteristics and other control variables. As expected, derivatives use has significant negative correlation with total risk and idiosyncratic risk. The correlation is mixed between derivatives use and market risk, however insignificant. These support the notion that firms that employ derivatives are likely to experience a decline in risk. The largest negative coefficients are between profitability and measures of firm financial risk. This is what we would expect to find, as firms that are more profitable will possess a lower financial risk. In addition, the positive correlation between leverage and firm financial risk measures is in line with our expectations, as a higher leverage will give rise to a risk. Firm size is negatively correlated with total risk and idiosyncratic risk. Market to book ratio and liquidity has positive correlation and dividend yield has positive correlation with firm financial risk measures. Overall, there is some preliminary evidence in support of hedging motives behind derivatives use by UK non-financial firms.

Table 4-3: Pearson Correlation Coefficients

This table provides Pearson correlation coefficients for the variables used in the analysis. ***All Derivative***

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[74] *Calculated as a percentage of 3693 derivative users.*

[75] *Calculated as a percentage of 3693 derivative users.*

Users *is a dummy variable set equal to 1 if a firm uses at least one type of derivatives and 0 otherwise.* ***FC Derivative Users (B)*** *is a dummy variable set equal to 1 if a firm uses FC derivatives and 0 otherwise.* ***IR Derivative Users (B)*** *is a dummy variable set equal to 1 if a firm uses IR derivatives and 0 otherwise.* ***Total Risk*** *is calculated as the annualised standard deviation of weekly stock returns over two years.* ***Market Risk*** *is calculated as the coefficient of the market index from a regression of individual stock returns on returns of the market index.* ***Idiosyncratic Risk*** *is calculated as the variance of residuals from the regression used to calculate market risk.* ***Leverage*** *is the ratio of total debt to market value of assets.* ***Firm Size*** *is a natural logarithm of total assets.* ***Profitability*** *is calculated as the sum of pre-tax profits and total interest charges divided by invested capital.* ***Market to Book*** *is the ratio of market value of assets to book value of assets.* ***Dividend Yield*** *is measured as dividend per share divided by the share price.* ***Liquidity*** *is the ratio of total current assets minus total stock and work in progress over total current liabilities.*

Variables		*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
All Derivatives Users	(1)	1.000											
FX Derivative Users (B)	(2)	0.664	1.000										
IR Derivative Users (B)	(3)	0.610	0.296	1.000									
Total Risk	(4)	-0.176	-0.073	-0.206	1.000								
Market Risk	(5)	-0.010	0.030	-0.041	0.480	1.000							
Idiosyncratic Risk	(6)	-0.199	-0.099	-0.236	0.878	0.412	1.000						
Leverage	(7)	0.188	0.007	0.314	0.131	0.011	0.052	1.000					
Firm Size	(8)	0.269	0.249	0.320	-0.268	0.046	-0.296	0.238	1.000				
Profitability	(9)	0.138	0.115	0.129	-0.399	-0.186	-0.469	-0.156	0.303	1.000			
Market to Book	(10)	-0.114	-0.016	-0.151	0.080	0.077	0.168	-0.386	-0.305	0.013	1.000		
Dividend Yield	(11)	0.075	0.095	0.076	-0.005	-0.099	-0.033	0.297	0.111	-0.059	-0.249	1.000	
Liquidity	(12)	-0.214	-0.063	-0.301	0.254	0.146	0.287	-0.278	-0.327	-0.209	0.223	-0.074	1.000

4.4. Empirical Analysis

In this section, we present and discuss the results of univariate and multivariate analysis examining the effects of derivatives use on the measures of firm financial risk.

4.4.1. Univariate Analysis

To begin, we compare the simple averages of firm financial risk measures and the sample characteristics by derivatives use. To measures the significance of differences between the derivative user and non-user firms we mean difference test, based on the parametric T-test, and the median difference test, based on the non-parametric Wilcoxon Test. We use several definitions of derivatives use in examining the differences. In particular, we use all derivatives, FC derivatives and IR derivatives.

In panel A of Table 4-4, we present results for all derivative user and non-user firms. The mean difference test results show that derivative user firms have considerably lower total risk than non-users firms. In general, derivative user firms have an average (median) 12.40% (12.51%) lower total risk than non-user firms. Our result is consistent with Guay (1999), Bartram (2006) and Bartram et al. (2011). Guay (1999) finds significant lower total risk for new derivative users compared to non-users. Bartram (2006) shows that the median standardised total risk is 20.8% lower for derivative users than non-users. Bartram et al. (2011) report that the firms that use derivatives have 5% to 10% lower total risk compared to the matched sample of non-users.[76] On contrary, Hentschel and Kothari (2001) show that the mean equity return volatility for derivative users firms is 1.85% compared to 1.77% for non-user firms. For market risk, we fail to find any significant difference between derivative users and non-users; that suggest derivative user firms have neither significantly lower nor higher market risk compared to non-users. Hentschel and Kothari (2001) report that the market risk is 1.07% for derivative users compared with 0.95% that of non-users. On the other hand, Bartram (2006) find that the median market risk is 13.3% lower for derivative users compared with non-users and Bartram et al. (2011) report that the market risk of derivative users firms is 15% to 31% lower than the matched non-user firms. The result shows that derivative user firms have an average (median) 13.46% (12.11%) lower idiosyncratic risk compared to non-users. The mean and median differences are both statistically significant. Our result is consistent with Guay (1999). Guay (1999) finds user firms have lower idiosyncratic risk and higher market risk. Hentschel and Kothari (2001) also find that firms with derivatives appear to have lower idiosyncratic risk. It is widely held belief that firms use derivatives to target either systematic risk or unsystematic risk[77] and our results for idiosyncratic risk and market risk suggest that UK non-financial firm's targets unsystematic risk using derivatives.

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[76] *Bartram et al. (2011) use a propensity score matching to match derivative a users firm with a non-user firm which is similar to derivative user firm on predefined variables except that it chose not to use derivatives.*

[77] *Nguyen and Faff (2010, p. 835)*

Table 4-4: Mean and Median Difference Tests for Firm Financial Risk and Firm Characteristics

*This table provides number of observations (N), mean, median, mean difference and median difference for derivative users and non-users. In particular, Panel A presents results for All Derivative users, Panel B presents results for FC Derivative users, and Panel C presents results for IR Derivative Users. The mean difference is based on the parametric t-test and the median difference test is based on Non-Parametric Wilcoxon Test *** indicates significance at 1%, ** at 5% and * at 10% level.*

Variables	*N*	*Mean*	*Median*	*N*	*Mean*	*Median*	*Mean Diff*	*Median Diff*
		Users			*Non-Users*			
				Panel A: All Derivative Users				
Total Risk	3151	41.4767	35.8320	435	53.8769	47.9848	-12.4002***	-12.1528***
Market Risk	3151	0.6310	0.5667	435	0.6421	0.5526	-0.0111	0.0141
Idiosyncratic Risk	3151	37.5600	32.6700	435	51.0200	44.7800	-13.4600***	-12.1100***
Leverage	2738	0.2532	0.2225	257	0.1061	0.0528	0.1472***	0.1697***
Firm Size	2738	13.5835	13.4768	257	12.2462	12.4774	1.3373***	0.9994***
Profitability	2738	0.1032	0.1017	257	0.1026	0.1255	0.0006	-0.0238*
Market to Book	2738	1.4388	1.0911	257	1.7213	1.2109	-0.2825***	-0.1198**
Dividend Yield	2738	3.2751	2.8282	257	2.5425	2.1560	0.7326***	0.6722***
Liquidity	2738	0.8666	0.7800	257	1.0503	0.9000	-0.1837***	-0.1200***
				Panel B: FC Derivative Users				
Total Risk	2693	42.0224	36.9468	435	53.8769	47.9848	-11.8546***	-11.0380***
Market Risk	2693	0.6405	0.5744	435	0.6421	0.5526	-0.0016	0.0217
Idiosyncratic Risk	2693	37.9000	33.3900	435	51.0200	44.7800	-13.1200***	-11.3900***
Leverage	2358	0.2426	0.2149	257	0.1061	0.0528	0.1366***	0.1621***
Firm Size	2358	13.7035	13.6052	257	12.2462	12.4774	1.4573***	1.1277***
Profitability	2358	0.1074	0.1052	257	0.1026	0.1255	0.0047	-0.0203
Market to Book	2358	1.4812	1.1063	257	1.7213	1.2109	-0.2402**	-0.1046*
Dividend Yield	2358	3.3416	2.8876	257	2.5425	2.1560	0.7991***	0.7316***
Liquidity	2358	0.9174	0.8200	257	1.0503	0.9000	-0.1329***	-0.0800*
				Panel C: IR Derivative Users				
Total Risk	2566	40.0036	34.7481	435	53.8769	47.9848	-13.8734***	-13.2367***
Market Risk	2566	0.6219	0.5710	435	0.6421	0.5526	-0.0202	0.0184
Idiosyncratic Risk	2566	35.8000	31.4400	435	51.0200	44.7800	-15.2200***	-13.3400***
Leverage	2295	0.2743	0.2465	257	0.1061	0.0528	0.1683***	0.1938***
Firm Size	2295	13.7821	13.6870	257	12.2462	12.4774	1.5358***	1.2096***
Profitability	2295	0.1055	0.0992	257	0.1026	0.1255	0.0029	-0.0263**
Market to Book	2295	1.3755	1.0689	257	1.7213	1.2109	-0.3458***	-0.1420***
Dividend Yield	2295	3.3250	2.8639	257	2.5425	2.1560	0.7825***	0.7079***
Liquidity	2295	0.7933	0.7400	257	1.0503	0.9000	-0.2570***	-0.1600***

Similar to Guay (1999) and Purnanandam (2008), we find that the average leverage ratio of derivative users is significantly higher than non-derivative users. This is consistent with the notion that derivative users can attract more debt because of lower financial risk. Hentschel and Kothari (2001) and Lin, Phillips and Smith (2008) also report higher leverage for their sample of derivative use firms. Similar to Bartram (2006) and Purnanandam (2008), we find that derivative user firms have significantly lower levels of liquidity than non-user firms. The univariate results also suggest that derivative use firms are more exposed to IR risk due to higher levels of leverage and lower liquidity.

Derivative user firms’ are also significantly larger than non-derivative user firms’. This finding supports the notion of scale economies in use of derivative instruments. Guay (1999) finds similar result. Mian (1996) finds that larger firms are more likely to use derivatives as they can benefit from economies of scale in derivative transaction costs. The results from parametric and non-parametric test of all derivative users and non-users show that derivatives users in general have more profits than non-derivative users. Bartram (2006) and Allayannis et al. (2012) also find similar results. Opposite to our expectations we find derivative user firms have lower growth opportunities than their non-user counterparts. The results show that derivative users firms have average 0.73% higher dividend yield than non-users suggesting that derivative user firms are financially healthy. Haushalter (2000) suggests that firms facing liquidity constraints might pay little or no dividend. We get qualitatively similar results when we examine the mean and median differences between 1) FC derivatives uses and non-users in panel B 2) IR derivative users and non-users in panel C.

Overall, these results indicate that derivative user firms have lower total risk and idiosyncratic risk (large economic magnitude) compared with non-users but similar market risk. These results provide some evidence that firms are using derivative instruments for risk reducing as witnessed by lower total risk and idiosyncratic risk. Derivative user firms also have lower firm characteristics that are shown to be related to firm financial risk such as firm size, dividend yield and liquidity. Derivative user firms have higher leverage and low market to book ratio. It is important to note that univariate analysis does not control for other firm characteristics and hence multivariate analysis is used to examine the relationship between firm risk measures and derivatives.

4.4.2. Multivariate Regression Analysis

The previous section describes the results of tests of differences in means and medians between derivative users and non-users for various firm risk measures and firm-level characteristics. However, the problem with univariate tests is that they do not control for the correlations between different firm characteristics and hence, cannot show differences in these characteristics, holding other firm-level attributes constant and also they cannot account for the differences in the risk that is not attributable to the use of financial derivatives use. Therefore, in this section we use multivariate tests to control the correlation between different firm characteristic variables while holding other firm-level attributes constant.

In this section, we employ multivariate regression models to examine the relationship between measures of firm financial risk (total risk, market risk and idiosyncratic risk) and derivatives. These different measures of firm financial risk are separately regressed on continuous and dummy variables for derivatives use and on a set of control variables measuring leverage, firm size, profitability, market to book, dividend yield and liquidity. All of the regressions are carried out with standard errors adjusted for clustering at the firm level.

4.4.2.1. Effects of Derivatives use on Firm Financial Risk Measures

In this section, we use equation [10] to examine the effects of derivatives on various measure of firm risk. We use dummy variables as a measure of derivatives. Table 4-5 shows the effect of derivatives use on total risk, market risk and idiosyncratic risk.[78] In this table, we examine the effect of all derivatives use, FC derivatives use (B) and IR derivatives use (B) on firm risk. In Table 4-6, we examine the effects of FC derivative users (UB) and IR derivative users (UB) on the firm risk. Several estimation methods such as OLS[79], RE[80] and FE[81] models are employed to examine the relationship. We employ various tests to select the best model among OLS, RE and FE.[82,83] The second raw of Table 4-5 shows the used model based on the tests.

[78] *Derivatives variables are defined in section 3.3.2*
[79] *See section 3.5.1 for more details*
[80] *See section 3.5.2 for more details*
[81] *See section 3.5.2 for more details*
[82] *See section 3.5.4 for more details.*
[83] *We report the results of only best model in Table 4-5. The results of these tests are reported in last rows.*

Table 4-5: The Effect of All Derivatives Use, FC Derivatives Use (B) and IR Derivatives Use (B) on Firm Financial Risk Measures

*This table provides the results of Derivatives use on Firm Financial Risk. **All Derivative Users** is a dummy variable set equal to '1' if a firm uses derivatives and '0' otherwise. **FC Derivative Users (B)** is a dummy variable set equal to '1' if a firm uses FC derivatives and '0' non-FC users. **IR Derivative Users (B)** is a dummy variable set equal to '1' if a firm uses IR derivatives and '0' non-IR users. We use 3 measures of Firm Financial Risk 1) **Total Risk** calculated as the annualised standard deviation of weekly stock returns over two years 2) **Market Risk** is calculated as the coefficient of the market index from a regression of individual stock returns on returns of the market index 3) **Idiosyncratic Risk** is calculated as the variance of residuals from the regression used to calculate market risk. **Leverage** is the ratio of total debt to market value of assets. **Firm Size** is a natural logarithm of total assets. **Profitability** is calculated as the sum of pre-tax profits and total interest charges divided by invested capital. **Market to Book** is the ratio of market value of assets to book value of assets. **Dividend Yield** is measured as dividend per share divided by the share price. **Liquidity** is the ratio of total current assets minus total stock and work in progress over total current liabilities. White heteroskedasticity consistent errors, corrected for correlation across observations of a given firm, are reported in parentheses [White (1980)]. ***, ** and * indicates statistical significance at 1% level, 5% level and 10% level respectively.*

Variables	*Panel A: Total Risk*			*Panel B: Market Risk*			*Panel C: Idiosyncratic Risk*		
	(1) RE	*(2) RE*	*(3) RE*	*(4) FE*	*(5) FE*	*(6) FE*	*(7) FE*	*(8) FE*	*(9) FE*
All Derivative Users	-4.1619***			-0.0352			-2.0264*		
	(1.590)			(0.038)			(1.094)		
FC Derivative Users (B)		-0.3364			0.0107			-0.2339	
		(1.189)			(0.030)			(1.164)	
IR Derivative Users (B)			-3.1541**			-0.0020			-2.0225
			(1.263)			(0.043)			(1.250)
Leverage	38.4212***	37.5528***	38.6695***	0.4030***	0.3591***	0.3982***	42.2737***	41.9839***	42.4312***
	(4.428)	(4.390)	(4.424)	(0.069)	(0.110)	(0.135)	(2.005)	(4.705)	(4.689)
Firm Size	-1.7279***	-1.8136***	-1.6084***	0.1741***	0.0931***	0.1745***	-3.6638***	-3.6462***	-3.5272***
	(0.520)	(0.532)	(0.513)	(0.021)	(0.019)	(0.038)	(0.604)	(1.050)	(1.038)
Profitability	-20.0668***	-20.2732***	-20.2723***	-0.1646***	-0.2102***	-0.1665**	-18.8754***	-18.9687***	-19.0104***
	(3.146)	(3.187)	(3.134)	(0.051)	(0.067)	(0.070)	(1.465)	(2.851)	(2.820)
Market to Book	0.5574*	0.5387*	0.5659*	0.0442***	0.0473***	0.0442***	0.4086**	0.4087	0.4170
	(0.301)	(0.308)	(0.302)	(0.007)	(0.008)	(0.010)	(0.208)	(0.390)	(0.387)
Dividend Yield	-0.7087***	-0.7108***	-0.7059***	-0.0221***	-0.0218***	-0.0221***	-0.8575***	-0.8596***	-0.8526***
	(0.178)	(0.176)	(0.180)	(0.003)	(0.005)	(0.005)	(0.095)	(0.168)	(0.170)
Liquidity	2.0000**	2.0198**	1.9667**	0.0945***	0.0928***	0.0948***	1.3812***	1.4025**	1.3734**
	(0.835)	(0.855)	(0.842)	(0.016)	(0.028)	(0.034)	(0.462)	(0.686)	(0.680)
Constant	65.9435***	63.7057***	62.7504***	-1.7699***	-0.5759**	-1.8041***	81.3268***	79.4866***	79.1508***
	(7.670)	(7.815)	(7.609)	(0.292)	(0.285)	(0.532)	(8.476)	(14.649)	(14.339)
N	2,936	2,936	2,936	2,993	2,993	2,993	2,993	2,993	2,993
R^2	0.4178	0.4155	0.4178	0.1588	0.1536	0.1585	0.4669	0.4663	0.4677
F-Test: Heterogeneity		6.8647	6.6669	5.2474	5.2487	5.2193	8.2588	8.3070	7.9923
LM Test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Hausman Test	0.2366	0.2054	0.2771	0.0831	0.0126	0.0293	0.0021	0.0017	0.0036

In panel A of Table 4-5, we use total risk as a measure of firm risk. The results in column 1 suggest that the all derivatives use is associated with a reduction in total risk, statistically significant at 1%. In economic terms, the results suggest that firms that use all derivatives have 4.16% lower total risk than non-user firms. This reduction in total risk for all derivative users is 10% compared to the mean total risk of our sample firms and indicates a larger difference in total risk. In column 2, we present the result of FC derivative user (B) firms. The results suggest that the coefficient on FC derivative users (B) is negative but not statistically different from zero. In this specification FC derivative user firms are compared against the non-FC derivative users where non-FC derivative users include firms that use IR only derivatives and hence the true effect of FC derivatives on total risk is underestimated. The results for IR derivative users (B) are presented in column 3. The results suggest that IR derivative users (B) have significantly lower total risk than non-IR users. This finding suggests that IR derivatives are more effective in reducing total risk than FC only derivatives. In terms of economic significance, the results suggest that IR derivative users have 3.15% lower total risk than non-IR users. In panel B, we use market risk as our firm risk measure and find that not any types of derivatives use have significant effect on market risk. These results are not surprising as we find in our univariate results that UK firms do not have significant market risk. In panel C, we use idiosyncratic risk as a measure of firm risk and find that derivative users have economically significant 2.03% lower idiosyncratic risk than non-users. We find negative but insignificant effect of FC derivatives (B) and IR derivatives (B) on the idiosyncratic risk.

The results in Table 4-5 also show that firm risk measures are function of leverage, firm size, profitability, growth, dividend yield and liquidity. The results suggest that other things being constant, a firm with high leverage ratio is more risky than a firm with low leverage ratio. Levered firms are generally perceived to be more risky as they have more liabilities. Guay (1999) finds significant positive relation between leverage and total risk. Purnanandam (2008) shows that in the event of financial distress, highly levered firms in concentrated industries are more likely to lose their competitive position. On contrary, Bartram (2006) finds negative relationship between leverage and total risk. We find that larger firms are less risky than smaller firms in panel A and B. Larger firms are considered less risky as they are usually well diversified with product and geographical diversification that may lead to lower firm risk with good risk management practices. This finding is largely consistent with Hentschel and Kothari (2001) and Nguyen and Faff (2010) who also observe a negative association between firm size and total risk. As expected, our results indicate that firms with higher profitability have lower stock return volatility. Profitability provides an indication to the capacity of a firm to internally finance itself rather than going for capital market or taking bank loans. By avoiding capital market and bank loans, a firm can reduce its costs of financial distress. Allayannis and Weston (2001) show that a firm with high gross profit margin could more easily pay IR payment. Allayannis and Weston (2001) find positive association between profitability and firm value. Bartram et al. (2012) also find significant negative impact of profitability on total risk. As expected we find that firms with more growth options have higher total risk. Nguyen and Faff (2010) and Bartram et al. (2012) also find positive effect of market to book on total risk. We find significant negative effect of dividend yield on total risk. This is consistent with our expectations that firms that pay dividends are less likely to be financially constrained and may thus have lower level of risk. Bartram (2006) and Nguyen and Faff (2010) also find significant negative effect of dividend yield on total risk. We find that firms that have higher liquidity are more risky. This finding is opposite to our expectation. However, Shleifer and Vishny (1989) show that managers of firms invest excess liquidity in projects where their special skills are needed and hence makes it harder for shareholders to replace them. The authors argue that managers' such behaviour increases firm risk, as in share holders' value maximising strategy a firm should distribute excess cash to shareholders as dividend. This suggests the problem of agency problem. Nguyen and Faff (2010) and Bartram et al. (2012) also find positive and significant effect of liquidity on total risk.

In Table 4-6, we remove IR only users from the sample of non-FC users and FC only users from the sample of non-IR users. These remove the bias from the non-users sample. In panel A we present the result of FC derivative user (UB) and IR derivative user (UB) firms. The results suggest that firms that use FC derivatives have 3.62% lower total risk than non-users. This shows that when non-users firms include IR only users the estimated effect of FC derivatives use on total risk is underestimated. Similarly, the results in column 2 suggest that IR derivative users have significantly larger negative effect on total risk once we remove FC only users from non-users sample. In terms of economic significance the results suggest that IR derivative users have 4.82% lower total risk than non-users. Consistent with results presented in Table 4-5, we find that FC derivatives use (UB) and IR derivatives use (UB) have no significant effect on market risk in panel B. In panel C, we show that IR derivative users (UB) have economically significant 2.55% lower idiosyncratic risk than non-users. However, the risk reducing effect of FC derivatives is absent for idiosyncratic risk.

Table 4-6: The Effect of FC Derivative Users (UB) and IR Derivative Users (UB) on Firm Risk[84]

This table provides the results of Derivatives use on Firm Financial Risk. ***FC Derivative Users (UB)*** *is a dummy variable set equal to '1' if a firm uses FC derivatives and '0' otherwise.* ***IR Derivative Users (UB)*** *is a dummy variable set equal to '1' if a firm uses IR derivatives and '0' otherwise. We use 3 measures of Firm Financial Risk 1)* ***Total Risk*** *is calculated as the annualised standard deviation of weekly stock returns over two years 2)* ***Market Risk*** *is calculated as the coefficient of the market index from a regression of individual stock returns on returns of the market index 3)* ***Idiosyncratic Risk*** *is calculated as the variance of residuals from the regression used to calculate market risk.* ***Leverage*** *is the ratio of total debt to market value of assets.* ***Firm Size*** *is a natural logarithm of total assets.* ***Profitability*** *is calculated as the sum of pre-tax profits and total interest charges divided by invested capital.* ***Market to Book*** *is the ratio of market value of assets to book value of assets.* ***Dividend Yield*** *is measured as dividend per share divided by the share price.* ***Liquidity*** *is the ratio of total current assets minus total stock and work in progress over total current liabilities. White heteroskedasticity consistent errors, corrected for correlation across observations of a given firm, are reported in parentheses [White (1980)]. ***, ** and * indicates statistical significance at 1% level, 5% level and 10% level respectively.*

Variables	*Panel A: Total Risk*		*Panel B: Market Risk*		*Panel C: Idiosyncratic Risk*	
	(1) RE	*(2) RE*	*(3) FE*	*(4) FE*	*(5) FE*	*(6) FE*
FC Derivative Users (UB)	-3.6193**		-0.0102		-1.8481	
	(1.554)		(0.041)		(1.182)	
IR Derivative Users (UB)		-4.8225**		0.0069		-2.5449*
		(1.896)		(0.045)		(1.470)
Leverage	34.0297***	37.5513***	0.2921***	0.2831**	36.9527***	36.7704***
	(4.125)	(4.853)	(0.075)	(0.119)	(2.141)	(4.490)
Firm Size	-1.5728***	-1.6632***	0.1982***	0.0875***	-2.8918***	-2.1487***
	(0.528)	(0.516)	(0.022)	(0.020)	(0.631)	(0.521)
Profitability	-20.2725***	-18.0543***	-0.1792***	-0.2504***	-19.1053***	-18.7159***
	(3.243)	(3.308)	(0.051)	(0.071)	(1.468)	(3.007)
Market to Book	0.4237	0.1638	0.0386***	0.0415***	0.2699	0.4838
	(0.302)	(0.339)	(0.007)	(0.009)	(0.208)	(0.353)
Dividend Yield	-0.5705***	-0.7279***	-0.0209***	-0.0202***	-0.6749***	-0.8014***
	(0.183)	(0.199)	(0.003)	(0.005)	(0.099)	(0.187)
Liquidity	1.8153**	1.7893*	0.0937***	0.0974***	1.1459**	0.9413
	(0.830)	(0.920)	(0.017)	(0.027)	(0.480)	(0.670)
Constant	63.5584***	66.5045***	-2.1353***	-0.4002	71.6922***	63.8551***
	(7.916)	(7.941)	(0.312)	(0.296)	(8.912)	(7.644)
N	2,572	2,496	2,613	2,550	2,613	2,550
R^2	0.4229	0.4274	0.1466	0.1835	0.4747	0.4763
F-Test: Heterogeneity	6.8699	5.8787	5.5695	5.4152	8.1573	7.7582
LM Test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Hausman Test	0.3567	0.1322	0.0010	0.1890	0.0027	0.0857

[84] We report the results of only best model. The results of these tests are reported in last rows and the associated model is shown in second raw.

These analysis shows that it is important to control for the other users in the sample of non-users as the inclusion of "other" users underestimate the actual effect of derivatives on firm risk. Our results are consistent with previous studies. Guay (1999) finds that the new derivative users have around 5% lower stock return volatility than non-users. Bartram (2006) uses standardised total risk and find significant negative effect of derivative use on it. The author also investigates the effect of FC derivatives and IR derivative use on total risk. The author finds positive but insignificant effect of FC derivatives use on total risk and significant negative effect of IR derivative use on total risk. However, Bartram (2006) find negative but insignificant results for all different types of derivatives variables when data for only UK firms are used.[85] Bartram et al. (2011) also find that the derivative users have significantly lower total risk. They report 5% to 10% lower total risk for derivative users compared with matched non-users.

Overall, the results in this section suggest that derivative users have 3.62% to 4.82% of significantly lower total risk and 1.84% to 2.55% of significantly lower idiosyncratic risk than non-user firms. The results from this section are also indicative that IR derivatives are more effective in reducing both total risk and idiosyncratic risk than FC derivatives. These findings support the notion that UK non-financial firms use derivatives for risk reduction.

4.4.2.2. Effects of Extent of Derivatives use on Firm Financial Risk Measures

In this section we examine the effect of extent of derivatives use on total risk, market risk and idiosyncratic risk using equation [11].[86] Panel A of Table 4-7 provides the results of OLS regression of total risk on the extent of various derivatives use and other control variables.[87] In column 1, we present the results for extent of all use of derivatives. The results suggest that the use of derivatives is associated with a significant reduction in total risk at 5% level. In economic terms, our result suggests that all derivative users with an average derivatives use have total risk that is 59% (-2.5288 * 0.2341 where 0.2341 (Table 4-1) is the average of extent of all derivatives) lower than non-users. Compared to average total risk of 42.98% (Table 4-1), this represents a reduction of 25.35% in total risk. A 1% increase in the extent of all derivatives use results in a reduction of 2.52% of stock return

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[85] Bartram (2006) sample consists of total 6896 firm-year-observations from 47 countries. Their sample consist 860 UK firms.

[86] Extent of derivatives use variables are defined in section 3.3.2

[87] Hentschel and Kothari (2001),Bartram (2006) and Nguyen and Faff (2010) also use OLS methodology.

volatility per annum. Our results are consistent with Guay (1999), Bartram (2006) and Bartram et al. (2011). Guay (1999) examines the effect of new derivative users on total risk. The author reports an average reduction of 5% in total risk. Bartram et al. (2009) find significant negative effect of derivatives use when they use a sample firms from many countries. However, the author finds no significant reduction in standardised total risk when the effect is examined only for UK firms. Bartram et al. (2011) use a matching analysis based on propensity score and find significantly lower average total risk for derivative user. Hentschel and Kothari (2001) and Nguyen and Faff (2010) use similar model in their study and find that the all use of derivative is either associated with an increase in total risk or it has no impact on it.

In column 2, we examine the effect of extent of FC derivative use on total risk. As expected we find negative but insignificant effect of extent of FC derivative use on total risk. However, this result is not surprising as firms mainly use FC derivatives to hedge short-term exposure. Bodnar et al. (1996) report that 84% of the firms use some FC derivatives with maturities less than 90 days and only 30% of firms use FC derivative with maturities greater than 3 years. The authors also reports that 91% of firms frequently or sometimes use FC derivatives to hedge anticipated transaction expected within 1 year. Nguyen and Faff (2010) find very weak effect of extent of FC derivative use on total risk. The authors report that for a 10% increase in the extent of FC derivatives the stock return volatility decreases by only 0.88% per annum.

The results of extent of IR derivative use in column 3 suggest that firms' use of IR derivatives is significantly associated with a reduction in total risk. In particular, a 1% increase in extent of IR derivatives use reduces total risk by 9.74% (represents 22% of mean total risk) suggesting that IR derivatives use has economically large effect on total risk. Bodnar et al. (1996) report that 73% of derivative user firms use IR derivatives and 83% of this IR users use IR swaps. IR swaps are generally for a longer period and hence should have larger impact on total risk. Nguyen and Faff (2010) report 3.51% reduction in total risk as a result of a 1% increase in extent of IR derivatives. With regards to control variables, we find leverage, firm size and dividend yield have expected sign and are significant at minimum 5% level.

Table 4-7: The Effect of Extent of Derivatives Use on Firm Financial Risk Measures

*This table provides the results of Extent of Derivatives use on Firm Financial Risk using OLS. **Extent of All Derivatives** is the notional values of All Derivatives scaled by total assets; **Extent of FC Derivatives** is the notional values of FC Derivatives scaled by total assets; **Extent of IR Derivatives** is the notional values of IR Derivatives scaled by total assets. We use 3 measures of Firm Financial Risk 1) **Total Risk** is calculated as the annualised standard deviation of weekly stock returns over two years 2) **Market Risk** is calculated as the coefficient of the market index from a regression of individual stock returns on returns of the market index 3) **Idiosyncratic Risk** is calculated as the variance of residuals from the regression used to calculate market risk. **Leverage** is the ratio of total debt to market value of assets. **Firm Size** is a natural logarithm of total assets. **Profitability** is calculated as the sum of pre-tax profits and total interest charges divided by invested capital. **Market to Book** is the ratio of market value of assets to book value of assets. **Dividend Yield** is measured as dividend per share divided by the share price. **Liquidity** is the ratio of total current assets minus total stock and work in progress over total current liabilities. White heteroskedasticity consistent errors, corrected for correlation across observations of a given firm, are reported in parentheses [White (1980)]. ***, ** and * indicates statistical significance at 1% level, 5% level and 10% level respectively.*

Variables	*Panel A: Total Risk*			*Panel B: Market Risk*			*Panel C: Idiosyncratic Risk*		
	(1) OLS	*(2) OLS*	*(3) OLS*	*(4) OLS*	*(5) OLS*	*(6) OLS*	*(7) OLS*	*(8) OLS*	*(9) OLS*
Extent of All Derivatives	-2.5288**			-0.0651**			-2.2284*		
	(1.122)			(0.032)			(1.195)		
Extent of FC Derivatives		-2.0803			-0.0945**			-2.3262	
		(1.364)			(0.041)			(1.421)	
Extent of IR Derivatives			-9.7463**			-0.1142			-6.8240*
			(4.354)			(0.123)			(4.010)
Leverage	34.4946***	35.4048***	38.2108***	0.4805**	0.5664***	0.5163**	28.7657***	28.0420***	29.6506***
	(6.014)	(6.590)	(7.461)	(0.189)	(0.188)	(0.236)	(5.738)	(5.293)	(7.065)
Firm Size	-1.6752***	-1.2418**	-1.6372***	0.0738***	0.0783***	0.0690***	-2.3626***	-1.8991***	-2.3140***
	(0.509)	(0.548)	(0.527)	(0.019)	(0.022)	(0.020)	(0.537)	(0.560)	(0.552)
Profitability	-5.4199	-6.9361	-5.9317	-0.1524	-0.1844	-0.1669	-8.0849**	-10.5440***	-8.6619*
	(4.234)	(4.964)	(5.055)	(0.129)	(0.157)	(0.150)	(3.863)	(4.029)	(4.670)
Market to Book	-1.0895	-0.5748	-0.3099	0.1227***	0.1423***	0.1298***	-2.3982**	-2.0086*	-2.1265*
	(1.242)	(1.447)	(1.413)	(0.035)	(0.040)	(0.036)	(1.055)	(1.198)	(1.128)
Dividend Yield	-0.7305**	-0.6981**	-0.9233***	-0.0216***	-0.0227**	-0.0255**	-0.6529**	-0.6118**	-0.8394**
	(0.286)	(0.308)	(0.339)	(0.008)	(0.009)	(0.010)	(0.269)	(0.262)	(0.334)
Liquidity	1.3704	1.6587*	1.1484	0.1135***	0.1178***	0.1051***	0.3103	0.6293	0.1746
	(0.894)	(0.845)	(1.102)	(0.030)	(0.031)	(0.036)	(0.821)	(0.729)	(0.989)
Constant	58.5055***	52.2950***	56.8409***	-0.5727*	-0.7755*	-0.5244	68.8512***	68.5994***	73.1740***
	(8.556)	(9.353)	(9.723)	(0.340)	(0.404)	(0.397)	(8.355)	(8.103)	(8.804)
N	980	728	787	995	737	801	995	737	801
R^2	0.5142	0.5136	0.4956	0.2409	0.2569	0.2450	0.5044	0.5092	0.4818
F-Test	22.3455	20.2333	17.8557	6.1302	6.2175	5.4953	19.0852	18.0140	13.7565

We further disaggregate total risk into market risk (systematic risk) and idiosyncratic risk (firm-specific risk). This helped us in further examining the effect of derivative use on type of risk being hedged. In panel B of Table 4-7, we examine the effect of derivative use on market risk measure. As expected, we find that use of derivatives has significant negative effect on market risk. In economic terms the results suggest that a 1% increase in extent of derivatives use lowers the marker risk by 0.07 basis points (represents 11.11% of mean market risk). Bartram (2006) and Nguyen and Faff (2010) find negative but insignificant effect of derivatives use on market risk. Bartram (2006) finds significant negative effect of all derivatives use on market risk when they use a sample of firms from 47 countries. In column 5, we investigate the effect of extent of FC derivatives use on market risk. Consistent with our expectations the results suggest that a 1% increase in the extent of FC derivatives use leads to a reduction of 0.094 basis points in market risk (represents 15% of average market risk). This reduction is economically and statistically significant. This result is consistent with Bartram (2006) and Nguyen and Faff (2010). Bartram (2006) finds significant negative effect of FC derivative use on market risk for their whole sample.[88] Nguyen and Faff (2010) find significant negative effect of FC derivatives on market risk, however weak.

In column 6, we use extent of IR derivative use. We find negative but insignificant effect of IR derivatives use on market risk. Our results are consistent with Nguyen and Faff (2010). Bartram (2006) finds significant effect of IR derivatives on market risk for the whole sample.

In panel C of Table 4-7, we examine the effect of derivatives use on idiosyncratic risk. We find that all use of derivatives have significant negative effect on idiosyncratic risk. In economic terms, the result suggests that a 1% increase in the extent of derivatives use result in a 2.22% decline in idiosyncratic risk (represents 5.66% of mean idiosyncratic risk). Nguyen and Faff (2010) also examine the effect of extent of all derivatives use on idiosyncratic risk and find negative but insignificant impact of extent of all derivative use on idiosyncratic risk. In column 8, we examine the effect of extent of FC derivatives use on idiosyncratic risk and find negative but insignificant effect. The result is consistent with Nguyen and Faff (2010) who also fail to find any significant effect of FC derivatives on

[88] *The author did not investigate the relationship for UK firms separately.*

idiosyncratic risk. In column 9, we use extent of IR derivatives use. Consistent with our expectations, we find that the use of IR derivatives is significantly associated with a reduction in idiosyncratic risk. The result suggests that a 1% increase in the extent of IR derivatives use lowers the idiosyncratic risk by 6.82% (represents 17.40% of idiosyncratic risk). Nguyen and Faff (2010) find negative but insignificant effect of extent of IR derivatives use on idiosyncratic risk.

Our results suggest that FC derivatives are more suitable to manage market risk whereas IR derivatives are more suitable to manage idiosyncratic risk. Overall, the results in this section suggest that derivative user firms have average 2.53% to 9.74% lower total risk, 0.07 to 0.1142 basis point lower market risk and 2.22% to 6.82% lower idiosyncratic risk indicating that UK non-financial firms use derivative for hedging and not for speculation.

4.4.2.3. 2Testing for Nonlinearity in the Use of Derivatives

The results presented in Table 4-7 show that extent of derivatives use is associated with a reduction in firm financial risk measures. However, it is important to know what levels of derivatives use can reduce firm financial risk. We argue that derivatives use has nonlinear effect on firm financial risk. Hence, it is important to investigate the effect of various levels of derivatives use on firm financial risk measures.

In Table 4-8, we divide extent of derivatives use into 5 categories based on the amount of derivatives used by firms. These categories are 1) firms with extent of derivatives use less than or equal to 20% (≤ 20% Derivatives Use) 2) firms with extent of derivatives use greater than 20% and less than or equal to 40% (20% < Derivatives Use ≤ 40%) 3) firms with extent of derivatives use greater than 40% and less than or equal to 60% (40% < Derivatives Use ≤ 60%) 4) firms with extent of derivatives use greater than 60% and less than or equal to 80% (60% < Derivatives Use ≤ 80%) and 5) firms with extent of derivatives use more than 80% (> 80% Derivatives Use). We create these categories for all derivative users, FC derivative users and IR derivative users.

Panel A of Table 4-8 presents the results for all derivative users. The results suggest that firms with "≤ 20% Derivatives Use" have significant negative effect on total risk. In terms of economic significance, the results suggest that a 1% increase in the extent of "<= 20% Derivatives Use" decreases the total risk of user firms by 19.48%. Our results also suggest that extent of "> 80% Derivatives Use" is associated with a reduction in total risk. The economic significance of this coefficient is lower compared to the coefficient on "≤ 20% Derivatives Use". We find negative but insignificant coefficient on "20% < Derivatives Use ≤40%", "40% < Derivatives Use ≤ 60%" and "60% < Derivatives Use ≤ 80%". For market risk, our results suggest that only extensive level of derivatives, "> 80% Derivatives Use", use has significant negative effect on market risk. In economic terms the risk reduction in market risk is not huge as the results suggest that a 1% increase in the extent of "> 80% Derivatives Use" leads to a risk reduction of 0.056 basis points in market risk. In column 3 we present the results for idiosyncratic risk. We find that firms with "≤ 20% Derivatives Use" and firms with "20% < Derivatives Use ≤ 40%" have statistically and economically significant negative effect on idiosyncratic risk. The results also show that "> 80% Derivatives Use" is associated with a reduction in idiosyncratic risk. The economic significance is comparatively smaller. The results suggest that derivatives use of more than 40% have little or no effect on firm financial risk. We test for the coefficient equality and find that the coefficient on "≤ 20% Derivatives Use" is statistically different from other levels of derivatives use for total risk model. For market risk we find that the coefficient on "> 80% Derivatives Use" is not statistically different from other levels of derivatives. For idiosyncratic risk, the coefficient on "≤ 20% Derivatives Use" is statistically different from other levels of derivatives use. However, that the coefficient on "20% < Derivatives Use ≤ 40%" is not different from other levels of derivatives use except "≤ 20% Derivatives Use". Our results are consistent with Nguyen and Faff (2010). The authors also find that derivative use of all less than 20% and less than 40% is associated with a reduction in total risk. Our results are in contrast to Hentschel and Kothari (2001), who find that total risk increases with derivatives.

In panel B, we use various extents of FC derivatives. Our results suggest that the "> 80% FC Derivatives Use" is associated with a reduction in total risk. The reduction in total risk as a result of FC derivatives use is small in economic significance compared to the reduction achieved using all derivatives. This reduction in total risk is 5.51% of mean total risk. FC derivatives use of less than 80% has no significant effect on total risk. The results suggest that FC derivatives use of "40% < FC Derivatives Use ≤ 60%" and "> 80% FC Derivatives Use" are associated with a reduction in market risk. Other levels of FC derivatives use have no significant effect on market risk. The results for idiosyncratic risk are qualitatively similar to that of total risk. The results of FC derivatives use suggest that low or medium use of FC derivatives is not economical enough to implement an effective risk management strategy.

In last panel, we present the results of IR derivatives use. The results suggest that "≤ 20% IR Derivatives Use" leads to a reduction of 38.65% in total risk and 29.67% in idiosyncratic risk. The use of "20% < Derivatives Use ≤ 40%" leads to a reduction of 16.69% in total risk and 12.71% in idiosyncratic risk. The results also show that the use "40% < Derivatives Use ≤ 60%" leads to a reduction of 13.06% in total risk. Our results show that medium to high levels of IR derivatives use has no significant effect on firm financial risks.

Overall, the results in this section show that there is a nonlinear relationship between the use of derivatives and firm financial risk measures. Our results suggest that medium to high levels of derivatives use have either small or no effect on firm financial risk; while low levels of derivatives are associated with an economically large reductions in total risk and idiosyncratic risk.

Table 4-8: Effects of Low to High Extensive Use of Derivatives on Firm Financial Risk Measures

This table provides the results of Low to High Extent of Derivatives use on Firm Financial Risk using OLS. We use 3 measures of Firm Financial Risk 1) ***Total Risk*** *is calculated as the annualised standard deviation of weekly stock returns over two years 2)* ***Market Risk*** *is calculated as the coefficient of the market index from a regression of individual stock returns on returns of the market index 3)* ***Idiosyncratic Risk*** *is calculated as the variance of residuals from the regression used to calculate market risk.* ***Leverage*** *is the ratio of total debt to market value of assets.* ***Firm Size*** *is a natural logarithm of total assets.* ***Profitability*** *is calculated as the sum of pre-tax profits and total interest charges divided by invested capital.* ***Market to Book*** *is the ratio of market value of assets to book value of assets.* ***Dividend Yield*** *is measured as dividend per share divided by the share price.* ***Liquidity*** *is the ratio of total current assets minus total stock and work in progress over total current liabilities. White heteroskedasticity consistent errors, corrected for correlation across observations of a given firm, are reported in parentheses [White (1980)]. ***, ** and * indicates statistical significance at 1% level, 5% level and 10% level respectively.*

	Panel A: All Derivative Users			Panel B: FC Derivative Users			Panel C: IR Derivative Users		
Variables	Total Risk	Market Risk	Idiosyncratic Risk	Total Risk	Market Risk	Idiosyncratic Risk	Total Risk	Market Risk	Idiosyncratic Risk
≤ 20% Derivatives Use	-19.4787**	0.0533	-18.9602**	-17.8282	-0.3440	-13.7893	-38.6532***	-0.1823	-29.6695***
	(7.897)	(0.298)	(7.434)	(11.825)	(0.369)	(10.357)	(11.497)	(0.378)	(9.739)
20% < Derivatives Use ≤ 40%	-7.5018	0.1046	-8.3347*	-3.2890	-0.0249	-3.2706	-16.6885**	-0.1996	-12.7075*
	(4.854)	(0.177)	(4.554)	(7.312)	(0.250)	(6.520)	(7.383)	(0.217)	(6.732)
40% < Derivatives Use ≤ 60%	-3.0630	-0.0665	-0.8835	-4.0903	-0.2714*	-5.5064	-13.0615*	-0.3065	-5.7212
	(3.882)	(0.106)	(3.436)	(5.832)	(0.143)	(4.964)	(7.203)	(0.204)	(6.133)
60% < Derivatives Use ≤ 80%	-3.6136	-0.0507	-4.1554	3.1948	0.0330	1.7090	-3.0511	-0.0539	-2.7512
	(4.618)	(0.113)	(3.705)	(5.108)	(0.241)	(5.737)	(11.962)	(0.301)	(9.066)
> 80% Derivatives Use	-2.6320**	-0.0574**	-2.3558**	-2.3743*	-0.0922***	-2.3774*	-7.5796	0.0495	-7.1773
	(1.096)	(0.029)	(1.181)	(1.221)	(0.031)	(1.417)	(4.732)	(0.184)	(5.449)
Leverage	35.5477***	0.4835**	29.6095***	35.7215***	0.5794***	28.3931***	39.7015***	0.5542**	30.4211***
	(6.042)	(0.198)	(5.804)	(6.477)	(0.185)	(5.235)	(7.647)	(0.251)	(7.220)
Firm Size	-1.6261***	0.0741***	-2.3235***	-1.2164**	0.0798***	-1.8672***	-1.5596***	0.0714***	-2.2923***
	(0.510)	(0.019)	(0.540)	(0.540)	(0.022)	(0.563)	(0.544)	(0.018)	(0.552)
Profitability	-4.9521	-0.1445	-7.9058**	-7.3588	-0.2011	-10.8744***	-5.1600	-0.1404	-8.4354*
	(4.247)	(0.128)	(3.852)	(4.957)	(0.162)	(4.066)	(4.962)	(0.152)	(4.547)
Market to Book	-0.9998	0.1244***	-2.3430**	-0.4602	0.1483***	-1.8704	-0.4557	0.1337***	-2.2780**
	(1.241)	(0.035)	(1.069)	(1.407)	(0.041)	(1.167)	(1.364)	(0.039)	(1.137)
Dividend Yield	-0.7409**	-0.0214***	-0.6668**	-0.6831**	-0.0223**	-0.5988**	-0.9252***	-0.0259**	-0.8309**
	(0.288)	(0.008)	(0.270)	(0.307)	(0.009)	(0.260)	(0.343)	(0.010)	(0.337)
Liquidity	1.2637	0.1149***	0.1910	1.6231*	0.1181***	0.6006	0.9188	0.1025***	0.0125
	(0.886)	(0.030)	(0.805)	(0.850)	(0.032)	(0.745)	(1.057)	(0.036)	(0.937)
Constant	64.4351***	-0.5931*	69.5026***	52.7309***	-0.7116*	62.4641***	56.4866***	-0.5687	74.5062***
	(8.039)	(0.343)	(8.487)	(9.123)	(0.393)	(8.593)	(9.894)	(0.382)	(8.940)
N	980	995	995	728	737	737	787	801	801
R^2	0.5175	0.2422	0.5091	0.5164	0.2598	0.5115	0.5037	0.2480	0.4882
F-Test	19.9099	5.5428	17.5640	17.7153	6.6232	15.9446	17.1336	4.7763	13.3468

4.4.3. Impact of Derivatives Use on the Firm Financial Risk Measures Over-Time

In this section, we investigate whether the effect of derivatives use on firm financial risk measures is influenced by macroeconomic conditions using equation [12]. In other words, are firms hedging both upside and downside risk or limiting their derivative activities to the hedging of downside risk and selectively hedging during favourable macroeconomic conditions. This is important for our study because our sample includes 2007 to 2009 period during which the UK economy experienced the worst financial crisis and deepest recession since 1930s. Our sample period also incorporates several years of global economic uncertainty around 2002 and a period of credit market tightening around 2003. Sandwiched between these episodes of economic downturn was a three-year period (2004 and 2006) during which the UK economy experienced strong economic growth with relatively loose credit market conditions and credit spreads on a downward trajectory.

Our key variables of interest are the interaction terms between derivatives and the year dummies. We estimate equation [12] using pooled OLS, RE and FE models. The results are reported only for the models that are suggested based on various tests.[89] The results of these tests are reported in last columns of Table 4-9. Third row in the table shows the regression type. Table 4-9 is divided into three panels; Panel A reports the results of all derivatives users, panel B reports the results of FC derivatives users and panel C reports the results of IR derivative users. Our results in panel A of Table 4-9 show that the derivatives coefficient was negative in some years, positive in others and not always significantly different from zero. The results in column 1 show the derivative coefficients vary from 4.75% in 2000 to -13.90% in 2005. Our results show that the derivative coefficients are significantly negative in the period 2002 and the period 2004 to 2009. These suggest that derivative user firms had significantly lower total risk than non-users during the period of global economic uncertainty of year 2002. During 2004 to 2006 period, macroeconomic conditions were relatively beginning to improve and firms' financial positions improved as profitability increased. This led to a decline in corporate sector credit risks and our results suggest that derivative user firms also witnessed significant lower total risk than non-users during this period.

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[89] *See section 3.5.4 for further details.*

Table 4-9: Effect of Derivatives use on Firm Financial Risk Measures Over-Time

*This table provides the results of effects of Derivatives use on Firm Financial Risk over-time. In panel A, we interact **All Derivative Users** dummy with the year dummies. In panel B, we interact **FC Derivative Users (UB)** dummy with year dummies. In panel C, we interact **IR Derivative Users (UB)** dummy with year dummies. We use 3 measures of Firm Financial Risk 1) **Total Risk** calculated as the annualised standard deviation of weekly stock returns over two years 2) **Market Risk** is calculated as the coefficient of the market index from a regression of individual stock returns on returns of the market index 3) **Idiosyncratic Risk** is calculated as the variance of residuals from the regression used to calculate market risk. **Leverage** is the ratio of total debt to market value of assets. **Firm Size** is a natural logarithm of total assets. **Profitability** is calculated as the sum of pre-tax profits and total interest charges divided by invested capital. **Market to Book** is the ratio of market value of assets to book value of assets. **Dividend Yield** is measured as dividend per share divided by the share price. **Liquidity** is the ratio of total current assets minus total stock and work in progress over total current liabilities. GDP growth rate is sourced from the International Monetary Fund (IMF) official website.[90] White heteroskedasticity consistent errors, corrected for correlation across observations of a given firm, are reported in parentheses [White (1980)]. ***, ** and * indicates statistical significance at 1% level, 5% level and 10% level respectively.*

	Panel A: All Derivative Users			Panel B: FC Derivative Users (UB)			Panel C: IR Derivative Users (UB)		
Variables	*Total Risk (1) FE*	*Market Risk (2) FE*	*Idiosyncratic Risk (3) FE*	*Total Risk (4) RE*	*Market Risk (5) FE*	*Idiosyncratic Risk (6) FE*	*Total Risk (7) FE*	*Market Risk (8) FE*	*Idiosyncratic Risk (9) FE*
Derivative Users	-0.5309	-0.0988*	2.9058	0.9304	-0.0828	3.5349*	-0.4744	-0.1273**	4.0317*
	(2.154)	(0.053)	(1.878)	(1.851)	(0.059)	(2.054)	(2.693)	(0.064)	(2.271)
Leverage	43.3579***	0.4159***	42.6417***	34.4960***	0.3039**	37.4124***	41.7257***	0.3435**	41.7052***
	(5.210)	(0.132)	(4.669)	(4.109)	(0.125)	(4.317)	(5.782)	(0.141)	(5.197)
Firm Size	-4.4756***	0.1704***	-4.1927***	-1.6600***	0.1928***	-3.4138***	-4.3281***	0.1381***	-3.9228***
	(1.198)	(0.038)	(1.053)	(0.534)	(0.040)	(1.025)	(1.311)	(0.041)	(1.181)
Profitability	-19.8962***	-0.1598**	-18.9105***	-20.5366***	-0.1772**	-19.2412***	-17.5097***	-0.1765**	-16.9130***
	(3.127)	(0.070)	(2.911)	(3.331)	(0.072)	(3.050)	(3.512)	(0.074)	(3.325)
Market to Book	0.6224*	0.0432***	0.5642	0.5346*	0.0380***	0.4108	0.1378	0.0350***	0.4128
	(0.355)	(0.009)	(0.387)	(0.304)	(0.011)	(0.401)	(0.382)	(0.011)	(0.428)
Dividend Yield	-0.6815***	-0.0217***	-0.8268***	-0.5165***	-0.0204***	-0.6448***	-0.7115***	-0.0191***	-0.8591***
	(0.179)	(0.005)	(0.169)	(0.182)	(0.005)	(0.169)	(0.203)	(0.005)	(0.192)
Liquidity	1.9794**	0.0918***	1.4551**	1.9440**	0.0913**	1.3438*	0.9979	0.0770**	0.6204
	(0.867)	(0.034)	(0.685)	(0.841)	(0.036)	(0.739)	(1.065)	(0.036)	(0.813)
GDP Growth	-2.2261***	-0.0249**	-1.5263***	-2.0053***	-0.0175*	-1.5005***	-2.3069***	-0.0257**	-1.6208***
	(0.416)	(0.010)	(0.397)	(0.422)	(0.010)	(0.409)	(0.429)	(0.010)	(0.400)
*2000 * Derivative*	4.7549***	-0.0534	5.0810***	4.7179***	-0.0585*	5.3374***	4.0219***	-0.0653*	4.6941***
	(1.088)	(0.033)	(0.902)	(1.111)	(0.034)	(0.935)	(1.068)	(0.034)	(0.904)
*2001 * Derivative*	0.0888	0.0959**	-0.0081	0.7280	0.1255***	0.4097	-2.0345	0.0451	-1.8147*
	(1.293)	(0.037)	(0.981)	(1.438)	(0.041)	(1.067)	(1.269)	(0.037)	(0.937)
*2002 * Derivative*	-2.7991**	0.0214	-4.5407***	-2.1884	0.0559	-4.2311***	-4.1071***	0.0076	-6.0240***
	(1.342)	(0.034)	(1.026)	(1.495)	(0.035)	(1.149)	(1.440)	(0.036)	(1.005)
*2003 * Derivative*	-0.6215	0.0227	-3.1747***	-1.0209	0.0506	-3.3009***	-1.7244	0.0219	-4.8727***
	(1.534)	(0.032)	(1.122)	(1.623)	(0.034)	(1.194)	(1.746)	(0.036)	(1.227)
*2004 * Derivative*	-8.5708***	0.0623*	-9.1276***	-9.6585***	0.0900**	-9.7742***	-8.9024***	0.0811**	-10.1548***
	(1.297)	(0.033)	(0.912)	(1.347)	(0.036)	(0.963)	(1.498)	(0.037)	(1.020)
*2005 * Derivative*	-13.8968***	0.1519***	-13.8654***	-15.7754***	0.1526***	-15.0948***	-14.0865***	0.1757***	-14.4185***
	(1.135)	(0.032)	(0.890)	(1.146)	(0.034)	(0.924)	(1.249)	(0.035)	(0.965)
*2006 * Derivative*	-12.2072***	0.2156***	-13.2964***	-14.4821***	0.1843***	-14.6209***	-12.4173***	0.2709***	-13.8490***
	(1.176)	(0.034)	(0.916)	(1.207)	(0.037)	(0.962)	(1.290)	(0.038)	(0.950)
*2007 * Derivative*	-8.8436***	0.1958***	-10.8369***	-11.0134***	0.1693***	-12.0364***	-8.5786***	0.2708***	-11.1203***
	(1.283)	(0.039)	(0.941)	(1.213)	(0.040)	(0.962)	(1.493)	(0.041)	(1.046)
*2008 * Derivative*	-4.8574**	0.1255**	-7.3221***	-5.9252***	0.1461***	-8.8001***	-4.3677**	0.1870***	-7.8238***
	(1.961)	(0.052)	(1.791)	(2.006)	(0.054)	(1.810)	(2.124)	(0.056)	(1.889)
*2009 * Derivative*	-5.9163*	0.0583	-6.4834*	-6.5933*	0.0969	-7.8051**	-5.9314	0.1122	-7.9424**
	(3.555)	(0.090)	(3.397)	(3.645)	(0.090)	(3.479)	(3.706)	(0.092)	(3.440)
*2010 * Derivative*	-0.6222	0.0363	-4.4047***	-2.9181*	0.0108	-6.0329***	-0.2394	0.1101**	-4.9372***
	(1.675)	(0.044)	(1.387)	(1.672)	(0.045)	(1.356)	(1.866)	(0.049)	(1.504)
Constant	100.2035***	-1.6400***	90.1331***	66.7233***	-1.9587***	81.4490***	99.8561***	-1.1668**	86.5203***
	(16.721)	(0.528)	(14.648)	(7.980)	(0.561)	(14.592)	(18.680)	(0.570)	(16.539)
Observations	2,935	2,992	2,992	2,571	2,612	2,612	2,495	2,549	2,549
R-squared	0.4066	0.1602	0.4480	0.4030	0.1464	0.4511	0.4147	0.1921	0.4575
F-Test: Heterogeneity	6.6691	5.2667	8.0577	6.6427	5.5750	7.9070	5.7217	5.4523	7.5665
LM Test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Hausman Test	0.0644	0.0286	0.0002	0.2386	0.0016	0.0002	0.0123	0.0970	0.0007

[90] *Available at the official IMF website at http://www.imf.org/external/pubs/ft/weo/2013/02/weodata/index.aspx*

During 2007 to 2009 period, the UK economy experienced a sharp decline and fell into a deep and prolonged recession. A significant deterioration in credit market conditions, a hike in market-wide IR spreads and an increase in corporate bankruptcies accompanied this. This is a period of economic decline and sharp market correction. During this period UK economy faced a significant economic downturn and also experienced recession. This economic downturn and recession led to an increase in corporate bankruptcies. Here we argue that if one of the goals of use of derivatives is to lower the probability of default, then firms that use financial derivatives may have experienced significant benefits in the form of lower probability of default during these periods. Our results show that hedging with derivatives during these periods had a significant negative impact on total risk.

In column 2, we examine the time-varying effect of derivatives use on market risk. We find the derivatives coefficients are all positive and significant during the period of 2004 to 2008. This suggests that derivative user firms witnessed an increase in market risk during this period. In column 3, we use idiosyncratic risk as a measure of firm financial risk. The results suggest that derivatives coefficients are negative significantly different from zero (except for year 2000-2001). The results are consistent with firm using derivatives to hedge, as the results show that use of derivatives lowered idiosyncratic risk during the period of economic downturn, credit market tightening and during the recent financial crisis. The largest effects of derivatives on idiosyncratic risk are during the strong economic growth period of 2005-2006 and during the beginning of recent financial crisis, 2007. We get similar results in panel B & C where we have interacted year dummies with FC derivatives use and IR derivatives use respectively.

Overall, these results suggest that there is noticeable difference in firm financial risk measures between derivative users and non-users firms over this period. Our results also suggest that the magnitude effect of derivatives is lower during the period of crisis compared to strong economic growth period of 2004-2006. All of our results are highly significant for the year 2004- 2006, period of strong economic growth with relatively loose credit market conditions, and 2007-2008, which is at the core of recent financial crisis.

In Figure 4-2, Figure 4-3 and Figure 4-4 we plot the yearly derivatives coefficients using the results from panel A, panel B and panel C respectively. The figure shows significant variation over-time in the effect of derivatives use on the firm financial risk measures. Taken together, these results suggest important time variation related to financial or economic conditions in the effect of derivatives use on the firm financial risk measures. In particular, our results suggest that derivative user firms get the most benefit of derivatives during the time of market downturns and the recovery period. Overall, our results support hedging motives behind the use of derivatives.

Figure 4-2: Effects of All Derivatives Use on Firm Financial Risk Measures Over-Time

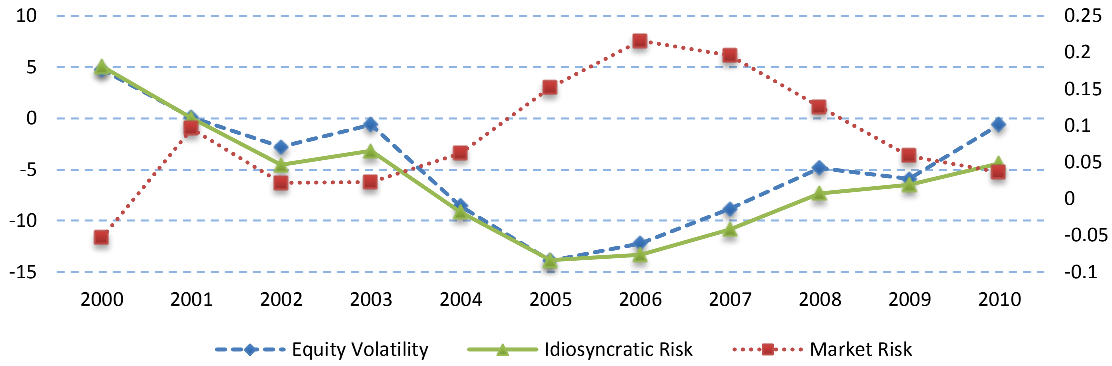


Figure 4-3: Effects of FC Derivatives Use on Firm Financial Risk Measures Over-Time

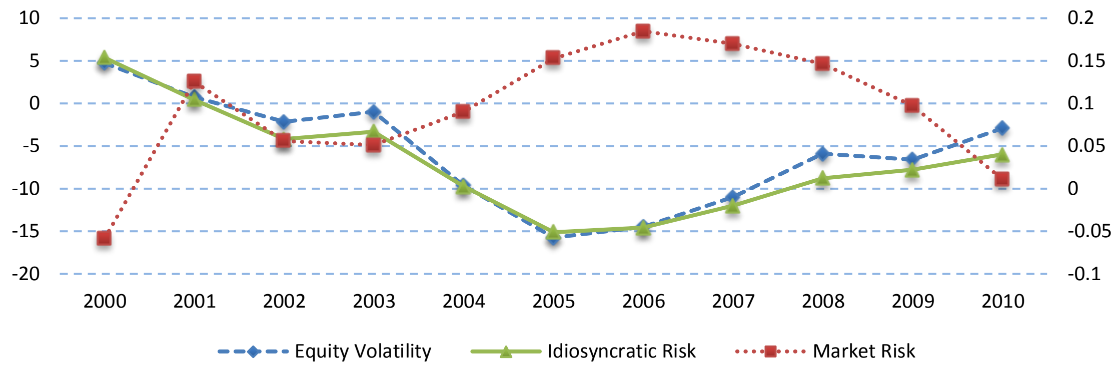
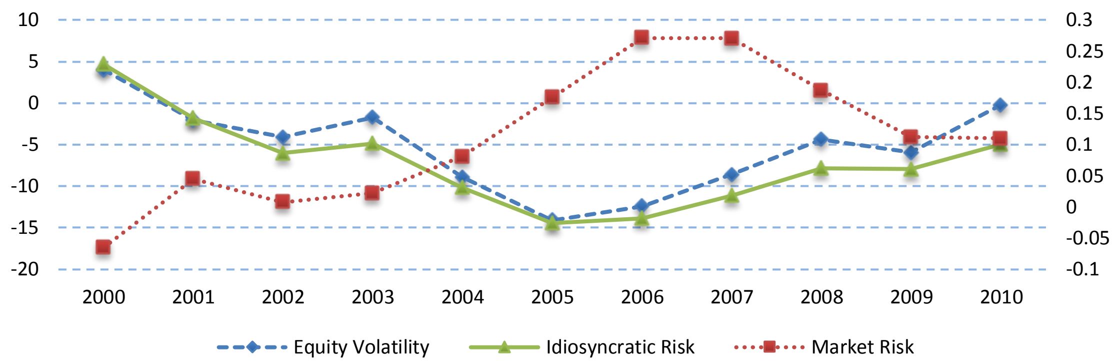


Figure 4-4: Effects of IR Derivatives Use on Firm Financial Risk Measures Over-Time



4.4.4. Issue of Endogeneity: Propensity Score Matching

It is not possible to rule out the possibility that the use of derivatives in above regression analysis is endogenous. It may be possible that there is simultaneity bias between derivatives use and firm risk measures. Endogeneity may also arise due to omitted variables that affect derivatives use and firm risk. If this is the case then a simple examination of derivatives use on risk measures may not provide compelling evidence of effects of derivatives use on firms various risks. Hentschel and Kothari (2001) argue that endogeneity problem affects all empirical research in corporate finance and is hard to solve entirely due to lack of exogenous variables. The authors also argue that except for prices, firms can partially control all other firm related variables including derivatives and hence they are all endogenous. Hence they argue that due to the lack of exogenous variables there is no obvious solution for the endogeneity of derivatives. However, by controlling for endogeneity problem we can at least reduce the bias. To control for this endogeneity problem we use PSM approach. Here we attempt to match derivative user firms with non-user firms based on their likelihood of using derivatives and then we compare the firms on various measures of firm risk.

We use PSM method to examine the impact of use of derivatives (treatment variable) on various firm risk measures (our outcome variables). This method is an alternative way of reducing selection bias by matching on a single index propensity score and making derivative user firms and non-user firms as comparable as possible on the confounding variables. This examination will provide unbiased estimation effects of derivative use, treatment, on the measures of risk, outcome variables. Propensity score is calculated for each firm using variables that are previously shown to influence firms' decision to use derivatives. Once, the propensity score is calculated, derivative user firms are matched with non-user firms based on the score; hence, a matched derivative user and non-user firms are similar on observed variables but differs on their decision to use derivatives. We use the Rosenbaum bounds method to test our results against bias from unobserved covariates.

4.4.4.1. Matching Analysis

In Table 4-10, we present the results of mean and median comparison tests for all derivative users and non-users after matching them on their likelihood of using derivatives for various firm risk measures. In particular, we examine the mean and median difference for total risk, idiosyncratic risk and market risk. The table provides the number of observations (N), caliper value, mean and median for users and non-users, mean and median difference and the wilcoxon p-value. In model 1, we match derivative user firms with non-user firms on one-to-one matching without replacement.[91] In model 2, we follow Bartram et al. (2011) and use a tolerance level of 0.01 and in model 3, we follow Austin (2011) and match derivative users and non-users using caliper of width equal to 0.2 of the standard deviation of the logit of the propensity score.[92] This limits the maximum propensity score distance for matching.[93] This reduces bad matches and increases the quality of matches.

The result in Table 4-10 for model 1 suggests that derivatives use has a significant negative effect for the users of -6.8093 for total risk. This suggests that the mean total risk of derivative users is 6.81% lower than the mean total risk of matched non-user firms. In model 2, we introduce a tolerance level of 0.01 and match the derivative user firms with non-user firms. This improves the matching as now a derivative user firms is marched against a non-user firm within a distance of ± 0.01. The result shows that derivative users have mean (median) 5.74% (4.27%) lower total risk than matched non-users. In model 3, we calculate the caliper value as 0.2 of the standard deviation of the logit of the propensity score. Austin (2011) argues that when the covariates used to calculate propensity score include continuous variables, then the caliper calculated using above formula or a one close to it minimizes the mean square error for the resultant treatment effects. Cochran and Rubin (1973) calculate caliper values using $a * \sqrt{(\sigma_1^2 + \sigma_2^2)/2}$, where $\sigma_1^2$is the variance on continuous confounding variable in *i*th group. The authors find that a bias of 99%, 95%, 89%, 82% and 74% is removed due to the confounding variables when they use values of "a" equal to 0.2, 0.4, 0.6, 0.8 and 1 respectively. Rosenbaum and Rubin (1985) use similar formula to calculate caliper; but instead of using the variance of continuous confounding variable they use variance of the logit of the propensity score in *i*th group. The authors suggest that the same level of bias will be removed by either of the method. The caliper size is 0.12 based on the formula and hence a derivative user firm is matched against a non-user firm whose propensity score is within ± 0.12. This improves the matching but

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[91] The one to one matching method is one of the most common and frequently used methods. In this matching method a firm from derivative user group is matched one by one with a firm from non-derivative user group without replacement that has closest propensity score. This method finds the pair of firms with the shortest distance of their propensity score.

[92] The standard deviation of the logit of the propensity score is calculated as $\sqrt{(\sigma_1^2 + \sigma_2^2)/2}$. Where σ_1^2 is the variance of logit of propensity score for derivative users and $\sigma_2^2$is the variance of logit of propensity score for non-users prior to matching.

[93] Caliendo and Kopeinig (2008)

results in fewer matches. The result suggests that derivative user firms have average 5.75% lower total risk than matched non-users. Both the differences in mean and median are statistically significant. In panel B, we find that derivative user firms have significantly lower idiosyncratic risk than matched non-user firms. In particular, the average idiosyncratic risk is 4.08% to 5.17% lower for derivative users. For market risk (panel C), we find that derivative users have lower but insignificant mean market risk than matched non-users. Our results suggest that derivative users have significantly lower median market risk than matched non-users for model 1 and 3.

Table 4-10: Firm Risk Matching Analysis Between All Derivative Users and Non-Users

*This table presents the results of mean and median differences for **Total Risk**, **Idiosyncratic Risk** and **Market Risk** for matched All Derivative Users and non-user firms. The table provides number of observations (N), caliper value, mean and median for derivative users and non-users, differences in mean and median and p-value of wilcoxon test. Propensity score in **Model 1** is calculated using common support and without replacement. Propensity score in **Model 2** is calculated with common support, without replacement and with a caliper of 0.01. Propensity score in **Model 3** is calculated with common support, without replacement and with a caliper of 0.2 of the standard deviation of the logit of the propensity score. The covariates that we use are **Z-score, Interest Coverage, Leverage, Liquidity, Firm Size, Market to book, Foreign Debt** and **Foreign Sales.***

Model	*N*	*Caliper*	*Users*		*Non-Users*		*Difference*		*Wilcoxon p-value*
			Mean	*Median*	*Mean*	*Median*	*Mean*[94]	*Median*	
					Panel A: Total Risk				
1	416	-	44.5683	37.6784	51.3776	45.6023	-6.8093***	-7.9239	0.002
2	394	0.01	44.4855	40.9886	50.2346	45.2612	-5.7491**	-4.2726	0.021
3	412	0.12	45.3434	38.2254	50.8443	45.3734	-5.5009***	-7.1480	0.007
					Panel B: Idiosyncratic Risk				
1	430	-	43.4685	38.0025	47.7033	41.9686	-4.2348**	-3.9661	0.051
2	412	0.01	41.6515	36.1997	46.8263	40.1658	-5.1748***	-3.9661	0.031
3	428	0.44	43.5119	38.0025	47.6007	41.9686	-4.0888*	-3.9661	0.051
					Panel C: Market Risk				
1	430	-	0.6482	0.5506	0.7212	0.6267	-0.0729	-0.0761	0.042
2	412	0.01	0.6567	0.5760	0.7123	0.6134	-0.0556	-0.0374	0.223
3	428	0.17	0.6578	0.5603	0.7245	0.6289	-0.0667	-0.0686	0.064

In Table 4-11 we match FC derivative user firms with non-user firms on the propensity score. The results in panel A show that FC derivatives use has significant negative effect on total risk. The results indicate that FC derivative users have statistically lower 6.12% lower total risk than matched non-user firms. In second and third model we introduce caliper value of 0.01 and 0.12 respectively. The results suggest that FC derivative user

[94] ****, ** and * are based on the t-test and shows the significance at 1%, 5% and 10% level respectively.*

firms have statistically lower 5.75% total risk for model 2 and 5.47% total risk for model 3 compared to matched non-users. The median differences between matched FC derivative users and non-user firms are -7.61%, -7.30% and -7.40% respectively for model 1, 2 and 3. These median differences are statistically significant at least at 5% significance level.

Table 4-11: Firm Risk Matching Analysis Between FC Derivative Users and Non-Users

*This table presents the results of mean and median differences for **Total Risk**, **Idiosyncratic Risk** and **Market Risk** for matched FC derivative users and non-user firms. The table provides number of observations (N), caliper value, mean and median for derivative users and non-users, differences in mean and median and p-value of wilcoxon test. Propensity score in **Model 1** is calculated using common support and without replacement. Propensity score in **Model 2** is calculated with common support, without replacement and with a caliper of 0.01. Propensity score in **Model 3** is calculated with common support, without replacement and with a caliper of 0.2 of the standard deviation of the logit of the propensity score. The covariates that we use are **Z-score, Interest Coverage, Leverage, Liquidity, Firm Size, Market to book, Foreign Debt** and **Foreign Sales.***

Model	*N*	*Caliper*	*Users*		*Non-Users*		*Difference*		*Wilcoxon p-value*
			Mean	*Median*	*Mean*	*Median*	*Mean*[95]	*Median*	
					Panel A: Total Risk				
1	416	-	45.2556	37.9563	51.3776	45.6023	-6.1220***	-7.6460	0.005
2	374	0.01	45.7637	37.9976	51.4103	45.2951	-5.7491**	-7.2975	0.022
3	406	0.12	45.6001	38.0537	51.0679	45.4516	-5.4677***	-7.3979	0.010
					Panel B: Idiosyncratic Risk				
1	430	-	43.4269	36.8487	47.7033	41.9686	-4.2276**	-5.1199	0.026
2	394	0.01	43.3354	38.0025	47.7221	41.9686	-4.3867***	-3.9661	0.125
3	424	0.44	43.0452	36.6685	47.6385	41.7883	-4.5933**	-5.1198	0.026
					Panel C: Market Risk				
1	430	-	0.6600	0.5653	0.7211	0.6267	-0.0611	-0.0614	0.092
2	394	0.01	0.6458	0.5772	0.7353	0.6426	-0.0896*	-0.0654	0.060
3	416	0.17	0.6614	0.5716	0.7272	0.6353	-0.0656	-0.0637	0.076

In panel B of Table 4-11, we examine the mean and median differences for matched FC derivative users and non-users for idiosyncratic risk. The results suggest that FC derivatives use has statistically significant negative effect on idiosyncratic risk for all three models. In particular, FC derivative users have statistically lower idiosyncratic risk of 4.23% for model 1, 4.39% for model 2 and 4.59% for model 3 compared to matched non-users. The median difference is statistically significant under model 1 and model 3 between matched FC derivative users and non-users. In panel C of Table 4-11 we examine the mean and median difference tests between matched FC derivative users and non-users

[95] ****, ** and * are based on the t-test and shows the significance at 1%, 5% and 10% level respectively.*

for market risk measure. The results suggest that FC derivative users have lower mean market risk compared to matched non-users for all three models but significant only for model 2. This shows that FC derivatives use has very weak negative effect on the market risk. The median difference for market risk is significant for all three models.

Table 4-12: Firm Risk Matching Analysis Between IR Derivative Users and Non-Users

*This table presents the results of mean and median differences for **Total Risk**, **Idiosyncratic Risk** and **Market Risk** for matched IR derivative users and non-user firms. The table provides number of observations (N), caliper value, mean and median for derivative users and non-users, differences in mean and median and p-value of wilcoxon test. Propensity score in **Model 1** is calculated using common support and without replacement. Propensity score in **Model 2** is calculated with common support, without replacement and with a caliper of 0.01. Propensity score in **Model 3** is calculated with common support, without replacement and with a caliper of 0.2 of the standard deviation of the logit of the propensity score. The covariates that we use are **Z-score, Interest Coverage, Leverage, Liquidity, Firm Size, Market to book, Foreign Debt** and **Foreign Sales.***

Model	*N*	*Caliper*	*Users*		*Non-Users*		*Difference*		*Wilcoxon p-value*
			Mean	*Median*	*Mean*	*Median*	*Mean*[96]	*Median*	
					Panel A: Total Risk				
1	416	-	42.4791	36.3371	51.3776	45.6023	-8.8985***	-9.2652	0.000
2	336	0.01	40.4416	35.7926	48.7374	41.732	-8.2958***	-5.9394	0.008
3	358	0.12	41.8008	35.2969	49.2919	42.0256	-7.4910***	-6.7287	0.001
					Panel B: Idiosyncratic Risk				
1	430	-	41.7660	36.3439	47.7032	41.9686	-5.9372**	-5.6247	0.003
2	352	0.01	39.4258	35.0099	46.3936	39.3726	-6.9677***	-4.3627	0.002
3	402	0.44	42.3173	36.4160	46.8861	40.2379	-4.5688**	-3.8219	0.033
					Panel C: Market Risk				
1	430	-	0.6579	0.6009	0.7211	0.6267	-0.0632	-0.0258	0.178
2	352	0.01	0.6844	0.6145	0.7056	0.6065	-0.0212	0.0080	0.559
3	378	0.17	0.6315	0.5884	0.7000	0.6061	-0.0684	-0.0177	0.153

In Table 4-12, we examine the mean and median difference test between matched IR derivative users and non-users. In panel A, we test the mean and median difference for total risk. Similar to our earlier results, the results suggest statistically significant effect of IR derivatives use on the total risk. The results suggest that a matched IR derivative user has statistically lower 7.49% to 8.90% total risk than a matched non-user firm for models with different caliper values. The matched IR derivative users have statistically lower median values for total risk than matched non-users. The results in panel B also show significant negative effect of IR derivatives use on the idiosyncratic risk. The results suggest that matched IR derivative users have statistically lower idiosyncratic risk than

[96] ****, ** and * are based on the t-test and shows the significance at 1%, 5% and 10% level respectively.*

matched non-users. In panel C, we examine the mean and median difference test for market risk for matched IR derivative users and non-users and find insignificant effect of IR derivatives use on market risk.

Overall, the results of Table 4-10, Table 4-11 and Table 4-12 suggest that, after controlling for firm-level characteristics that are associated with a firm's decision to use derivatives, derivatives use is associated with a statistically and economically significant lower total risk and idiosyncratic risk. Our results also suggest that derivatives use has weak or no significant effect on market risk. These results support results presented above and support the notion that firms use derivatives with the intention of reducing risk and not to speculate.

4.4.4.2. Balancing Test for Covariates

In Table 4-13 we report the balancing results of one-to-one matching used in model 2 for total risk of Table 4-10. The table reports pre and post matching results of mean for users and non-users, % bias, % reduction in bias, t-test statistics and associated p-values. The *t-test* and the SB are the main tests to ensure the balance of the strata for the covariates.[97]

For our covariates we find that the bias in firm size, foreign debt dummy, interest coverage, leverage and liquidity prior to matching is 98.60%, 79.40%, 56.60%, 54.90% and 46.20% respectively. After matching, the bias for covariates is reduced by at least 71.90%. According to Rosenbaum and Rubin (1985) the covariates between treatment and control group are out of balance when the absolute value of the SB is greater than 20.0 after matching. The bias statistics are less than 20.0 for all covariates after matching. This result confirms that we have achieved balance on all the covariates that are used to calculate the propensity score. This ensures that firms with the same propensity score values have a chance of being both treated and untreated. The results of *t-tests* show that matched derivative user and non-user firms are not statistically different after matching. The process of matching created a high degree of covariate balance between the treatment and control group for the study.

[97] *We calculate the SB for all the observed covariates. See section 3.5.9.1.3 for more information.*

Table 4-13: Balancing Test for Covariates

This table presents the balancing test results for the covariates that are used to calculate the propensity score before and after matching. ***Z-score*** *is Altman's Z-score for UK firms;* ***Interest Coverage*** *is the ratio of Earnings Before Interest and Taxes to Interest Expenses on Debt;* ***Leverage*** *is the ratio of total debt to market value of assets;* ***Liquidity*** *is the ratio of total current assets minus total stock and work in progress over total current liabilities.* ***Firm size*** *is a natural logarithm of total assets.* ***Market to Book*** *is the ratio of market values of assets to book value of assets;* ***FC Debt*** *is a dummy variable set is equal to '1' if a firm uses Foreign Debt and '0' otherwise;* ***Foreign Sales*** *is the ratio of foreign sales to total sales.*

Variables	*Sample*	*Mean*		*SB (%)*	*Reduction in SB (%)*	*T-Test*	*p > |t|*
		Users	*Non-Users*				
Z-score	Unmatched	3.0940	4.0797	-25.90		-4.36	0.000
	Matched	3.8964	4.0861	-5.00	80.80	-0.43	0.665
Interest Coverage	Unmatched	12.7610	30.1790	-56.60		-9.89	0.000
	Matched	26.1160	28.7650	-8.60	84.80	-0.74	0.462
Leverage	Unmatched	0.2324	0.1285	54.90		7.75	0.000
	Matched	0.1338	0.1347	-0.50	99.10	-0.06	0.956
Liquidity	Unmatched	1.0061	1.8052	-46.20		-9.57	0.000
	Matched	1.4295	1.6542	-13.00	71.90	-1.24	0.215
Firm Size	Unmatched	13.4000	11.5370	98.60		14.25	0.000
	Matched	11.6760	11.6860	-0.50	99.50	-0.05	0.959
Market to Book	Unmatched	1.5733	2.0158	-21.80		-3.48	0.001
	Matched	1.9660	2.0587	-4.60	79.10	-0.41	0.683
FC Debt	Unmatched	0.8165	0.4615	79.40		12.20	0.000
	Matched	0.4416	0.4670	-5.70	92.90	-0.50	0.614
Foreign Sales	Unmatched	0.5686	0.5238	13.20		1.82	0.069
	Matched	0.5273	0.5234	1.10	91.50	0.11	0.914

4.4.4.3. Hidden Bias and Sensitivity Analysis

Rosenbaum (1991) argues that under the situation of hidden or unobserved variables, where groups differ on unobserved characteristics that are not measured, the groups are not comparable. This situation is hard to resolve as the hidden or unobserved variables are difficult to measure. If there are unobserved or hidden variables that affect the decision to use derivatives or firm risk measures, then there is a problem of endogenous selection and under such circumstances the estimates obtained from PSM are inconsistent and the results are no longer unbiased. These unobserved variables may compromise the validity of inferring causality from observational data. PSM allows sensitivity analysis on the selection bias and also allows the estimation of the extent to which this hidden bias may affect the inference about the effects of derivatives use. We perform a sensitivity analysis by looking at Rosenbaum bounds and hidden bias equivalents (Diprete and Gangl, 2004). This method determines the extent to which selection on unobserved variables needed in order to change the inferences calculated by the PSM. Using Rosenbaum bound this sensitivity of observed effects can be calculated for number of scenarios with various levels of gamma. The results of the sensitivity analysis are presented in (Diprete and Gangl, 2004). This method determines the extent to which selection on unobserved variables needed in order to change the inferences calculated by the PSM. Using Rosenbaum bound, this sensitivity of observed effects can be calculated for number of scenarios with various levels of gamma. The results of the sensitivity analysis are presented in Table 4-14. The table presents the value of gamma, Γ, required in order to overturn our inferences from the PSM method.[98]

In this study negative selection bias occurs, when firms most likely to use derivatives also have lower firm risk measures even without derivatives use; hence, the estimated treatment effects underestimate the true treatment effect. As we have negative estimated treatment effect we use p-values of negative bounds to calculate the hidden bias equivalent. We use following equitation to calculate hidden bias equivalent:

$$x = \frac{log(\Gamma)}{log\left(exp(\beta)\right)} \qquad [49]$$

In equation [49] Γ is the critical value of gamma and $\beta$is the coefficient value from logit estimation that used to calculate propensity score.

Other columns in Table 4-14 show the magnitude of hidden bias required for each covariate that would cause us to review our findings of the causal effect of derivatives use on firm risk measures. For Z-score, the critical level of Γ is reached at a difference of 4.53. To alter our conclusions, the unobserved or hidden bias would have to produce a difference of similar magnitude. The unobserved variable would have to produce the effect of a difference of 0.29 in leverage, -8.33 in liquidity, 8.25 in market to book and 0.96 in foreign sales. All these differences are very large suggesting that to overturn our results of risk reducing effect of derivatives. The unobserved variables must have an effect that is as large as the magnitude of changes in the covariates. For model 2, the treatment effect is significant under the assumption of no hidden bias at Γvalue of 1.07. Hence, our conclusion that total risk after derivatives use is lower for user firms than non-user firms

[98] *Significant at 5% level*

would be suspicious if an unobserved covariate would increase the odds of using derivatives for the firms that actually use derivatives by 7% against firms that do not use derivatives. To revise our findings of the causal effect of derivatives use on idiosyncratic risk, the unobserved variable or hidden bias has to produce an effect of 7% to 12% to alter our results.[99]

Table 4-14: Sensitivity Analysis and Hidden Bias for the Effects of All Derivatives Use

This table calculates the sensitivity analysis and Hidden Bias Equivalents for the effect of All Derivatives use on Total Risk and Idiosyncratic Risk. The table presents the critical values of gamma at 5% level of significance. The hidden bias equivalents are calculated using equation [49].

Model	*Gamma*	*Z-score*	*Interest Coverage*	*Leverage*	*Liquidity*	*Firm Size*	*Market to Book*	*FC DEBT Dummy*	*Foreign Sales*
				Panel A: Total Risk					
1	1.25	4.5254	-41.5112	0.2885	-8.3332	0.8359	8.2510	0.2663	0.9565
2	1.07	1.3721	-12.5865	0.0875	-2.5267	0.2534	2.5018	0.0807	0.2900
3	1.15	2.8344	-25.9998	0.1807	-5.2194	0.5235	5.1679	0.1668	0.5991
				Panel B: Idiosyncratic Risk					
1	1.08	1.9700	-15.4832	0.1026	-3.7685	0.3110	2.7875	0.0962	0.3574
2	1.12	2.9009	-22.7998	0.1512	-5.5493	0.4580	4.1047	0.1417	0.5263
3	1.07	1.7319	-13.6118	0.0902	-3.3130	0.2734	2.4506	0.0846	0.3142

The sensitivity analysis and hidden bias in

[99] *We do not calculate the sensitivity analysis or hidden bias for Market risk variable as the effect of derivatives use on market risk is not significant.*

Table 4-15 is calculated for the matching analysis presented in. The critical level of Γ is reached at the values of 1.1 and 1.15. This shows that the observed effect of FC derivatives use on total risk is sensitive to unobserved confounding variable that could change the odds of using derivatives for firms that actually use derivatives by 10% to 15% versus firms that do not use derivatives. Similarly, the results in panel B for the effect of FC derivatives on idiosyncratic risk shows that the critical values of gamma are reached at 1.05 and 1.15 at 5% significance level. This shows that the observed effect of FC derivatives on idiosyncratic risk is sensitive to unobserved covariate.

Table 4-15: Sensitivity Analysis and Hidden Bias for the Effects of FC Derivatives Use

This table calculates the sensitivity analysis and Hidden Bias Equivalents for the effect of FC derivatives use on Total Risk and Idiosyncratic Risk. The table presents the critical values of gamma at 5% level of significance. The hidden bias equivalents are calculated using equation [49].

Model	*Gamma*	*Z-score*	*Interest Coverage*	*Leverage*	*Liquidity*	*Firm Size*	*Market to Book*	*FC DEBT Dummy*	*Foreign Sales*
				Panel A: Total Risk					
1	1.1	1.9275	-17.4073	0.1517	-9.8167	0.3537	2.8120	0.0890	0.4805
2	1.1	1.9275	-17.4073	0.1517	-9.8167	0.3537	2.8120	0.0890	0.4805
3	1.15	2.8264	-25.5259	0.2225	-14.3951	0.5187	4.1235	0.1306	0.7047
				Panel B: Idiosyncratic Risk					
1	1.15	3.5532	-26.4540	0.2382	-9.9804	0.5717	3.9599	0.1355	0.7464
2	1.05	1.2404	-9.2350	0.0831	-3.4841	0.1996	1.3824	0.0473	0.2606
3	1.15	3.5532	-26.4540	0.2382	-9.9804	0.5717	3.9599	0.1355	0.7464

In Table 4-16, we calculate sensitivity analysis and hidden bias equivalent for the matching analysis presented in Table 4-12. For total risk, the critical values of gamma are reached at 1.30 to 1.45. These suggest that the estimated effect of IR derivatives on total risk is questionable when the odds ratio of derivatives use between users and non-users differs by more than the critical values of gamma. We also calculate the hidden bias equivalent for the covariates. These shows how much effect the unobservable variables needs to produce to alter the results of effect of IR derivatives on total risk. For example, Table 4-16 shows that the unobserved covariates have to produce an effect of 5.1804 for Z-score and 0.4045 for leverage. In panel B we calculate the sensitivity analysis and hidden bias for the effect of IR derivatives on idiosyncratic risk. The critical values of gamma are reached at the values of 1.10 and 1.25. This shows that the observed effect of IR derivatives use on idiosyncratic risk is sensitive to unobserved confounding variable that could change the odds of using IR derivatives for firms that actually use IR derivatives by 10% to 25% versus firms that do not use derivatives.

Diprete and Gangl (2004) argue that Rosenbaum bound is the “worst case” scenario. Therefore, a low gamma value does not suggest that an unobserved variable or a hidden bias exists and that there is no effect of derivatives use on firm risk measures. This only suggests that the effect of derivatives use on firm risk would be zero if there were an unobserved or a hidden bias that would change the odds ratio treatment assignment.

Table 4-16: Sensitivity Analysis and Hidden Bias for the Effects of IR Derivatives Use

This table calculates the sensitivity analysis and Hidden Bias Equivalents for the effect of IR derivatives use on Total Risk and Idiosyncratic Risk. The table presents the critical values of gamma at 5% level of significance. The hidden bias equivalents are calculated using equation [49].

Model	*Gamma*	*Z-score*	*Interest Coverage*	*Leverage*	*Liquidity*	*Firm Size*	*Market to Book*	*FC DEBT Dummy*	*Foreign Sales*
				Panel A: Total Risk					
1	1.45	5.1804	-34.5361	0.4045	-4.0299	1.3317	13.4153	0.4220	1.9320
2	1.30	3.6579	-24.3862	0.2856	-2.8456	0.9403	9.4727	0.2980	1.3642
3	1.35	4.1841	-27.8941	0.3267	-3.2549	1.0756	10.8353	0.3408	1.5604
				Panel B: Idiosyncratic Risk					
1	1.25	4.4040	-23.8391	0.2448	-3.8215	0.8488	7.0068	0.2717	1.3472
2	1.25	4.4040	-23.8391	0.2448	-3.8215	0.8488	7.0068	0.2717	1.3472
3	1.10	1.8810	-10.1823	0.1046	-1.6323	0.3625	2.9928	0.1161	0.5754

4.5. Summary of Research Findings

The main focus of this chapter was to investigate the effect of derivatives use on equity price risk measures using a large dataset of UK non-financial firms for the period 1999-2010. Our results in this chapter show that the use of derivatives is, on average, associated with a reduction in various measures of firm risks. In univariate tests we find that firms that use derivatives have lower estimated values of total risk and idiosyncratic risk suggesting that derivatives are associated with lower firm risk. We find that market risk for derivative users is not statistically different from non-users. Univariate results also shed light on the characteristics of derivative user and non-user firms and suggest that derivative user firms are generally larger, more indebted, pay more dividends and hold less cash.

We find that firms' use of derivatives is associated with a reduction in financial risk measures. Our results suggest that a 1% increase in the use of all derivatives lowers the total risk by 2.53%, market risk by 0.0651 basis points and idiosyncratic risk by 2.23%. We find that a 1% increases in the extent of FC derivatives use lowers the market risk by 0.0945 basis points while it has no effect on total risk and idiosyncratic risk. The results for extent of IR derivatives suggest that a 1% increase leads to a reduction of 9.75% in total risk and 6.82% in idiosyncratic risk. We test for the nonlinearity in the use of derivatives and find that firms that use moderate to low levels of derivatives have economically larger negative effect on total risk than other levels of derivative use. We also use indicator variables for derivatives use and find that derivative users have economically lower 4.16% to 4.82% total risk and 2.02% and 2.55% lower idiosyncratic risk than non-users. We examine the effect of derivatives on financial risk measures over-time by interacting year dummies with derivatives dummies. We find that derivative users have lowest total risk and idiosyncratic risk during the economically stable period of 2004-2006 followed by the period of recent financial crisis of 2007-2008.

It is argued that empirical works in corporate financial field are affected by the problem of endogeneity. We control for the endogeneity problem by examining the mean and median differences between derivative users and identical non-users. We use PSM analysis to match derivative users and non-users. We employ different matching methods and find that derivative users have statistically lower mean total risk and idiosyncratic risk. In particular, derivative users have 5.50% to 6.80% statistically lower total risk and 4.08% and 5.17% lower idiosyncratic risk.

Overall, our results in this chapter suggest that UK firms use of derivatives is associated with a reduction in equity price risk. Our results also suggest that IR derivatives have statistically and economically larger negative effect on total risk and idiosyncratic risk than FC derivatives. These findings are consistent with the results of Guay (1999); Bartram (2006); Nguyen and Faff (2010); Marin (2013).

Chapter 5. The Effect of Derivatives Use on The Probability of Default

5.1. Introduction

> *"I have never bought into the argument that corporate users of derivatives give rise to systemic risk – that's a completely misguided view of the significance of corporate transactions," Richard Raeburn*, chairman of the European Association of Corporate Treasurers in London, Risk Magazine, 15 June 2010[100]

In October 2008, a month after the collapse of Lehman Brothers, financial market regulators in the European Union began an investigation into the global derivatives market looking at ways of reducing systemic risk within the financial sector. The concern for European regulators is that when a derivatives trade goes "bad", an outcome that is more likely when derivatives are used for speculation, they have the potential to spread the negative consequences of defaults to all corners of the global financial market.

Regulators in both the US and Europe are primarily concerned about the systemic risks arising from positions in the OTC derivatives market. Establishing central clearing houses or central counterparties (CCP) is considered a way of reducing systemic risk related to derivatives transactions. Instead of being exchanged privately via the OTC market, they could be processed through an intermediary, a move that is expected to improve transparency and reduce risk. However, non-financial firms using derivatives to hedge their risks would be required to keep large amounts of extra financing available for the purposes of putting up margin dependent on daily mark-to-market valuations. Capital and undrawn lines of credit will need to be held against potential margin for significant price changes in the price of the asset underlying the derivative transaction.

Companies will be required to be able to pay margin to their contracted counterparty for negative positions during the life of a derivative contract; although the offsetting, hedged, underlying cash flows will not materialize until the maturity of the underlying exposure. While margin payments would be received for derivatives positions showing a gain, they

[100] *http://www.risk.net/risk-magazine/news/1685735/ec-derivatives-consultation-stops-short-corporate-exemptions*

could not be used in the business prior to maturity as this cash could flow out again just as quickly as underlying prices moved in the opposite direction.

One of the advantages of OTC derivatives is that they usually require no cash flows prior to maturity. But if the move to CCP will require non-financial firms to provide collateral to their counterparty daily during the life of the derivative hedge, the hedge cash flows become immediate and companies would have to finance them up to maturity. This could be a significant financial burden for many companies particularly at a time when the flow of bank credit to the corporate sector is running at historically low levels. The net result could be an increase in liquidity risk for firms. Another problem with enforcing clearing on non-financial firms is that it could stop them meeting hedge accounting requirements, as standardized, exchange-traded contracts would not match the financial exposures on their balance sheet.

Many voices from the corporate sector are arguing that there is a strong possibility that compulsory clearing will hamper firms' ability to hedge because they would have to post initial and variation margin, utilizing a firm's scarce working capital. For example, Richard Raeburn, chairman of the European Association of Corporate Treasurers in London, is lobbying hard for non-financial firms to be exempt from being required to post margin. Speaking to Risk Magazine Christopher Whittall[101] says,

> *"Forcing corporates into central clearing creates an unmanageable liquidity risk challenge. You can also argue that incremental systemic risk is created because of the hazards corporates will face if they are required to set aside almost unlimited liquidity to meet uncertain future margin calls. I would argue that faced with the volatility of currency and interest rate markets, corporates are left with a very large contingent exposure to post collateral if the mark-to-market goes against them…If corporates don't get some kind of exemption from central clearing, they'll basically just see prices go up, as banks will have to pass prices on. That's the biggest issue at the moment."*

[101] *16 June 2010 - Corporates should be forced onto central counterparties – BIS, http://www.risk.net/risk-magazine/news/1686244/corporates-forced-central-counterparties-bis*

Christopher Whittall from Risk Magazine points out that many corporate treasurers have previously told “Risk” of their opposition to central clearing. He provides the following quote from a treasurer of a major airline,

> *"When fuel prices spiked prior to the financial crisis and then dropped significantly, the mark-to-market impact was huge. Margin calls would have tied up a good few $100 million at the very time we needed the money. Clearing would be a disaster: all it will do is stop people hedging as they can't afford it."* [102]

Corporate end-users are lobbying hard to be exempted from any clearing obligations, arguing that their use of derivatives does not impose any systemic risk and that any mandatory clearing requirement would require them to eat into vital working capital to meet margin calls by CCP. Derivative end–users are concerned that the requirement to centrally clear all OTC derivatives trades will force them to put aside large amounts of cash for margin calls and consequently increase their costs of derivatives use. This will lower the net benefits of derivatives use and hence decrease firm value. The tying up of cash in this way has the potential to adversely affect firm value in another way, (as firms may be forced to forego valuable investment opportunities) as that cash could otherwise be deployed in the firm, such as for investment purposes. For practitioners it seems that there are clear economic and financial implications to the proposed clearing rules. Firstly, increased costs of derivative use leading to less derivative use and therefore firms subjected to greater financial price exposure. It follows that this could result in greater credit risk for firms’ financial counterparties (such as the banks that lend to corporate) that could increase systemic risk within the financial sector. This outcome would be opposite to that envisaged by regulators. Secondly, firm’s cash resources are likely to be diverted away from productive use, such as funding value increasing investment, for the purposes of meeting margin and collateral requirements on their derivative transactions. The implications of this would be a likely reduction in corporate economic activity with obvious consequences for employment, growth and the real economy. Given the strong possibility that the proposed clearing and margin obligations could significantly hinder firms’ ability to hedge their financial price exposures. An important question is whether

[102] *16 June 2010 - Corporates should be forced onto central counterparties – BIS, http://www.risk.net/risk-magazine/news/1686244/corporates-forced-central-counterparties-bis.*

the proposed move to central clearing is really necessary or not. It will be necessary only if corporate users of derivative instruments give rise to systematic risk. We should therefore attempt to establish if the corporate use of derivatives poses a systemic threat. We would argue that it would only do so if non-financial firms are using derivatives for speculation.

In this chapter we examine the link between the use of derivatives by UK non-financial firms and their likelihood of default measured using expected default frequencies. A key advantage of our indicator of firm risk is that it is a direct measure of firm's credit risk.

The focus of this chapter is to examine the effect of derivatives use on the probability of default. We do this by investigating the effect of derivatives use on the probability of default for the period from 1999 to 2010. For the overwhelming majority of our firms, disclosures in annual reports indicate that firms are using financial derivatives for hedging, that is, risk reduction. Our empirical results are consistent with this as they show that derivative using firms have a significantly lower probability of default than non-users. This result is consistent with the notion that firms are using derivatives for hedging rather than speculation. Furthermore, we find that the use of IR derivatives lowers the probability of default more than FC derivatives. We use a treatment effects, instrumental variable and PSM approach to control for endogeneity of derivative use and the probability of default and find a strong negative association between derivative use and the probability of default.

This chapter is organized as follow. Section 5.2 provides description of pre-derivative measure of exposure, dependent variables, derivatives variables and other control variables. Section 5.3 provides Descriptive Statistics for the variables used in this analysis. Section 5.4 presents the empirical results and section 5.5 draws some conclusions.

5.2. Variable Description

This section presents definitions of pre-derivative use measures of exposures, dependent variables, derivatives variables and other control variables.

5.2.1. Pre-Derivative Measures of Exposure

- *Foreign Sales:* Calculated as foreign sales divided by total sales. This provides a pre-derivative measure of exposure to FX rate risk.

- *Foreign Assets:* Calculated as foreign assets divided by total assets. This provides a pre-derivative measure of exposure to FX rate risk.
- *Foreign Income*: Calculated as foreign income divided by total income. This provides a pre-derivative measure of exposure to FX rate risk.
- *Foreign Debt*: Calculated as foreign debt divided by total debt. This provides a pre-derivative measure of exposure to FX rate risk.
- *Z-score*: Z-score is Altman's modified Z-score for UK and is a measure of distress calculated using accounting ratios.[103]
- *Interest Coverage*: Calculated as earnings before interest, taxes, depreciation and amortisation divided by interest payments. This provides a pre-derivative measure of exposure to IR risk.

5.2.2. Measures of the Likelihood of Financial Distress

In order to examine the effects of derivative use on the likelihood of firms suffering financial distress, we need a variable that can capture a firms' likelihood of bankruptcy. Proxies for the probability of financial distress can be calculated using both accounting and market-based structural models. The problem with accounting-based measures of the likelihood of bankruptcy is that they use information from financial statements that by definition are backward looking and hence may not be very informative about the future financial prospects of a firm. In contrast, market-based structural models use information contained in the market value of a firms' equity to calculate the probability of financial distress and since market prices reflects the market's expectations about the future financial performance of a firm they contain forward looking information which in turn is more likely to provide a better assessment of a firms future creditworthiness. Hillegeist et al. (2004) investigate the performance of the accounting-based and market-based models of bankruptcy. The authors conclude that the market-based measure of bankruptcy provided richer information due to forward-looking characteristics of financial markets. In view of this we use a market-based measure of the likelihood of firm defaulting on its debt commitments. We use a firm's one-year and five-year EDF or probability of default as a measure for the likelihood of financial distress. This is estimated using Merton's (1974)

[103] *For more details see Section 3.3.1.3.3*

option pricing model.[104] We source this data from Moody's KMV. In simple terms the probability of default measures the likelihood that the market value of a firm's assets will be less than the book value of its liabilities by the time the debt matures.

5.2.3. Main Explanatory Variables

The main explanatory variable for our analysis is the coefficient on the derivatives variable. We are interested in knowing the effect of derivatives on the probability of default. Following measures of derivatives are employed in this chapter:

- *Dummy Measure of Derivatives*

  We create dummy measures of derivatives based on the firm's decision to use derivatives. We create following categories of derivatives use 1) All Derivative users: A dummy variable set equal to 1 if a firm use FC and/or IR and/or CP derivatives and 0 for non-users[105] 2) FC Derivative users with bias: A dummy variable set equal to '1' if a firm uses FC derivatives and '0' for non-FC users[106] 3) FC Derivative users without bias: A dummy variable set equal to '1' if a firm uses FC derivatives and '0' for non-users[107] 4) IR derivative users with bias: A dummy variable set equal to '1' if a firm uses IR derivatives and '0' for non-IR users[108] and 5) IR derivative users without bias: FC Derivative users without bias: A dummy variable set equal to '1' if a firm uses FC derivatives and '0' for non-users[109]

  In section 0, we examine the effects of different numbers and combinations of derivatives use on the probability of default. We have created different categories of derivatives based on the numbers and types of derivatives firms use. We have created: 1) One type of derivative user which is set equal to 1 if a firm uses only one type of derivative i.e. either FC or IR or CP and 0 otherwise 2) Two types of derivatives user which is set equal to 1 if a firm uses two types of derivatives i.e. Foreign Currency and Interest Rate (FC&IR) or Foreign Currency and Commodity

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[104] Detailed information on how a firm's expected default frequency is calculated is provided in Section 3.3.1.2.2.
[105] We do not investigate the effects of CP only derivatives as there are very few firms in our sample that use CP only derivatives.
[106] Non-FC users include "Other"users that use IR only, CP only or a combination of both.
[107] We exclude "Other" users from non-user sample.
[108] Non-IR users include "Other"users that use FC only, CP only or a combination of both.
[109] We exclude "Other" users from non-user sample.

Price (FC&CP) or Interest Rate and Commodity Price (IR&CP) and 0 otherwise and 3) Three types of derivatives which is set equal to 1 if a firm uses all three types of derivatives i.e. FC&IR&CP and 0 otherwise. We also breakdown one type of derivative users into its 3 components: 1) FC derivative users, 2) IR derivative users and 3) CP derivative users and two types of derivatives into 3 subcategories: 1) FC&IR derivative users, 2) FC&CP derivative users and 3) IR&CP derivative users. In all subcategories we assign 1 to users and 0 to non-users. Majority of the firms in our sample are FC and IR derivative users and there are few firms that use all three types of derivatives FC, IR and CP together.

- *Continuous Measure of Derivatives:*

  We use year-end outstanding notional values of derivatives as a continuous measure of derivatives use. We scale notional values of derivatives by total assets. This gives an extent of derivatives use and can differentiate between a firm with high derivative usage with a firm with low derivative usage. We calculate this for 1) extent of all derivatives 2) extent of FC derivatives and 3) extent of IR derivatives.

5.2.4. Control Variables[110]

In multivariate analysis we control for other factors that also affect the firm financial risk. In particular, we control for following variables:

- *Leverage: W*e calculate leverage as the ratio of total debt to book value of assets minus book value of equity plus market value of equity. We expect a positive association between leverage and the probability of default.
- *Profitability:* We use the return on invested capital as a measure for profitability. We expect a negative association between profitability and the probability of default.
- *Firm Size:* We use natural log of total assets as a measure for firm size. We expect that firm size will be negatively associated with the probability of default.

[110] *See section 3.3.3 for information on the theoretical and empirical reasoning behind using these control variables.*

- *Equity Volatility:* We calculate equity volatility as the standard deviation of each firm's daily stock return over the entire fiscal year. We expect a positive coefficient for this variable.
- *Excess Return:* We calculate excess return as annual equity return minus the value weighted FTSE all shares index annual return over the entire fiscal year. Each firm's annual return is calculated by cumulating its monthly return. We expect a negative association between excess return and the probability of default.
- *Liquidity:* We measure liquidity as ratio of total current assets minus total stock and work in progress over total current liabilities. We expect a negative association between profitability and the probability of default.

5.3. Descriptive Statistics

This section provides the summary analysis of pre-derivatives measures of exposure, the probability of default variables, extent of derivatives use and control variables. It presents frequency distribution of the derivatives variable and the Pearson correlation coefficients for derivatives, probability of default measures and control variables. Finally, this section provides the time-series profile of the probability of default measures for various derivative users and non-users.

5.3.1. Summary Statistics

In Table 5-1, we present summary statistics of the variables used in the analysis. In panel A we display data for variables described as pre-derivative use measures of exposure. We define these as measures of financial exposure that generally do not incorporate the effect of derivatives, in other words they are not affected by the use of derivatives.[111] Firms in our sample have high levels of foreign sales with the mean and median values of foreign sales close to 60 per cent. On average a little over a third of firms' income is generated outside the UK and a quarter of firms' assets are located in foreign countries. Firms in our sample possess higher levels foreign trading activity than the firms in Bartram et al. (2011), where the mean level of foreign sales and foreign income are 23% and 20%, respectively. However, firms in Bartram et al. (2011) sample originate from several countries and so their mean values might mask large differences across countries. A more appropriate

[111] *Bartram et al. (2011) refer to these as measures of gross or pre-hedging exposure.*

comparison might be against another developed country such as the US. Allayannis and Ofek (2001) show that non-financial US firms in the S&P 500 have on average around 20 per cent of foreign sales with a median value of only 12.5 per cent. Our sample made up of firms in the FTSE 500 possess nearly five (three) times the median (mean) level of foreign sales which suggests that UK firms have relatively large levels of foreign operations which could generate high levels of FX exposure and resulting cash flow variability. These exposure characteristics support our assertion that the UK is a good setting for examining the effects of derivatives on firm default probabilities.[112]

Panel B of Table 5-1 shows summary statistics for our probability of default variable, which we consider to be a post-derivative use measure of firm risk, which means that its value incorporates the effects of the firm's risk management activities such as the use of derivatives. The average one-year default probability (EDF1YEAR) is 1.3116 per cent and the median value is 0.1637 per cent. For our five-year default probability (EDF5YEAR) variable the mean and median values are 1.2436 and 0.3727 per cent, respectively. A comparison of median values shows that as expected one-year default probabilities are smaller than five-year probabilities.[113]

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[112] *Bartram et al. (2011) include leverage, interest cover and liquidity as measures of gross interest rate exposure. It is conceivable that leverage and interest cover could also be post derivative (or net) measures of exposure as the use of derivatives for hedging should lower firm risk and so can facilitate the uptake of greater levels of debt (Graham and Rogers, 2002).*

[113] *A small proportion of extreme values influences the mean one-year EDF values. If we winsorize at the 2.5 percentile top and bottom we find in a paired t-test that five year EDF values are greater than one year EDF values.*

Table 5-1: Summary Statistics

This table presents the standard summary statistics for the variables used in this analysis. This table includes following variables. ***Foreign Sales*** *is foreign sales over total sales.* ***Foreign Assets*** *is foreign assets over total assets.* ***Foreign Income*** *is foreign income over total income.* ***Foreign Debt*** *is foreign Debt over total debt.* ***Z-score*** *is Altman's Z-score for UK firms.* ***Interest Coverage*** *is earnings before interest and taxes over interest expense.* ***EDF1YEAR*** *is probability of default in 1-year time.* ***EDF5YEAR*** *is probability of default in 5-years time.* ***Extent of Derivatives*** *is notional values of derivatives scaled by total assets.* ***Extent of FC Derivatives*** *is notional values of FC derivatives scaled by total assets* ***Extent of IR Derivatives*** *is notional values of IR derivatives scaled by total assets* ***Leverage*** *is the ratio of total debt to market value of assets.* ***Profitability*** *is measured as return on invested capital, which is calculated as the sum of pre-tax profits and total interest charges divided by invested capital.* ***Excess Return*** *is the annual return on the firm minus the value weighted FTSE all shares index annual return over the entire fiscal year.* ***Equity Volatility*** *is expressed as square root of number of trading days multiplied by standard deviation of natural log of the daily price growth rate.* ***Firm Size*** *is a natural logarithm of total assets.* ***Liquidity*** *is the ratio of total current assets minus total stock & work in progress over total current liabilities.*

Variables	*N*	*Mean*	*Median*	*Minimum*	*Maximum*	*Standard Deviation*
Panel A: Pre-Derivative use Measures of Exposure						
Foreign Sales	3422	56.9791	59.095	0.0000	100.0000	34.3514
Foreign Assets	3374	24.9075	18.4000	0.0000	91.9500	25.2718
Foreign Income	2881	34.7812	19.7900	0.0000	100.0000	37.0461
Foreign Debt	2845	46.6638	46.8700	0.0000	100.0000	38.8519
Z-score	3422	3.6566	3.2996	-47.4732	48.6113	11.2632
Interest Coverage	3422	17.1008	5.3818	0.0000	100.0000	28.9672
Panel B: Post-Derivative use Measure of Risk						
EDF1YEAR	3422	1.3351	0.1701	0.0100	28.5976	4.0100
EDF5YEAR	3422	1.2682	0.3715	0.0133	18.5867	2.7450
Panel C: Extent of Derivatives Use						
Extent of All Derivatives	1152	0.2341	0.1280	0.0000	2.9237	0.3888
Extent of FC Derivatives	845	0.1387	0.0536	0.0000	2.4139	0.2988
Extent of IR Derivatives	942	0.1371	0.0789	0.0000	1.1909	0.1810
Panel D: Control Variables						
Leverage	3422	0.2220	0.1852	0.0000	0.8920	0.1943
Profitability	3422	0.0700	0.0953	-1.0365	0.7632	0.2271
Firm Size	3422	13.5545	13.3873	9.0882	17.9283	1.7893
Equity Volatility	3422	0.4024	0.3455	0.0979	1.2841	0.2148
Excess Return	3422	-0.0238	0.0331	-1.9106	1.3488	0.5016
Liquidity	3422	1.1436	0.8500	0.0000	8.8000	1.2801

Panel C displays summary statistics for our variables measuring the notional amount of derivatives scaled by total assets, which we use as proxy for the extent of derivatives use. Not all of the firms in our sample disclose in their annual reports notional values of derivatives employed and hence the numbers of firm-year observations for these notional value variables are around a third of those available for the derivative dummy variables. If we include firms that do not use derivatives the mean (median) notional value of all derivatives as a percentage of total assets is 23.4% (12.8%). The mean value of total FC derivatives as a percentage of total assets is 13.9% and the mean value of total IR derivative as a percentage of total assets is very similar at 13.7%.

Panel D of Table 5-1 presents summary statistics results for our control variables. The mean value for leverage is 22.2%, which is a little lower, but not too dissimilar to the 25.5% reported by Bartram et al. for their sample of firms.[114] Our sample firms' profitability ranges between -103.7% to 76.3% indicating both profitable and loss making firms in our sample. On average the firms in our sample earn returns lower than the market as a whole albeit with a median excess return of 3.3%. The average value of liquidity for our sample is 1.14 and the median value is 0.85, which are lower than the corresponding values reported by Bartram et al. (2011). Overall, our summary statistics suggest that our sample is made up of a rich cross-section of firms, some of which possess financial price exposure characteristics that might necessitate the use of derivatives for risk mitigation.

5.3.2. Frequency Distribution of Derivative Usage

Table 5-2 presents the frequency distribution of derivatives usage among our sample firms. Panel A provides usage data for all derivatives use (FC, IR, CP) and shows that 86.6% of our sample discloses in their annual reports that they use derivatives, while 13.4% do not use derivatives. The proportion of derivative users in our sample is greater than that reported by Bartram et al. (2011) for their sample of UK firms (64%), French firms (66%) and German firms (47%) and that indicated by Campello et al. (2011) for US firms (50%). In panel B we break down our sample into firms that use FC derivatives and those that do not. Nearly three quarters of our sample, 74%, use FC derivatives. Again this is greater than the corresponding derivative usage frequencies in Bartram et al. (2011) (UK=55%, France=53%, Germany=39%) and Campello et al. (2011) (27%). In panel C we show that 70.6% of our sample use IR derivatives which is double the figure reported by Bartram et al. (2011) for their sample of UK firms (36.5%) and also double the proportion of US firms using IR derivatives as reported by Campello et al. (2011) (35.6%). Notwithstanding the possibility that the size composition of the Bartram et al. (2011) and Campello et al. (2011) samples are not directly comparable with our sample; these comparisons suggests that the use of derivative instruments is more prevalent among UK firms. This implies that an investigation into the impact of derivatives on the risk of default is highly relevant within a UK context. Finally, only 10% of our sample firms use CP derivatives, which is consistent with the relatively low exposure to commodity prices faced by our sample firms.

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[114] *We calculate leverage similar Bartram et al. (2011) and also source our data from DataStream.*

Table 5-2: Frequency Distribution of Derivative Usage

This table provides data on the use of derivatives by our sample firms. In panel A we present data for all derivatives usage. In panel B we present broad categories of FC derivatives used by our sample. In panel C we present broad categories of IR derivatives used by our sample.

Derivative Categories	*Frequency*	*Percentage*
Panel A: Derivative users and Non-users		
Derivative Users	3693	86.61
Non-users	571	13.39
Total	4264	100
Panel B: FC Derivative users and FC Non-users		
FC Derivatives	3156	74.02
IR Derivatives Only	508	11.91
IR&CP Derivatives	22	0.52
CP Derivatives Only	7	0.16
Non-users	571	13.39
Total	4264	100
Panel C: IR Derivative users and IR Non-users		
IR Derivatives	3011	70.61
FC Derivatives Only	646	15.15
FC&CP Derivatives	29	0.68
CP Derivatives Only	7	0.16
Non-users	571	13.39
Total	4264	100

5.3.3. Correlation Analysis

Table 5-3 presents the Pearson correlation coefficients for probability of default, derivative use and our independent variables. As expected, the results indicate a negative correlation between EDF1YER and derivative dummy variables and EDF5YEAR and derivative dummy variables. This suggests that derivative user firms have a lower probability of default. As expected, leverage and equity volatility are positively correlated and firm size, profitability, liquidity and excess return are negatively correlated with EDF1YEAR and EDF5YEAR. The highest correlation of EDF1YEAR and EDF5YEAR is with equity volatility, 0.5507 & 0.5953 respectively. These suggest that firms that have higher equity volatility also have higher probability of default. The observed positive correlation of EDF1YEAR and EDF5YEAR with leverage is of higher magnitude, 0.4115 & 0.4443 respectively. The highest negative correlation of EDF1YEAR and EDF5YEAR is with excess return. This shows that firms that generate excess return have lower probability of default.

Table 5-3: Pearson Correlation Coefficients

*This table presents the correlation coefficients for the main variables used in this analysis. **EDF1YEAR** and **EDF5YEAR** measure expected default frequencies and proxy for the probability of financial distress. **All Derivatives** is a dummy variable set equal to 1 if a firm is derivative user and 0 otherwise. **FC Derivative Users (B)** is a dummy variable set equal to 1 if a firm uses FC derivatives and 0 otherwise. **IR Derivative Users (B)** is a dummy variable set equal to 1 if a firm uses IR derivatives and 0 otherwise. **Leverage** is the ratio of total debt to market value of assets. **Profitability** is measured as return on invested capital, which calculated as the sum of pre-tax profits and total interest charges divided by invested capital. **Excess Return** is the annual return on the firm minus the value weighted FTSE all shares index annual return over the entire fiscal year. **Equity volatility** is expressed as square root of number of trading days multiplied by standard deviation of natural log of the daily price growth rate. **Firm size** is a natural logarithm of total assets. **Liquidity** is the ratio of total current assets minus total stock & work in progress over total current liabilities.*

		1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*
EDF1YEAR	1	1.0000										
EDF5YEAR	2	0.9854	1.0000									
All Derivative Users	3	-0.1234	-0.1243	1.0000								
FC Derivative Users (B)	4	-0.1127	-0.1169	0.6653	1.0000							
IR Derivative Users (B)	5	-0.1128	-0.1195	0.6111	0.2968	1.0000						
Leverage	6	0.4115	0.4443	0.1894	0.0086	0.3153	1.0000					
Firm Size	7	-0.2884	-0.3325	0.3191	0.2641	0.4348	0.1444	1.0000				
Profitability	8	-0.3618	-0.3930	0.1374	0.1151	0.1299	-0.1446	0.2781	1.0000			
Liquidity	9	-0.0314	-0.0225	-0.2116	-0.0619	-0.3005	-0.2777	-0.2700	-0.2085	1.0000		
Equity Volatility	10	0.5507	0.5953	-0.0860	-0.0230	-0.1241	0.1535	-0.2498	-0.4059	0.2319	1.0000	
Excess Return	11	-0.4460	-0.4705	0.0405	0.0222	0.0232	-0.2531	0.1965	0.2268	-0.0663	-0.3469	1.0000

5.3.4. Time-Series Profile of Probability of Default for Derivative Users and Non-Users

In this section, we examine the time-series variation in the probability of default by plotting the mean values of EDF1YEAR and EDF5YEAR for all derivative users and non-users, FC derivative users and non-FC users and IR derivative users and non-IR users for the period 1999 to 2010. It is important to note that we are not controlling for firm-level difference between users and non-users in this graphical analysis.

Figure 5-1 shows that derivative users and non-users have similar default probabilities at the start of our sample period in 1999; but as we move towards 2002 average one-year and five-year default probabilities for derivative user firms fall below those of non-user firms. Although default probabilities for both groups are increasing, they are going up at a faster rate for non-users. Default probabilities reach a peak for both users and non-users in 2002, which coincides with a period of global macroeconomic uncertainty and heightened credit risk. After 2002 the probability of default is falling for both the types of firm and on the whole the difference between users and non-users decreases until the beginning of 2007. In 2007 the plot shows that average default probabilities for non-users start to increase whereas those for users remain very stable. Non-users experience a rapid increase in default probabilities from the middle of 2007 and accelerate further in 2008 reaching a peak by the end of 2008. Derivative users show an increase in default probabilities from the middle of 2008 peaking at the end of 2008 but remaining well below those witnessed by non-users. The plot also shows that the highest levels of default probabilities for user firms in recent financial crisis are still lower than the default probabilities during the heightened credit risk conditions of year 2002. This highlights that derivatives are much more important in recent financial crisis than they were in 2002. The difference in default probabilities between derivative users and non-users reaches its maximum at the end of 2008 at the height of the financial crisis. The previous maximum difference between derivative users and non-users was during the economic slowdown of 2002, which seems to suggest that derivatives have their greatest impact on default probabilities during periods of heightened economic and financial market uncertainty. Additionally this plot shows that since 2001 derivative users have had lower default probabilities than non-users and that they are less volatile for users compared to non-users.

Figure 5-2 and Figure 5-3 plot the average probability of default for FC derivative users and IR derivative users and their corresponding non-users, respectively. The time-series variation in default probabilities for users and non-users depicted in these plots are very similar to that presented in Figure 5-1.

Figure 5-1: Time-Series plot of Mean Probability of default of All Derivative Users and Non-user

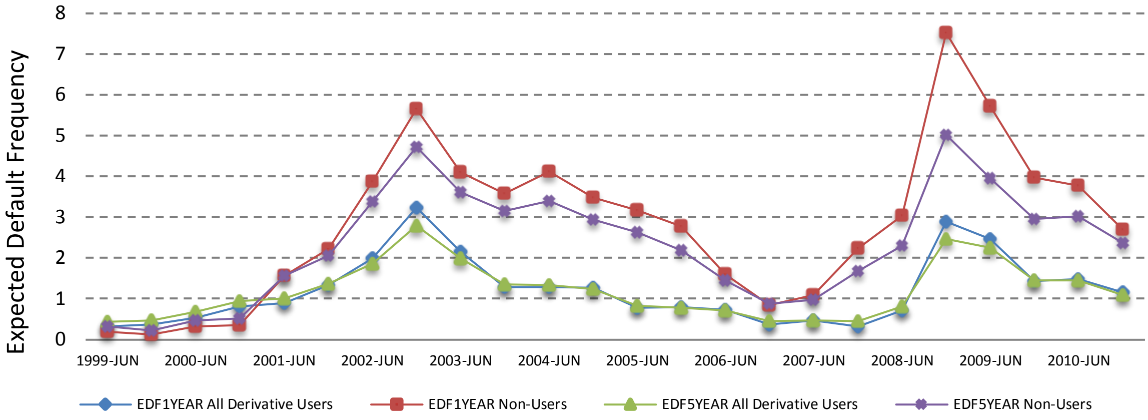


Figure 5-2: Time-Series plot of Probability of default of FC Derivative Users and Non-FC Derivative Users

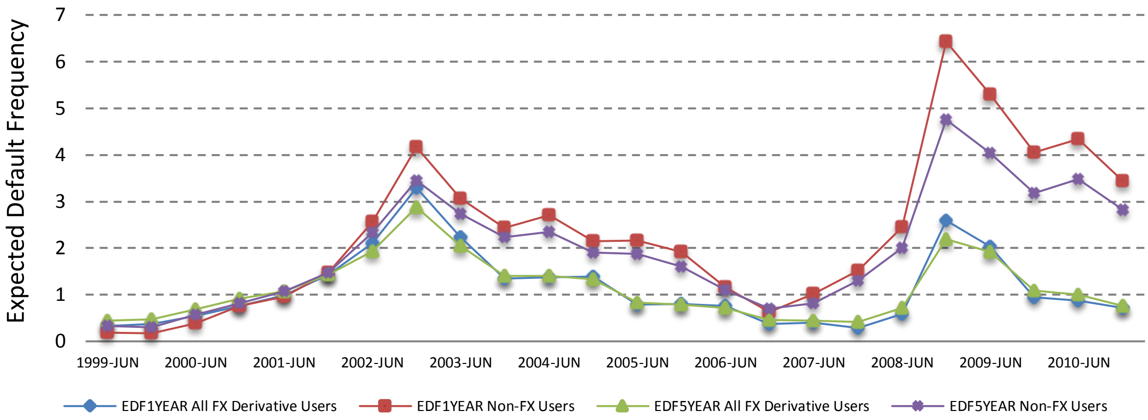
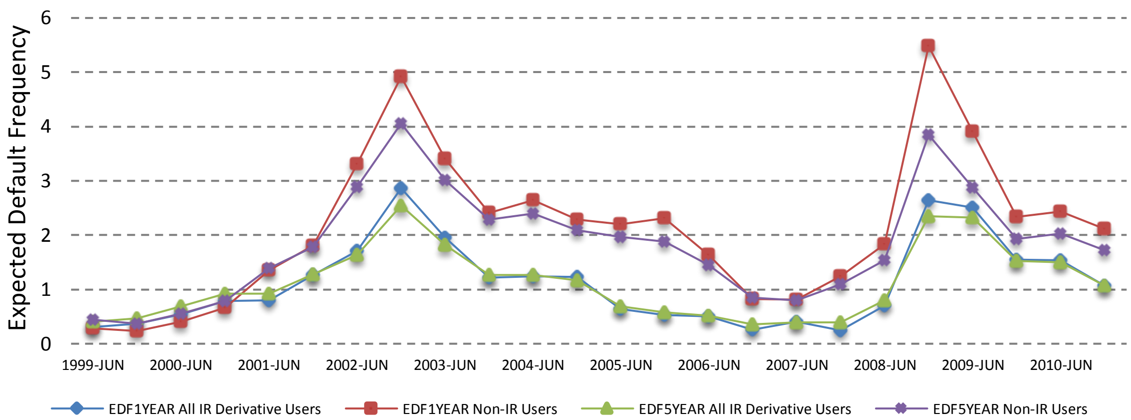


Figure 5-3: Time-Series plot of Probability of default of IR Derivative Users and Non-IR Derivative Users



5.4. Empirical Results

In this section, we present the results of our empirical analysis. We start analysis with univariate analysis where we examine the mean and median difference between various derivative users and non-users for the probability of default measures, control variables and pre-derivatives measures. This will highlight the significance differences in the characteristics of derivative users and non-user firms. Next, we use multivariate analysis to examine the effects of derivatives use on the probability of default. We use various regression models to investigate the research question.

5.4.1. Univariate Tests

Previous studies suggest that there are substantive differences, on an average, in the characteristics of the firms that use derivatives and those that do not.[115] In order to examine such differences in characteristics in our sample firms, we use univariate tests for difference in means and medians between derivative users and non-users. We present univariate results in Table 5-4 to Table 5-7. Table 5-4 shows the results of comparisons between derivative users and non-users, Table 5-5 presents the results for FC derivative users and non-users, and Table 5-6 for IR derivative users and non-users using both parametric (t-test) and non-parametric (Wilcoxon rank sum test) tests. The number of observations may differ for the various comparisons due to data availability.

Table 5-4 presents mean and median difference tests for the variables proxying for financial distress and firm-level characteristics between derivative users and non-user firms. Our results show that the probability of default for derivative users is statistically lower than for non-users based upon both means and medians tests. In particular, the results show that derivative users have 1.60% and 1.11% lower EDF1YEAR and EDF5YEAR. As our probability of default measure is market based and therefore measured post the effect of derivatives, our results are consistent with firms using derivatives for hedging purposes.

In line with Guay (1999) and Purnanandam (2008), we find a statistically higher leverage ratio for derivative user firms than non-users under both means and medians difference

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[115](Gay and Nam, 1998; Guay, 1999; Allayannis and Ofek, 2001; Bartram et al., 2009).

tests. This is consistent with firm using derivatives in an effort to increase debt capacity. Hentschel and Kothari (2001) and Lin et al. (2008) also report higher leverage for their sample of derivative use firms. Bartram et al. (2011) include leverage as a pre-hedging measure of exposure, which might be because firms with higher leverage are considered to have higher IR exposure. However, it is conceivable that a firm's leverage includes the effect of derivatives use via debt capacity effects as demonstrated by Graham and Rogers (2002). Several previous studies such as Bartram et al. (2011) find that derivative users have higher leverage than non-users. This is usually interpreted as derivatives users having greater exposure to IR changes. However, it could be argued that while measuring IR exposure it is not the amount of debt that matters but more so the ability to service the interest payments. Therefore, perhaps a more appropriate measure of IR exposure might be the interest cover ratio. Consistent with this, we find derivative users have lower interest coverage ratios. This is opposite to the finding of Bartram et al. (2011) who report higher coverage ratios for derivative users.

Table 5-4: Mean Difference Test and Wilcoxon Rank Sum Test of All Derivative Users Versus Non-Users

*Table displays the results of tests of mean differences and Wilcoxon Rank Sum Test between derivative user firms and non-user firms across firm risk measures and firm-level characteristics. ***, **, * denote significance at the 1%, 5%, or 10% for a two-tailed test.*

Variables	*All Derivative Users*			*Non-Users*			*Difference Test*	
							Mean	*Median*
	N	*Mean*	*Median*	*N*	*Mean*	*Median*	*T-Test*	*Wilcoxon*
EDF1YEAR	3005	1.1398	0.1604	417	2.7428	0.3232	-1.6030***	-0.1629***
EDF5YEAR	3005	1.1329	0.3496	417	2.2431	0.5957	-1.1102***	-0.2461***
Leverage	3005	0.2364	0.2032	417	0.1184	0.0284	0.1180***	0.1748***
Firm Size	3005	13.7755	13.6078	417	11.9623	12.0670	1.8132***	1.5408***
Liquidity	3005	1.0243	0.8200	417	2.0034	1.1600	-0.9791***	-0.3400***
Profitability	3005	0.0835	0.0968	417	-0.0271	0.0574	0.1106***	0.0394***
Equity Volatility	3005	0.3906	0.3392	417	0.4874	0.4162	-0.0968***	-0.0769***
Excess Return	3005	-0.0127	0.0393	417	-0.1042	-0.0371	0.0916***	0.0764***
Interest cover	3005	14.4845	5.1637	417	35.9548	10.7402	-21.4703***	-5.5765***
Z-score	3005	3.8858	3.2786	417	2.0055	3.5478	1.8803**	-0.2692
Foreign Sales	3005	57.6556	59.8800	417	52.1043	52.1700	5.5513***	7.7100***
Foreign Assets	2686	27.2901	21.8500	362	17.7204	1.8400	9.5696***	20.0100***
Foreign Income	2223	36.1355	22.9100	328	32.3199	6.5700	3.8156***	16.3400**
Foreign Debt	2577	48.5558	50.6300	268	28.4708	0.5900	20.0850*	50.0400***

Similar to Guay (1999), we find derivative user firms are also significantly larger than non-derivative user firm based upon both means and medians tests. This finding supports the hypothesis of scale economies in use of derivative instruments; the findings of Mian

(1996), Hentschel and Kothari (2001) and Bartram (2006) also reveals that larger firms are more likely to use derivatives as they can benefit from economies of scale in derivative transaction costs. The results from means and medians tests of derivative users and non-users show that derivatives users in general have higher profits than non-derivative users. Bartram (2006) and Allayannis et al. (2012) also find similar results. Similar to Bartram (2006), we find derivative users are less liquid than non-derivative users for both mean and medians tests. Purnanandam (2008) also reports that derivative users keep less liquid assets as compared to the non-derivative users. Results from Table 5-4 also shows that derivative users have statistically lower equity volatility and higher excess return than non-users for both means and medians difference tests.

Another variable of interest is the Z-score. A Z-score is an accounting based measure of the likelihood of default. Accounting based models of default utilise data from financial statements which tend to focus on recent historical financial performance rather than a forward looking financial assessment and therefore the Z-score may not fully reflect a firm's future financial prospects. Furthermore, since derivatives can have an impact on future cash flows a backward looking assessment of default risk, such as Z-score, is less likely to incorporate the effects of derivatives. We would therefore argue that Z-score would display characteristics in common with that of a pre-derivative measure of risk. The non-parametric tests in Tables 5, 6 and 7 show that all derivative users, FX derivative users and IR derivative users possess lower median Z-scores than non users with the difference being statistically significant in the case of IR derivative users. These results are consistent with our assertion above that the Z-score provides a pre-derivative measure of the likelihood of default, that is, firms with lower Z-scores, which implies a higher likelihood of default, are more likely to use derivatives for hedging. Furthermore, the fact that IR derivative users possess the lowest median Z-score compared to all derivative and FX derivative users would also imply that Z-score is a pre-derivative indicator of firm credit risk. Firms with low Z-scores are more likely to use IR derivatives as this type of derivative is expected to have the greatest impact on a firm's probability of default. These univariate tests together with those relating to expected default frequencies show that derivative users have higher default risk than non-users when default risk is measured using Z-score but lower default risk when it is measured using EDFs. Bartram et al. (2011) report a somewhat similar result as they find that firms that use derivatives possess lower Z-scores but have similar default probabilities. We would argue that our findings and those of Bartram et al. are consistent with our assertion that Z-score is a pre-derivative measure of default risk whereas EDF is post-derivative measure of default risk. Interestingly, Campello et al. (2011) find that derivative users (hedgers) have higher Z-scores and therefore lower default risk than non-users. This result is contrary to what we find and that reported by Bartram et al. The use of derivatives may materially change the probability of bankruptcy but until recently derivative values were not included in firms' financial statements. Our results on the efficacy of Z-score as a measure of default prediction are consistent with recent evidence that suggests that the Z-score measure needs to be treated with caution with respect to the prediction of financial distress (Charalambakis, Espenlauby and Garrett, 2009). Our evidence suggests that this might be the case in part because the Z-score measure does not appear to take derivatives used by a firm into consideration when calculating the probability of bankruptcy This is because a firm's derivative transactions have until recently been off the balance sheet and therefore not reflected in the financial ratios used in the Z-score calculation. International Accounting Standard (IAS) 39 brought derivatives that used to be off-balance sheet on to financial statements. IAS 39 requires all derivative instruments to be carried at fair value on the balance sheet with any changes in values being recognised in the profit and loss statement. The inclusion of derivative transactions in the balance sheet values of firms' assets and liabilities and the increased disclosure of derivatives in the notes to financial statements will only help, that is make Z-score more like a post derivative measure, if their effects are then reflected in the ratios that make up the Z-score formula. If this does not happen then the Z-score computation would require the inclusion of a separate variable to control for the effect of derivatives.

We also examine differences between FC derivative users against non-FC users & non-users and between IR derivative users against non-IR users & non-users. In Table 5-5**,** we present mean and median difference test between FC derivative users and non-FC derivative users and between FC derivative users and non-users.

Table 5-5: Mean Difference Test and Wilcoxon Rank Sum Test of FC Derivative Users and Non-FC Derivative Users and Non-users

*Table displays the results of tests of mean differences and Wilcoxon Rank Sum Test between FC derivative user firms and non-user firms across firm risk measures and firm-level characteristics. ***, **, * denote significance at the 1%, 5%, or 10% for a two-tailed test.*

	FC Derivative Users			*Non-FC Users*			*Non-Users*			*Mean Difference Test*		*Median Difference Test*	
Variables	N	Mean (1)	Median (2)	N	Mean (3)	Median (4)	N	Mean (5)	Median (6)	1- 3	1 – 5	2- 4	2-6
EDF1YEAR	2646	1.0658	0.1596	776	2.2534	0.2250	417	2.7428	0.3232	-1.1876***	-1.6770***	-0.0654***	-0.1636***
EDF5YEAR	2646	1.0770	0.3469	776	1.9201	0.4679	417	2.2431	0.5957	-0.8431***	-1.1661***	-0.1210***	-0.2487***
Leverage	2646	0.2284	0.1984	776	0.2003	0.1097	417	0.1184	0.0284	0.0282***	0.1100***	0.0888***	0.1701***
Firm Size	2646	13.8263	13.6538	776	12.6278	12.6897	417	11.9623	12.0670	1.1985***	1.8641***	0.9641***	1.5868***
Liquidity	2646	1.0648	0.8500	776	1.4123	0.8300	417	2.0034	1.1600	-0.3475***	-0.9386***	0.0200	-0.3100***
Profitability	2646	0.0855	0.0985	776	0.0173	0.0805	417	-0.0271	0.0574	0.0682***	0.1126***	0.0180***	0.0411***
Equity Volatility	2646	0.3922	0.3432	776	0.4370	0.3545	417	0.4874	0.4162	-0.0449***	-0.0952***	-0.0113***	-0.0730***
Excess Return	2646	-0.0114	0.0350	776	-0.0661	0.0308	417	-0.1042	-0.0371	0.0546***	0.0928***	0.0041	0.0721***
Interest Coverage	2646	14.9080	5.2461	776	24.5779	6.5782	417	35.9548	10.7402	-9.6699**	-21.0468***	-1.3321***	-5.4941***
Z-score	2646	3.8860	3.2442	776	2.8745	3.5023	417	2.0055	3.5479	1.0115*	1.8805**	-0.2581	-0.3037
Foreign Sales	2646	57.7694	59.9000	776	54.2844	56.4900	417	52.1042	52.1700	3.4850**	5.6651***	3.4100**	7.7300**
Foreign Assets	2335	29.2951	24.6800	713	15.8651	0.0800	362	17.7204	1.8400	13.4301***	11.5747***	24.6000***	22.8400***
Foreign Income	1886	39.9217	32.7100	665	23.5153	0.0000	328	32.3199	6.5700	16.4064***	7.6019***	32.7100***	26.1400***
Foreign Debt	2229	52.1815	56.6200	616	26.6979	0.0000	268	28.4708	0.5900	25.4836***	23.7107***	56.6200***	56.0300***

Similar to Table 5-4, Table 5-5 shows similar results on risk and firm-level characteristics. In particular FC derivative user firms have lower EDF1YEAR and EDF5YEAR than non-FC users based on both mean and median difference tests. These results are as expected and in line with theories and previous findings. We find that FC derivative user firms have statistically higher average leverage ratio, firm size, profitability and excess return than non-FC user firms. We also see that FC derivative user firms have lower liquidity ratio and lower equity volatility than non-FC users. FC derivative users have significantly higher values for foreign exposure variables and lower interest coverage. We find qualitatively similar results when we examine the mean and median difference test between FC derivative users and non-users. These results suggest that FC derivative users firms have significantly higher pre-derivatives measure of exposure and lower post-derivatives measure of firm risk.

Table 5-6: Mean Difference Test and Wilcoxon Rank Sum Test of IR Derivative Users and Non-IR Derivative Users & Non-users

*Table displays the results of tests of mean differences and Wilcoxon Rank Sum Test between IR derivative user firms and non-user firms across firm risk measures and firm-level characteristics. ***, **, * denote significance at the 1%, 5%, or 10% for a two-tailed test.*

Variables	IR Derivative Users			Non-IR Users			Non-Users			Mean Difference Test		Median Difference Test	
	N	Mean (1)	Median (2)	N	Mean (3)	Median (4)	N	Mean (5)	Median (6)	1- 3	1 – 5	2- 4	2 - 6
EDF1Year	2419	1.0369	0.1451	1003	2.0543	0.2807	417	2.7428	0.3232	-1.0173***	-1.7058***	-0.1356***	-0.1781***
EDF5Year	2419	1.0481	0.3269	1003	1.7989	0.5572	417	2.2431	0.5957	-0.7508***	-1.1950***	-0.2302***	-0.2688***
Leverage	2419	0.2619	0.2293	1003	0.1260	0.0431	417	0.1184	0.0284	0.1359***	0.1435***	0.1862***	0.2010***
Firm Size	2419	14.0806	13.9467	1003	12.2859	12.2687	417	11.9623	12.0670	1.7947***	2.1183***	1.6780***	1.8798***
Liquidity	2419	0.8758	0.7700	1003	1.7896	1.1300	417	2.0034	1.1600	-0.9138***	-1.1276***	-0.3600***	-0.3900***
Profitability	2419	0.0925	0.0982	1003	0.0157	0.0865	417	-0.0271	0.0574	0.0769***	0.1197***	0.0117***	0.0408***
Equity Volatility	2419	0.3789	0.3331	1003	0.4590	0.3867	417	0.4874	0.4162	-0.0801***	-0.1085***	-0.0536***	-0.0831***
Excess Return	2419	-0.0118	0.0363	1003	-0.0528	0.0203	417	-0.1042	-0.0371	0.0409*	0.0924***	0.0161	0.0735***
Interest Coverage	2419	10.5321	4.7241	1003	32.9429	9.7750	417	35.9548	10.7402	-22.4108***	-25.4227***	-5.0509***	-6.0161***
Z-score	2419	3.20001	3.0961	1003	4.7577	4.1322	417	2.0055	3.5479	-1.5576***	1.19451	-1.0361***	-0.4518
Foreign Sales	2419	56.7949	58.9700	1003	57.4233	59.4400	417	52.1042	52.1700	-0.6284	4.6907***	-0.4700	6.8000**
Foreign Assets	2241	28.0604	23.2000	807	20.85823	11.3700	362	17.7204	1.8400	7.2022***	10.3399***	11.8300***	21.3600***
Foreign Income	1854	36.8975	24.0750	697	32.31301	11.4400	328	32.3199	6.5700	4.5845***	4.5776*	12.6350***	17.5050***
Foreign Debt	2150	47.6980	49.2450	695	43.46439	37.7700	268	28.4708	0.5900	4.2336**	19.2272***	11.4750**	48.6550***

Table 5-6 shows that IR derivative user firms have statistically lower interest coverage, liquidity and equity volatility than non-IR users. We also find that the mean difference for foreign sales is not statistically different between IR derivative users and non-IR derivatives users. These show that IR derivatives are used to manage interest rate. In the same table, we examine mean and median differences between IR derivative users and non-users, where we remove firms that use derivatives other than IR. The mean and median differences are larger once we remove other derivative users from non-users sample. As expected, we find that the mean difference on probability of default is lower for IR only derivative users than non-users for both EDF1YEAR and EDF5YEAR under means and medians difference tests. Consistent with the economies of scale argument we find that IR derivative user firms are bigger than non-user firms. IR derivative user firms are more profitable and have more excess return. Average leverage ratio is statistically higher for IR derivative user firms than non-user firms. IR only derivative users have significantly lower equity volatility and interest coverage.

Table 5-7: Mean Difference Test and Wilcoxon Rank Sum Test of IR Derivative Only Users and FC Derivative Only Users

*Table displays the results of tests of mean differences and Wilcoxon Rank Sum Test between IR derivative only user firms and FC Derivative only user firms across firm risk measures and firm level characteristics. ***, **, * denote significance at the 1%, 5%, or 10% for a two-tailed test.*

Variables	IR Derivative Only Users			FC Derivative Only Users			Difference Test	
	N	Mean (1)	Median (2)	N	Mean (3)	Median (4)	Mean (1)-(3)	Median (2)-(4)
EDF1Year	330	1.8042	0.1678	556	1.6114	0.2591	0.1928	-0.0913**
EDF5Year	330	1.6329	0.3893	556	1.5182	0.5429	0.1147	-0.1536**
Leverage	330	0.3044	0.2473	556	0.1295	0.0509	0.1749***	0.1964***
Firm Size	330	12.9769	13.0505	556	12.0176	12.2160	0.9593***	0.8345***
Liquidity	330	0.7287	0.6300	556	1.6552	1.1100	-0.9265***	-0.48***
Profitability	330	0.0632	0.0870	556	0.0437	0.0903	0.0195	-0.0033**
Equity Volatility	330	0.3830	0.3051	556	0.4419	0.3787	-0.0589***	-0.0736***
Excess Return	330	-0.0295	0.0757	556	-0.0238	0.0400	-0.0057	0.0357
Interest Coverage	330	10.8726	3.8470	556	31.0347	8.9679	-20.1621***	-5.1209***
Z Score	330	3.7467	3.4923	556	6.5365	4.4681	-2.7898***	-0.9758**
Foreign Sales	330	56.4346	58.8700	555	61.4800	65.3900	-5.0454	7.62
Foreign Assets	331	13.3839	0.0000	419	23.2316	15.4000	-9.8477***	-15.4***
Foreign Income	317	13.8989	0.0000	347	32.1222	17.4500	-18.2233***	-17.45***
Foreign Debt	330	24.2661	0.0000	400	52.6395	58.0800	-28.3734***	-58.08***

In Table 5-7, we report univariate tests for differences for IR only derivative users and FC only derivative users. We believe this categorisation of derivative users is helpful when trying to disentangle pre and post-derivative measures of financial risk, in effect to identify which measures of financial risk are pre and post derivative. Our results show that firms that only use FC derivatives possess lower EDFs (i.e., default probabilities) than non-users, which implies they have lower credit risk. These firms also possess higher Z-scores, which also indicates lower credit risk. For firms that use IR derivatives only the results are a little different. Like FC only derivative users IR only derivative users have lower default probabilities than non-users, which suggest they have lower credit risk, however, unlike FC only users, IR only derivative users possess lower Z-scores than non-users, implying they have higher credit risk. Both of these categories of derivative user have lower default probabilities than non-users but their results for Z-score differ in a manner, which is consistent with Z-score being a pre-derivative measure of credit risk. We would argue that the lower Z-score for IR only users explains why they use IR derivatives and the higher Z-score of FC only derivative users explains why they do not use IR derivatives, the former need to use IR derivatives because they possess a high level of pre-derivative credit risk whereas the latter have no need to use IR derivatives because they have low pre-derivative level of credit risk as indicated by the high Z-score. Both IR only and FC only derivative users possess lower default probabilities than non-users, which we argue is consistent with our measure of default probability being a post-derivative measure of credit risk. The results in Table 5-7 suggest that other measures of credit risk also seem to display characteristics consistent with being pre-derivative indicators of credit risk. For example, the median leverage for IR derivative only users is nearly five times that of FC derivative only users, the median interest coverage for IR derivative only users is less than half the median level of FC derivative only users and the median liquidity for IR derivative only users is just over half the median level of FC derivative only users. All these results are consistent with these measures of credit risk being pre-derivative.

These results provide some support for the argument that firms are using derivatives for hedging rather than speculating with derivatives.

5.4.2. Multivariate Tests

The previous section showed the results of tests of differences in mean and median between derivative users and non-users for various default measures and firm-level characteristics. However, the problem with univariate tests is that they do not control for the correlations between different firm characteristics and hence, cannot show differences in these characteristics, holding other firm-level attributes constant. Therefore, in this section we use multivariate tests to control the correlation between different firm characteristic variables while holding other firm-level attributes constant. We have used binary measures of derivative use in multivariate tests.

5.4.2.1. Impact of Derivative Use on the Probability of Default

We examine the effects of all derivatives use on the probability of default using various regression models such as OLS, RE, FE and FD.

Table 5-8 presents the results of FE and first difference regressions from equation [13]. The main variable of interest is a dichotomous variable representing derivatives use. The dependent variable is EDF1YEAR in panel A and EDF5YEAR in panel B. Prior to discussing our regression results, we present the results of a F-test, the Breusch and Pagan LM test and a hausman test to choose the best model. The results of the F-test are provided under FE model in

Table 5-8 for both EDF1YEAR and EDF5YEAR. The F-tests in panel A (*F = 3.7468*) and panel B (*F = 3.9506*) of

Table 5-8 are statistically significant, which suggest a firm-specific effect in data and a significant probability of default difference across different firms that is not accounted for by the explanatory variables. The rejection of the null hypothesis suggests that the FE model is better suited than pooled OLS model. The results of LM test are presented under FE model and are statistically significant implying rejection of null hypothesis for both EDF1YEAR (*p-value* < 0.001) and EDF5YEAR (*p-value* < 0.001). These indicate the differences across units and suggest that random effects model is suitable than pooled OLS model. The results of hausman test between FE and random effects are statistically significant for both EDF1YEAR (*p-value* < 0.001) and EDF5YEAR (*p-value* < 0.001). Based on all the above three tests, we conclude that the FE model is the better choice among OLS, random effects and FE and we therefore discuss results from this model.

In

Table 5-8, we estimate FE within estimates based on firm variation. In this specification, derivative use cannot be a proxy for any unobservable firm factor that reduces the firm's probability of default. Once we include a dummy for each firm in sample, the coefficient on firms' use of derivatives is -0.8653% (*p-value* < 0.05) for EDF1YEAR. The coefficient shows that derivative users have economically and statistically lower EDF1YEAR by 66% (0.8653 as a per cent of mean EDF1YEAR 1.3116) than non-users. The results in panel B of

Table 5-8 also show that derivative users have a statistically and economically lower EDF5YEAR by 41 per cent (0.5145 as a per cent of mean EDF5YEAR 1.2436) than non-users. When we include firm-specific dummies in the FE regression, we are able to explain around 50% (59%) of the variability in firms EDF1YEAR (EDF5YEAR). This suggests derivatives use has a strong, sizable impact on the probability of default. This finding supports the finding of Guay (1999), Bartram (2006), Marin (2013), Bartram et al. (2011) and Magee (2013) who also find that firms use of derivatives lowers the risk.

Regarding the control variables, each of the firm characteristics in the model has expected coefficient and all of them are statistically significant under both panel A and panel B in

Table 5-8. For example, leverage has positive and statistically significant impact on EDF1YEAR and EDF5YEAR, which is consistent with the theories that more debt increases financial risk. Marin (2013), Campbell et al. (2008) and Magee (2013) also find that firms with more leverage have higher measure of financial distress. Profitability has statistically significant positive effect on EDF1YEAR and EDF5YEAR and suggests that firms with higher profits have lower probability of default. Campbell et al. (2008) and Magee (2013) also find that profitability has negative impact on financial distress measure. As expected, large firms have lower probability of default; the coefficient on firm size has negative and statistically significant effect on EDF1YEAR and EDF5YEAR. In unreported regression results, we use the square of size to control for potential nonlinear effects of size and find negative (positive) relationship between firm size and EDF1YEAR for moderate (Larger) firm size. This suggests that the relationship between firm size and probability of default is nonlinear. We find that equity volatility has positive and statistically significant effect on EDF1YEAR and EDF5YEAR. Theories also indicate that firms with higher equity volatility should have higher probability of default. We find that excess return has negative and statistically significant effect on EDF1YEAR and EDF5YEAR. Finally, firms with more liquidity also have lower probability of default.

The inclusion of the firm-specific dummies in the FE model suggests that the firm characteristics that are constant and unobserved over-time cannot affect our results. Thus, the only explanation in which our derivative variable could be a proxy for reduction in the probability of default is if a firm’s probability of default falls over the sample period in unobserved ways. If the firm also starts using derivatives during the sample period, then it could induce a spurious correlation between derivative use and the probability of default.

Table 5-8: Impact of Derivative Use on the Probability of Default

*This table presents the results of FE and FD regressions of Derivatives on the probability of default. In panel A we use **EDF1YEAR** as the probability of default in 1-year time and in panel B we use **EDF5YEAR** as the probability of default in 5-years time five-year probability of default. **All Derivative Users** is a dummy variable set equal to 1 if a firm uses derivatives and 0 otherwise. **Leverage** is the ratio of total debt to market value of assets. **Profitability** is measured as return on invested capital, which is calculated as the sum of pre-tax profits and total interest charges divided by invested capital. **Firm size** is a natural logarithm of total assets. **Equity volatility** is expressed as square root of number of trading days multiplied by standard deviation of natural log of the daily price growth rate. **Excess Return** is the annual return on the firm minus the value weighted FTSE all shares index annual return over the entire fiscal year. **Liquidity** is the ratio of total current assets minus total stock & work in progress over total current liabilities. In parentheses are standard errors adjusted for heteroskedasticity (White (1980)) and clustering at the firm level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. The regressions also include year and industry dummies.*

VARIABLES	*PANEL A: EDF1YEAR*		*PANEL B: EDF5YEAR*	
	(1) FE	*(2) FD*	*(3) FE*	*(4) FD*
All Derivative Users	-0.8653**	-0.6777**	-0.5145**	-0.4327**
	(0.356)	(0.301)	(0.200)	(0.170)
Leverage	9.9778***	12.4190***	7.2328***	8.6383***
	(1.224)	(1.554)	(0.714)	(0.892)
Profitability	-1.1342*	-1.0342*	-0.7648*	-0.6946*
	(0.634)	(0.613)	(0.390)	(0.374)
Firm Size	-1.0954***	-0.6211***	-0.8521***	-0.4191***
	(0.159)	(0.223)	(0.102)	(0.142)
Equity Volatility	4.8616***	3.0445***	3.6286***	2.2595***
	(0.610)	(0.817)	(0.373)	(0.494)
Excess Return	-1.0744***	-1.4753***	-0.7014***	-0.9827***
	(0.161)	(0.209)	(0.098)	(0.118)
Liquidity	-0.1459*	-0.0726	-0.1000*	-0.0398
	(0.078)	(0.106)	(0.056)	(0.083)
Constant	13.1694***	0.1883	10.3889***	0.1557
	(2.233)	(0.254)	(1.407)	(0.147)
N	3,422	2,947	3,422	2,947
R^2	0.5081	0.4146	0.5931	0.4837
F-Test Heterogeneity	3.7468		3.9506	
LM Test	0.0000		0.0000	
Hausman Test	0.0000		0.0000	

To test this hypothesis, we estimate a first difference version of the model. The first difference estimator uses the one-period changes for each firm.[116]

If, during the sample period, a firm's probability of default is decreasing in unobservable ways, then the estimate of FE model in column 1 of

[116] *In this regression estimation we lose the first observations for each firm because of differencing and we have* $N\ (T-1)$ *observations.*

Table 5-8 will be much larger than the estimate under first difference model, column 2. The first difference coefficient is the difference between EDF1YEAR in the first year the firm uses derivatives and the EDF1YEAR in the previous year. Our results show that the first difference coefficient, -0.6777, is relatively larger compared to the within estimate -0.8653 for EDF1YEAR. A comparison of the coefficients shows that an economically significant 78% (-0.6777 as a per cent of-0.8653) of the reduction in EDF1YEAR is accounted for in the first year the firm starts using derivatives. Similarly, 84% (-0.4327 as a per cent of -0.5145) of economically significant reduction in EDF5YEAR is witnessed in the first year the firms start using derivatives. This result highlights the importance of derivatives in reducing the probability of default. We would argue that the only way our finding could be driven by unobserved financial risk factors is, if these factors are constant across time, then change dramatically in the year the firm starts using derivatives, and finally then remain constant for the rest of the sample period.

5.4.2.2. Impact of FC Derivatives Use on the Probability of Default

In this study we also examine separately the impact of FC and IR derivative use on the probability of default. We begin by looking at the impact of FC derivative use on EDF1YEAR and EDF5YEAR.

Table 5-9 shows the regression results of FC derivatives use on both EDF1YEAR and EDF5YEAR. The main variables of interests are the derivatives dummy 1) FC derivatives use dummy, which is set equal to 1 if a firm uses FC derivatives and 0 for non-FC derivative users (includes "other" derivative users firms which are those firms that use derivatives other than FC such as IR and/or CP) 2) FC derivatives use dummy, which is set equal to 1 if a firm uses FC derivatives and 0 for non-users derivative users (excludes "other" derivative users).[117] The results for EDF1YEAR are reported in panel A and EDF5YEAR are reported in panel B of

[117] *We argue that the inclusion of these firms, referred to as "other" derivative user firms, in the non-user firms' sample might potentially bias the results against finding particular hypothesized relationships. Since majority of "other" derivative users are interest rate derivative users, this might make it difficult to detect a meaningful relationship between FC derivative user and probability of default as probability of default might have greater relevance with IR derivative user.*

Table 5-9 for FE and FD models. In unreported results we use OLS and RE model and employ 3 tests to select the best model among OLS, RE and FE.[118] The results support FE model and hence we discuss these results only.

[118] *See section 3.5.4 for more details*

Table 5-9: Impact of FC Derivative Use on the Probability of Default

This table presents the results of FE & FD regressions of FC Derivatives use on the probability of default. In panel A we use ***EDF1YEAR*** *as the probability of default in 1-year time and in panel B we use* ***EDF5YEAR*** *as the probability of default in 5-years time five-year probability of default.* ***FC Derivative Users (B)*** *is dummy variables set equal to 1 if a firm uses FC derivatives and 0 otherwise.* ***FC Derivative Users (UB)*** *is dummy variables set equal to 1 if a firm uses FC derivatives and 0 for non-users.* ***Leverage*** *is the ratio of total debt to market value of assets.* ***Profitability*** *is measured as return on invested capital, which calculated as the sum of pre-tax profits and total interest charges divided by invested capital.* ***Firm size*** *is a natural logarithm of total assets.* ***Equity volatility*** *is expressed as square root of number of trading days multiplied by standard deviation of natural log of the daily price growth rate.* ***Excess Return*** *is the annual return on the firm minus the value weighted FTSE all shares index annual return over the entire fiscal year.* ***Liquidity*** *is the ratio of total current assets minus total stock & work in progress over total current liabilities. In parentheses are standard errors adjusted for heteroskedasticity (White (1980)) and firm clustering. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. The regressions also include year and industry dummies.*

	PANEL A: EDF1YEAR				PANEL B: EDF5YEAR			
Variables	*(1) FE*	*(2) FD*	*(3) FE*	*(4) FD*	*(5) FE*	*(6) FD*	*(7) FE*	*(8)FD*
	FC Derivative Users (B)		*FC Derivative Users (UB)*		*FC Derivative Users (B)*		*FC Derivative Users (UB)*	
FC Derivatives	-0.4886**	-0.3964*	-0.9759**	-0.8079**	-0.3195**	-0.2508**	-0.5627**	-0.4811**
	(0.236)	(0.204)	(0.422)	(0.379)	(0.140)	(0.119)	(0.241)	(0.214)
Leverage	9.8419***	12.3910***	9.0324***	12.0065***	7.1516***	8.6203***	6.5955***	8.3527***
	(1.215)	(1.554)	(1.340)	(1.674)	(0.709)	(0.891)	(0.792)	(0.959)
Profitability	-1.1336*	-1.0475*	-1.2145*	-0.9548	-0.7637*	-0.7032*	-0.8721**	-0.6727*
	(0.637)	(0.613)	(0.682)	(0.646)	(0.392)	(0.374)	(0.420)	(0.395)
Firm Size	-1.1073***	-0.6227***	-0.9977***	-0.6111***	-0.8569***	-0.4201***	-0.7952***	-0.4154***
	(0.161)	(0.223)	(0.156)	(0.222)	(0.102)	(0.142)	(0.100)	(0.142)
Equity Volatility	4.9053***	3.0315***	4.8527***	3.2600***	3.6553***	2.2511***	3.5385***	2.3837***
	(0.609)	(0.813)	(0.679)	(0.868)	(0.372)	(0.492)	(0.417)	(0.530)
Excess Return	-1.0801***	-1.4758***	-1.1054***	-1.4478***	-0.7055***	-0.9830***	-0.7215***	-0.9597***
	(0.161)	(0.208)	(0.169)	(0.224)	(0.098)	(0.118)	(0.102)	(0.126)
Liquidity	-0.1401*	-0.0720	-0.1415*	-0.0762	-0.0966*	-0.0394	-0.1015*	-0.0416
	(0.077)	(0.106)	(0.081)	(0.114)	(0.056)	(0.083)	(0.059)	(0.089)
Constant	12.9512***	0.1873	12.1856***	0.0446	10.2517***	0.1551	9.8713***	0.1028
	(2.220)	(0.255)	(2.222)	(0.273)	(1.398)	(0.147)	(1.389)	(0.156)
N	3,422	2,947	3,063	2,585	3,422	2,947	3,063	2,585
R^2	0.5066	0.4141	0.4818	0.4053	0.5921	0.4976	0.5683	0.4729
F-Test Heterogeneity	0.0000		0.0000		0.0000		0.0000	
LM Test	0.0000		0.0000		0.0000		0.0000	
Hausman Test	3.7884		3.8570		3.9956		4.0383	

Column 1 in

Table 5-9 presents the results of FE model for EDF1YEAR for FC derivatives use. Consistence with the expectations of this study, we find that FC derivative users have statistically lower EDF1YEAR. The coefficient value for FC derivative use is -0.4886% (p-value < 0.05) suggesting that FC derivative users have 37% (0.4886 as a per cent of mean EDF1YEAR 1.3116) lower probability of default than non-FC derivative users. The coefficient on FC derivatives use in column 5 of panel B for EDF5YEAR shows similar results. However, the reduction in EDF5YEAR as a result of firms FC derivatives use is about 25% (0.3195 as a per cent of mean EDF5YEAR 1.2436) than non-user firms, which is lower than the reduction observed for EDF1YEAR. All of the control variables are significant and have expected sign. We also use first difference model (column 2 of

Table 5-9) for FC derivative users. The coefficient on first difference model is -0.3964 for EDF1YEAR. The comparison of this coefficient with the coefficient on FE model shows that 81% (-0.3964 as a per cent of -0.4886) reduction in EDF1YEAR is accounted for in the first year the firms started using FC derivatives. Similarly, a reduction of 78% (-0.2508 as a per cent of -0.3195) is observed for EDF5YEAR in the first year firms started using FC derivatives (column 6 of

Table 5-9).

In

Table 5-9 we also use FC users where we remove “other” derivative users from the sample of non- derivative and remove the bias from the non-user sample. When we compare these results with the results where non-users include “Other” users, we detect the effect of bias. The coefficient on FC derivative use is now bigger and almost double for EDF1YEAR. The FC derivatives use coefficient under FE model in column 3 increases to -0.9759 per cent after we remove the bias. This result suggests that FC derivative users have 74% (0.9759 as a per cent of mean EDF1YEAR 1.3116) lower probability of default than non-user firms where as it is 37% when the non-users sample includes “other” users. Column 7 also suggests that FC derivatives users have 45% (0.5627 as a per cent of mean EDF5YEAR 1.2436) lower EDF5YEAR than non-users. The reduction in EDF1YEAR in the first year of derivatives use is 83% (-0.8079 as a per cent of -0.9759), a 2% increase after we removed “Other” derivative users from non-users sample. For EDF5YEAR the reduction in first year of derivative use is 85% (-0.4811 as a per cent of -0.5627), an increase of 7% after “other” derivative users are removed from non-users. We find that all of the control variables have expected sign and majority of them are statistically significant. Overall, the results from

Table 5-9 show that FC derivative users have statistically and economically lower probability of default than non-users.

5.4.2.3. Impact of IR Derivatives Use on the Probability of Default

Table 5-10 shows the regression results of IR derivatives use on both EDF1YEAR and EDF5YEAR. Following similar methodology to FC we use 1) IR derivatives use dummy, which is set equal to 1 if a firm uses IR derivatives and 0 for non-IR derivative users (includes "other" derivative users firms which are those firms that use derivatives other than IR such as FC and/or CP) 2) IR derivatives use dummy, which is set equal to 1 if a firm uses IR derivatives and 0 for non-users derivative users (excludes "other" derivative users). The results from F-test, Breusch and Pagan LM test and over identification tests are presented under the FE model and suggest that the FE model is best suitable to the data.

Table 5-10: Impact of IR Derivative Use on the Probability of Default

*This table presents the results of FE & FD regressions of IR derivatives use on the probability of default. In panel A we use **EDF1YEAR** as the probability of default in 1-year time and in panel B we use **EDF5YEAR** as the probability of default in 5-years time five-year probability of default. **IR Derivative Users (B)** is dummy variable set equal to 1 if a firm uses IR Derivatives and 0 otherwise. **IR Derivative Users (UB)** is dummy variable set equal to 1 if a firm uses IR Derivatives and 0 for non-users. **Leverage** is the ratio of total debt to market value of assets. **Profitability** is measured as return on invested capital, which calculated as the sum of pre-tax profits and total interest charges divided by invested capital. **Firm size** is a natural logarithm of total assets. **Equity volatility** is expressed as square root of number of trading days multiplied by standard deviation of natural log of the daily price growth rate. **Excess Return** is the annual return on the firm minus the value weighted FTSE all shares index annual return over the entire fiscal year. **Liquidity** is the ratio of total current assets minus total stock & work in progress over total current liabilities. In parentheses are standard errors adjusted for heteroskedasticity (White (1980)) and firm clustering. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. The regressions also include year and industry dummies.*

Variables	*PANEL A: EDF1YEAR*				*PANEL B: EDF5YEAR*			
	(1) FE	*(2) FD*	*(3) FE*	*(4) FD*	*(5) FE*	*(6) FD*	*(7) FE*	*(8)FD*
	IR Derivative Users (B)		*IR Derivative Users (UB)*		*IR Derivative Users (B)*		*IR Derivative Users (UB)*	
IR Derivative Users	-0.5178**	-0.3903*	-1.0382**	-0.5518*	-0.3156**	-0.2981**	-0.6426**	-0.3881*
	(0.244)	(0.234)	(0.447)	(0.324)	(0.149)	(0.145)	(0.257)	(0.212)
Leverage	9.9854***	12.4185***	9.3490***	11.5991***	7.2393***	8.6432***	6.7776***	8.0013***
	(1.234)	(1.552)	(1.377)	(1.778)	(0.720)	(0.891)	(0.799)	(1.025)
Profitability	-1.1761*	-1.0537*	-1.0397	-0.5912	-0.7902**	-0.7057*	-0.6908	-0.4492
	(0.633)	(0.614)	(0.701)	(0.708)	(0.389)	(0.374)	(0.423)	(0.428)
Firm Size	-1.1134***	-0.6247***	-1.1672***	-0.8677**	-0.8623***	-0.4221***	-0.9243***	-0.5241**
	(0.162)	(0.224)	(0.206)	(0.378)	(0.103)	(0.143)	(0.134)	(0.238)
Equity Volatility	4.8417***	3.0133***	4.9779***	3.7833***	3.6160***	2.2401***	3.7579***	2.7447***
	(0.610)	(0.812)	(0.762)	(1.033)	(0.373)	(0.492)	(0.460)	(0.625)
Excess Return	-1.0758***	-1.4786***	-1.0856***	-1.3456***	-0.7023***	-0.9847***	-0.7117***	-0.9290***
	(0.161)	(0.209)	(0.183)	(0.231)	(0.098)	(0.118)	(0.114)	(0.137)
Liquidity	-0.1458*	-0.0740	-0.1249	-0.0240	-0.1000*	-0.0406	-0.0489	0.0185
	(0.077)	(0.106)	(0.109)	(0.133)	(0.056)	(0.082)	(0.074)	(0.103)
Constant	13.0309***	0.1948	14.2499***	0.2484	10.3059***	0.1608	11.4179***	0.1845
	(2.231)	(0.255)	(2.914)	(0.275)	(1.403)	(0.147)	(1.872)	(0.165)
N	3,422	2,947	2,836	2,358	3,422	2,947	2,836	2,358
R^2	0.5071	0.4141	0.4991	0.3946	0.5923	0.4977	0.5863	0.4860
F-Test	3.7058		3.8325		3.8958		3.8522	

Heterogeneity				
LM Test	0.0000	0.0000	0.0000	0.0000
Hausman Test	0.0000	0.0000	0.0000	0.0000

The results are consistent with our earlier results and suggest that IR derivative user firms have 39% (0.5168 as a per cent of mean EDF1YEAR 1.3116) lower EDF1YEAR and 25% (0.3156 as a per cent of mean 1.2436 in EDF5YEAR) lower EDF5YEAR than non-IR users. Compared to FC derivatives use the reduction in EDF1YEAR is bigger for IR derivatives use. This may not be surprising as probability of default measures firms probability of failure on its debt covenants and IR derivatives are used to manage the interest rate exposure that reduces firm's risk and hence lower probability of default. With regards to control variables, all of them attract expected sign and all are significant at least at 10%. The results from first difference model show that in the first year of initiation of IR derivatives use a reduction of 75% (0.3903 as a per cent of 0.5178) and 94% (0.2981 as a per cent of 0.3156) is observable for EDF1YEAR and EDF5YEAR respectively. Majority of the control variables are significant under FE model and have predicted sign.

Table 5-10 also shows that when we remove the "other" users from the non-user sample, the results improved significantly. The impact of IR derivatives use on EDF1YEAR increased and it shows that IR derivative users have 79% (51%) lower EDF1YEAR (EDF5YEAR) while the reduction in EDF1YEAR (EDF5YEAR) in the first year of IR derivatives use is 53% (60%) than non-users. As discussed above we expect that IR derivatives may have higher relevance with the probability of default. Our findings suggest that the use of IR derivatives have significant negative effect on the probability of default.

5.4.2.4. Impact of Different Combinations of Derivatives Use on The Probability of Default

Hedging theory suggests that firms that use derivatives have greater expertise and lower transaction costs in entering into derivatives contract (Géczy et al., 1997) and hence they are more likely to use different types of derivatives. We argue that if derivatives are used for hedging than we expect that firms that use different derivative instruments to manage their exposure may benefit more as a result of larger reduction in the probability of default.

The regressions in Table 5-11 are analysed using different categories of derivatives.[119] The results in columns 1 to 2 are for EDF1YEAR. The result in column 1 shows that one type, two types and three types of derivatives users have statistically lower probability of default than non-users. The results show that the probability of default is 0.78% to 0.99% lower for various types of derivative users than non-users. In terms of economic significance it shows that the use of one type of derivatives reduces EDF1YEAR by 59%, two types of derivatives use reduces EDF1YEAR by 75% and three types of derivatives reduces EDF1YEAR by 65%.[120] Our results suggest that two types of derivatives use has largest negative impact on EDF1YEAR. There are very few firms in our sample that use three types of derivatives together and that could be the reason that we have a smaller reduction in EDF1YEAR as a result of three types of derivatives use compare to the use of two types of derivatives. In column 3, panel B, we repeat the analysis for EDF5YEAR and find qualitative similar results.

In column 2 and 4 of Table 5-11 we use the subcategories of one type of derivatives and two types of derivatives. The results show that firms that use FC derivatives and IR derivatives have significantly lower EDF1YEAR than non-users. The coefficient sign on CP only is negative; however, we fail to find any significant effect of CP derivatives on EDF1YEAR. FC only derivative use reduces EDF1YEAR of user firms by 58% while IR only derivatives use reduces EDF1YEAR by 62%. Under the two types of derivative user breakup, FC&IR and IR&CP have statistically significant negative effect on EDF1YEAR. In economic terms the reduction in EDF1YEAR is 75% for FC&IR derivatives users while 85% for firms that use IR&CP. It is important to note that there are very few firms that use both IR&CP derivatives and that the reduction is in EDF1YEAR may be driven by IR derivatives use as CP only derivatives on its own has no significant impact on EDF1YEAR. The coefficient on FC&CP is negative but not significant. The coefficient on three types of derivatives user is still negative and significant. We observe similar signs on coefficients of various derivative variables for EDF5YEAR. All other control variables have expected sign and are significant. Overall, our results suggest that IR derivative user

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[119] See Section 5.2.3 for more details

[120] The percentage reduction in probability of default is calculated as coefficient value as a per cent of mean EDF1YEAR or EDF5YEAR.

firms have larger negative effect on the probability of default than other types of derivative user firms.

Table 5-11: Impact of Different Combinations of Derivatives Use on The Probability of Default

*This table presents the results of FE regressions of different derivatives variables on the probability of default. In panel A we use **EDF1YEAR** as the probability of default in 1-year time and in panel B we use **EDF5YEAR** as the probability of default in 5-years time five-year probability of default. **One Type of Derivative User** is dummy variables set equal to 1 if a firm use either FC only or IR only or CP only derivatives and 0 otherwise. **Two Types of Derivatives User** is a dummy variable set equal to 1 if a firm uses either FC&IR or FC&CP or IR&CP derivatives and 0 otherwise. **Three Types of Derivatives User** is a dummy variable set equal to 1 if a firm uses FC and IR and CP derivatives and 0 otherwise. **Leverage** is the ratio of total debt to market value of assets. **Profitability** is measured as return on invested capital, which calculated as the sum of pre-tax profits and total interest charges divided by invested capital. **Firm size** is a natural logarithm of total assets. **Equity volatility** is expressed as square root of number of trading days multiplied by standard deviation of natural log of the daily price growth rate. **Excess Return** is the annual return on the firm minus the value weighted FTSE all shares index annual return over the entire fiscal year. **Liquidity** is the ratio of total current assets minus total stock & work in progress over total current liabilities.. In parentheses are standard errors adjusted for heteroskedasticity (White (1980)) and firm clustering. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. The regressions also include year and industry dummies.*

VARIABLES	*PANEL A: EDF1YEAR*		*PANEL B: EDF5YEAR*	
	(1)FE	*(2)FE*	*(3)FE*	*(4)FE*
One Type Of Derivative Used	-0.7805**		-0.4511**	
	(0.349)		(0.193)	
CP Derivative		-0.4009		-0.1441
		(0.811)		(0.472)
FC Derivative		-0.7611**		-0.4594**
		(0.367)		(0.205)
IR Derivative		-0.8188**		-0.4503**
		(0.405)		(0.229)
Two Types Of Derivative Used	-0.9869**		-0.6055***	
	(0.392)		(0.227)	
FC & CP		-0.1113		-0.0396
		(0.493)		(0.315)
IR & CP		-1.1240**		-0.7351**
		(0.449)		(0.306)
FC & IR		-0.9961**		-0.6119***
		(0.394)		(0.228)
Three Types Of Derivative Used	-0.8537**	-0.8127*	-0.5065**	-0.4819*
	(0.434)	(0.432)	(0.257)	(0.255)
Leverage	9.9958***	10.0139***	7.2462***	7.2516***
	(1.225)	(1.230)	(0.713)	(0.717)
Profitability	-1.1417*	-1.1427*	-0.7704**	-0.7691**
	(0.632)	(0.631)	(0.389)	(0.389)
Firm Size	-1.0868***	-1.0886***	-0.8456***	-0.8461***
	(0.161)	(0.160)	(0.103)	(0.102)
Equity Volatility	4.8539***	4.8560***	3.6228***	3.6269***
	(0.609)	(0.610)	(0.373)	(0.373)
Excess Return	-1.0791***	-1.0801***	-0.7049***	-0.7061***
	(0.160)	(0.160)	(0.097)	(0.097)
Liquidity	-0.1464*	-0.1488*	-0.1003*	-0.1018*
	(0.078)	(0.078)	(0.057)	(0.057)
Constant	13.1100***	13.1327***	10.3442***	10.3505***
	(2.246)	(2.242)	(1.413)	(1.409)
N	3,422	3,422	3,422	3,422
R^2	0.5085	0.5088	0.5935	0.5938
F-Test Heterogeneity	3.7191	3.6962	3.9227	3.8952
LM Test	432.66	425.58	450.23	442.58
Hausman Test	91.035	92.963	111.613	112.907

5.4.3. Credit Risk Conditions and The Effect of Derivatives Use on the Probability of Default

In this section we take different approach to examine the link between macroeconomic conditions and the impact of derivatives use on firms' probability of default. We use economy-wide measures of firms' ability to service their debt as proxies for market–wide credit risk. We interact our derivative variables with these aggregate indicators of economic and financial wellbeing. We use several proxies for aggregate credit risk conditions in the UK. Our regression specification now includes interaction terms between derivative use and various proxies for changes in aggregate credit risk conditions.

In equation [14] we use several measures of credit market conditions.[121] In particular, we use corporate capital gearing, interest payment, default spread, debt relative to profit, income gearing and Deloitte stress index. We include annual GDP growth rate to control for macroeconomic conditions. All of the credit market condition proxies are standardised.[122] This facilitates an easy interpretation of the coefficients and suggests % change in EDF1YEAR and EDF5YEAR for a one standard deviation change in the credit market proxies. Definitions and sources of these proxies are defined in section 3.3.4.

In the regression analysis that follows, we interact our derivative variables with the aggregate credit risk variables (see equation [14]). A negative coefficient on our derivative interaction term will show that at higher levels of credit risk the negative difference in the probability of default between derivative users and non-users increases. In effect the analyses will show whether derivatives use leads to a greater reduction in the probability of default at higher levels of credit risk, that is, when firms are more financially vulnerable. It is conceivable that firms that use derivatives for hedging will employ derivatives more intensively during periods of high credit risk. If this is the case, then the impact of derivatives on the probability of default should be greater during these periods and we would expect a significant negative value for our derivative-credit risk interaction term.

Our key variables of interest are the interaction terms between derivatives use and proxies for aggregate credit risk conditions. Consistent with our earlier results, we use pooled

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[121] *All the variables are winsorised at 1% from both tails to control for the outliers.*

[122] *We subtract sample mean from actual values and divide it by standard deviation for each variable*

OLS, RE and FE regression methodology with standard errors adjusted for clustering at the firm level. To avoid redundancy, we only discuss the results of the best model based on the tests.[123] This controls for the residual correlation across years for a given firm and is an alternative method to the FE demeaning method to control for each firm's individual characteristics.[124]

The regression results, for EDF1YEAR as dependent variable, are presented in panel A and EDF5YEAR are presented in panel B of Table 5-12 to Table 5-14. In Table 5-12, we interact credit risk proxies with all derivatives use. We expect that un-interacted credit risk proxies to have positive impact on EDF1YEAR and EDF5YEAR since, all else equal, probability of default should be higher in the period of higher levels of credit risk. This is what we find in Table 5-12. The results show the coefficients on credit risk proxies are positive and statistically significant. The coefficient values range from 0.3637 to 0.6146 for EDF1YEAR and 0.2565 and 0.5057 for EDF5YEAR. These suggest that a one standard deviation increase in credit risk proxies increases EDF1YEAR by 27.73% to 46.86% of the mean EDF1YEAR and 20.68% and 40.78% of the mean in EDF5YEAR for non-users. Consistent with our expectations and hedging theories, the coefficient on interaction term between derivatives use and credit risk proxies is negative and statistically significant for all credit risk proxies for EDF1YEAR and EDF5YEAR (except for debt to profit for EDF1YEAR). These suggest that derivatives are valuable during the period of high capital gearing, interest payment than profits, default spread, debt to profit, financial stress and default rate loan. The interaction coefficients suggest that derivative users have statistically lower -0.3763 (28.69% of mean) to -0.7324 (55.84% of mean) for EDF1YEAR and -0.2912 (23.42% of mean) to -0.3845 (30.92% of mean) for EDF5YEAR than non-users during the times of higher credit risk. The coefficients of credit risk proxies and its interaction with derivatives show that the effects of credit risk proxies are mixed in their magnitude for non-derivative users than derivative users, that is higher levels of credit risks increases the probability of default of non-derivative users more/less than they reduce the probability of default of derivative users. As a result, the difference between derivative users and non-users with the credit risk conditions depends on the level of credit risk conditions. This suggests that the magnitude of probability of default difference between

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[123] See section 3.5.4 for more details.
[124] See Chapter 11 for more details of Wooldridge (2002)

firms with and without derivatives is greater in periods of high aggregate credit risk conditions and smaller in periods of low aggregate credit risk conditions. All of the control variables in Table 5-12 have predicted sign and majority of them are highly significant.

We repeat the analysis presented in Table 5-12 for FC derivative users and IR derivative users. The regression results of FC derivative users and non-users are presented in Table 5-13. The results show that the interaction term between FC derivative users and credit risk proxies are negative and highly significant in both panel A and panel B. These suggest that EDF1YEAR and EDF5YEAR of FC derivative users are statistically lower than non-users in the period of high credit risk. The positive and statistically significant coefficient on un-interacted credit risk proxies is consistent with our expectations suggesting higher probability of default during heightened credit risk period. In Table 5-14, we present regression results for IR derivative users and non-users. The results show that the interaction term between IR derivative users and credit market conditions is negative and statistically significant except for debt to profit credit risk proxy.

In summary, our results show that the estimated coefficients on the interaction term between derivative users and aggregate credit risk conditions are negative and significant. These results suggest that derivative is most valuable to firms during the periods of high credit risk conditions when borrowing cost is higher, more chances of firms' bankruptcy and lower chances of profits. Our results provide strong evidence in support of the notion that use of financial derivatives has a greater impact on the probability of default of the firm, and therefore is more important for firms in terms of lowering their probability of default, when financial market conditions are weak or gloomy.

Table 5-12: Credit Market Conditions: The Effects of Derivatives Use on the Probability of Default

*The table presents estimates of equation [14] using annual data of UK listed non-financial firms for the period from 1999 to 2010 using FE Model. The dependent variable is EDF1YEAR in panel A and EDF5YEAR in panel B. **All Derivatives Users** is a dummy variable set equal to 1 if a firm is a derivative user and 0 otherwise. **Corporate Capital Gearing** is defines as debt net of liquid assets relative to the market value of capital. **Interest Payment** is defined as the percentage of firms with interest payments greater than their profits for firms with £1 million turnover. **Default Spread** is the difference between Moody's yield on seasoned AAA and BBB Corporate Bond. **Debt Relative to Profit** is defines as debt net of an estimate of liquid assets, relative to a four-quarter moving sum of gross operating surplus. **Leverage** is the ratio of total debt to market value of assets. **Profitability** is measured as return on invested capital, which calculated as the sum of pre-tax profits and total interest charges divided by invested capital. **Firm size** is a natural logarithm of total assets. **Equity volatility** is expressed as square root of number of trading days multiplied by standard deviation of natural log of the daily price growth rate. **Excess Return** is the annual return on the firm minus the value weighted FTSE all shares index annual return over the entire fiscal year. **Liquidity** is the ratio of total current assets minus total stock & work in progress over total current liabilities. All specifications include annual **GDP** growth rate to control for macroeconomic conditions. GDP growth rate is sourced from the International Monetary Fund (IMF) official website.[125] Standard errors (in parenthesis) are adjusted for heteroskedasticity and clustering by firms. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels respectively.*

	Panel A: EDF1YEAR					Panel B: EDF5YEAR				
VARIABLES	Corporate Capital Gearing	Interest Payment	Default Spread	Debt Relative to Profit	Deloitte Financial Stress Index	Corporate Capital Gearing	Interest Payment	Default Spread	Debt Relative to Profit	Deloitte Financial Stress Index
All Derivative Users	-0.6129**	-0.8314**	-0.8758***	-0.7977**	-0.9827***	-0.3247*	-0.4734**	-0.5180***	-0.4468**	-0.5682***
	(0.310)	(0.363)	(0.334)	(0.331)	(0.354)	(0.174)	(0.207)	(0.189)	(0.184)	(0.199)
All Derivative Users * Corporate Capital Gearing	-0.5408**					-0.3845***				
	(0.235)					(0.146)				
Corporate Capital Gearing	0.6146***					0.4988***				
	(0.220)					(0.140)				
All Derivative Users * Interest Payment		-0.3763*					-0.2912**			
		(0.220)					(0.139)			
Interest Payment		0.3637*					0.3357**			
		(0.207)					(0.132)			
All Derivative Users * Default Spread			-0.7324***					-0.3809***		
			(0.232)					(0.125)		
Default Spread			0.5109**					0.2565**		
			(0.239)					(0.130)		
All Derivative Users *Debt Relative to Profit				-0.4964					-0.3617*	

[125] Available at the official IMF website at http://www.imf.org/external/pubs/ft/weo/2013/02/weodata/index.aspx

				(0.304)					(0.185)	
Debt Relative to Profit				0.6073**					0.5057***	
				(0.283)					(0.173)	
*All Derivative Users * Deloitte Financial Stress Index*					-0.7174***					-0.3516**
					(0.266)					(0.139)
Deloitte Financial Stress Index					0.4782*					0.1718
					(0.253)					(0.132)
Leverage	9.5970***	10.1921***	10.4412***	10.0838***	10.4533***	6.9266***	7.3540***	7.5453***	7.2775***	7.5848***
	(1.151)	(1.222)	(1.224)	(1.212)	(1.212)	(0.655)	(0.712)	(0.713)	(0.701)	(0.704)
Profitability	-1.5170**	-1.4101**	-1.4363**	-1.3756**	-1.3503**	-1.0572***	-0.9788**	-1.0408***	-0.9671**	-0.9351**
	(0.608)	(0.627)	(0.635)	(0.639)	(0.635)	(0.375)	(0.386)	(0.395)	(0.392)	(0.392)
Firm Size	-1.0658***	-1.0657***	-1.0554***	-1.0532***	-1.0626***	-0.8467***	-0.8362***	-0.8590***	-0.8423***	-0.8675***
	(0.164)	(0.160)	(0.160)	(0.156)	(0.162)	(0.100)	(0.102)	(0.104)	(0.099)	(0.104)
Equity Volatility	3.7901***	3.7907***	3.8700***	3.8537***	4.1271***	2.9887***	2.9620***	3.0021***	3.0192***	3.2494***
	(0.485)	(0.473)	(0.505)	(0.474)	(0.527)	(0.306)	(0.297)	(0.316)	(0.299)	(0.328)
Excess Return	-1.1519***	-1.0942***	-1.0786***	-1.1032***	-1.0598***	-0.7517***	-0.6988***	-0.6798***	-0.7025***	-0.6690***
	(0.159)	(0.160)	(0.165)	(0.159)	(0.164)	(0.095)	(0.097)	(0.100)	(0.097)	(0.100)
Liquidity	-0.1554**	-0.1294	-0.1160	-0.1249	-0.1296	-0.0963*	-0.0866	-0.0737	-0.0818	-0.0839
	(0.079)	(0.081)	(0.080)	(0.079)	(0.081)	(0.057)	(0.058)	(0.059)	(0.058)	(0.059)
Constant	12.7261***	12.8631***	12.7987***	12.5731***	12.8188***	10.2725***	10.2587***	10.6415***	10.2316***	10.6692***
	(2.296)	(2.246)	(2.219)	(2.185)	(2.258)	(1.388)	(1.408)	(1.418)	(1.362)	(1.424)
N	3,220	3,422	3,422	3,422	3,422	3,220	3,422	3,422	3,422	3,422
R^2	0.4998	0.4948	0.4987	0.4957	0.5006	0.5873	0.5804	0.5813	0.5821	0.5839
F-Test Heterogeneity	3.6488	3.7357	3.7465	3.7347	3.7857	3.8197	3.9375	3.9468	3.9392	3.9779
LM Test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Hausman Test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 5-13: Credit Market Conditions: The Effects of FC Derivatives Use on the Probability of Default

*The table presents estimates of equation [14] using annual data of UK listed non-financial firms for the period from 1999 to 2010 using FE Model. The dependent variable is EDF1YEAR in panel A and EDF5YEAR in panel B. **FC Derivatives Users (UB)** is a dummy variables set equal to 1 if a firm is a FC derivative user and 0 for non- users. **Corporate Capital Gearing** is defines as debt net of liquid assets relative to the market value of capital. **Interest Payment** is defined as the percentage of firms with interest payments greater than their profits for firms with £1 million turnover. **Default Spread** is the difference between Moody's yield on seasoned AAA and BBB Corporate Bond. **Debt Relative to Profit** is defines as debt net of an estimate of liquid assets, relative to a four-quarter moving sum of gross operating surplus. **Leverage** is the ratio of total debt to market value of assets. **Profitability** is measured as return on invested capital, which calculated as the sum of pre-tax profits and total interest charges divided by invested capital. **Excess Return** is the annual return on the firm minus the value weighted FTSE all shares index annual return over the entire fiscal year. **Equity volatility** is expressed as square root of number of trading days multiplied by standard deviation of natural log of the daily price growth rate. **Firm size** is a natural logarithm of total assets. **Liquidity** is the ratio of total current assets minus total stock & work in progress over total current liabilities. All variables are winzorised at 1% level in order to prevent potential outliers driving the results. All specifications include annual GDP growth rate to control for macroeconomic conditions. Annual GDP growth rate is sourced from the IMF official website.[126] Standard errors (in parenthesis) are adjusted for heteroskedasticity and clustering by firms. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels respectively.*

	Panel A: EDF1YEAR					*Panel B: EDF5YEAR*				
VARIABLES	*Corporate Capital Gearing*	*Interest Payment*	*Default Spread*	*Debt To Profit*	*Deloitte Financial Stress Index*	*Corporate Capital Gearing*	*Interest Payment*	*Default Spread*	*Debt Relative to Profit*	*Deloitte Financial Stress Index*
FC Derivative Users (UB)	-0.6385*	-0.8952**	-0.9747**	-0.8564**	-1.0912***	-0.3176	-0.4909*	-0.5550**	-0.4576**	-0.6134**
	(0.356)	(0.433)	(0.400)	(0.394)	(0.421)	(0.204)	(0.253)	(0.232)	(0.224)	(0.241)
*FC Derivative Users (UB) * Corporate Capital Gearing*	-0.6647***					-0.4648***				
	(0.242)					(0.150)				
Corporate Capital Gearing	0.7357***					0.5820***				
	(0.220)					(0.140)				
*FC Derivative Users (UB) * Interest Payment*		-0.4244*					-0.3181**			
		(0.228)					(0.144)			
Interest Payment		0.4379**					0.3867***			
		(0.212)					(0.135)			
*FC Derivative Users (UB) * Default Spread*			-0.7881***					-0.4258***		
			(0.234)					(0.126)		
Default Spread			0.6345***					0.3370***		

[126] *Available at the official IMF website at http://www.imf.org/external/pubs/ft/weo/2013/02/weodata/index.aspx*

			(0.234)					(0.128)		
*FC Derivative Users (UB) * Debt Relative to Profit*				-0.6005*					-0.4317**	
				(0.317)					(0.193)	
Debt Relative to Profit				0.6922**					0.5672***	
				(0.292)					(0.179)	
*FC Derivative Users (UB) * Financial Stress Index*					-0.7271***					-0.3718***
					(0.270)					(0.141)
Financial Stress Index					0.5027*					0.1903
					(0.257)					(0.135)
Leverage	9.0092***	9.2754***	9.4968***	9.2167***	9.5351***	6.5016***	6.7135***	6.9133***	6.6869***	6.9760***
	(1.229)	(1.341)	(1.333)	(1.318)	(1.322)	(0.712)	(0.790)	(0.788)	(0.772)	(0.780)
Profitability	-1.5156**	-1.4383**	-1.5117**	-1.4270**	-1.4326**	-1.1195***	-1.0629**	-1.1543***	-1.0668**	-1.0476**
	(0.648)	(0.676)	(0.684)	(0.687)	(0.684)	(0.399)	(0.417)	(0.425)	(0.422)	(0.423)
Firm Size	-1.0183***	-0.9859***	-0.9683***	-0.9808***	-0.9919***	-0.8203***	-0.7870***	-0.8108***	-0.8003***	-0.8290***
	(0.160)	(0.157)	(0.157)	(0.154)	(0.162)	(0.098)	(0.099)	(0.102)	(0.097)	(0.104)
Equity Volatility	3.7712***	3.7169***	3.7126***	3.7762***	4.0260***	2.9096***	2.8450***	2.8414***	2.9032***	3.1452***
	(0.532)	(0.506)	(0.555)	(0.510)	(0.580)	(0.334)	(0.318)	(0.347)	(0.322)	(0.361)
Excess Return	-1.1620***	-1.1303***	-1.1255***	-1.1360***	-1.0883***	-0.7588***	-0.7236***	-0.7077***	-0.7241***	-0.6850***
	(0.169)	(0.169)	(0.174)	(0.169)	(0.175)	(0.101)	(0.102)	(0.105)	(0.102)	(0.106)
Liquidity	-0.1448*	-0.1343	-0.1191	-0.1256	-0.1328	-0.0923	-0.0929	-0.0782	-0.0847	-0.0889
	(0.082)	(0.083)	(0.083)	(0.082)	(0.084)	(0.060)	(0.061)	(0.062)	(0.061)	(0.062)
Constant	12.2363***	12.0797***	11.9309***	11.8901***	12.2219***	10.0344***	9.8070***	10.2091***	9.8691***	10.3881***
	(2.240)	(2.215)	(2.173)	(2.157)	(2.263)	(1.342)	(1.372)	(1.391)	(1.332)	(1.418)
N	2,883	3,063	3,063	3,063	3,063	2,883	3,063	3,063	3,063	3,063
R^2	0.4749	0.4689	0.4735	0.4698	0.4748	0.5638	0.5560	0.5564	0.5573	0.5589
F-Test Heterogeneity	3.7102	3.8532	3.8652	3.8531	3.8949	3.8795	4.0355	4.0417	4.0373	4.0661
LM Test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Hausman Test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 5-14: Credit Market Conditions: The Effects of IR Derivatives Use on the Probability of Default

*The table presents estimates of equation [14] using annual data of UK listed non-financial firms for the period from 1999 to 2010 using FE Model. The dependent variable is EDF1YEAR in panel A and EDF5YEAR in panel B. **IR Derivatives Users (UB)** is a dummy variables set equal to 1 if a firm is a IR derivative user and 0 for non- users. **Corporate Capital Gearing** is defines as debt net of liquid assets relative to the market value of capital. **Interest Payment** is defined as the percentage of firms with interest payments greater than their profits for firms with £1 million turnover. **Default Spread** is the difference between Moody's yield on seasoned AAA and BBB Corporate Bond. **Debt Relative to Profit** is defines as debt net of an estimate of liquid assets, relative to a four-quarter moving sum of gross operating surplus. **Leverage** is the ratio of total debt to market value of assets. **Profitability** is measured as return on invested capital, which calculated as the sum of pre-tax profits and total interest charges divided by invested capital. **Excess Return** is the annual return on the firm minus the value weighted FTSE all shares index annual return over the entire fiscal year. **Equity volatility** is expressed as square root of number of trading days multiplied by standard deviation of natural log of the daily price growth rate. **Firm size** is a natural logarithm of total assets. **Liquidity** is the ratio of total current assets minus total stock & work in progress over total current liabilities. All specifications include annual GDP growth rate to control for macroeconomic conditions. Annual GDP growth rate is sourced from the IMF official website.[127] Standard errors (in parenthesis) are adjusted for heteroskedasticity and clustering by firms. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels respectively.*

	Panel A: EDF1YEAR					*Panel B: EDF5YEAR*				
VARIABLES	*Corporate Capital Gearing*	*Interest Payment*	*Default Spread*	*Debt To Profit*	*Deloitte Financial Stress Index*	*Corporate Capital Gearing*	*Interest Payment*	*Default Spread*	*Debt Relative to Profit*	*Deloitte Financial Stress Index*
IR Derivative Users (UB)	-0.7873**	-1.0386**	-1.1180***	-1.0211**	-1.2037***	-0.4539**	-0.6247**	-0.6928***	-0.6100***	-0.7306***
	(0.373)	(0.454)	(0.425)	(0.411)	(0.442)	(0.214)	(0.264)	(0.245)	(0.234)	(0.254)
*IR Derivative Users (UB) * Corporate Capital Gearing*	-0.4793*					-0.3683**				
	(0.247)					(0.153)				
Corporate Capital Gearing	0.5679**					0.4706***				
	(0.229)					(0.145)				
*IR Derivative Users (UB) * Interest Payment*		-0.4275*					-0.3368**			
		(0.219)					(0.139)			
Interest Payment		0.3934*					0.3438**			
		(0.207)					(0.133)			
*IR Derivative Users (UB) * Default Spread*			-0.6750***					-0.3590***		
			(0.242)					(0.136)		
Default Spread			0.3843					0.1908		
			(0.240)					(0.136)		
*IR Derivative Users (UB) * Debt Relative to Profit*				-0.4322					-0.3276	

[127] *Available at the official IMF website at http://www.imf.org/external/pubs/ft/weo/2013/02/weodata/index.aspx*

				(0.330)					(0.199)	
Debt Relative to Profit				0.5690*					0.4813***	
				(0.302)					(0.183)	
*IR Derivative Users (UB) * Financial Stress Index*					-0.6967***					-0.3368**
					(0.267)					(0.144)
Financial Stress Index					0.4128*					0.1456
					(0.247)					(0.133)
Leverage	8.8629***	9.6429***	9.9662***	9.4302***	9.9786***	6.4306***	6.9848***	7.1884***	6.8064***	7.2117***
	(1.243)	(1.355)	(1.375)	(1.349)	(1.350)	(0.706)	(0.789)	(0.800)	(0.778)	(0.784)
Profitability	-1.4954**	-1.3282*	-1.3383*	-1.3048*	-1.2456*	-1.0236***	-0.9050**	-0.9448**	-0.8933**	-0.8470**
	(0.653)	(0.682)	(0.708)	(0.704)	(0.703)	(0.394)	(0.412)	(0.432)	(0.425)	(0.425)
Firm Size	-1.1100***	-1.1018***	-1.0872***	-1.0924***	-1.0789***	-0.9012***	-0.8876***	-0.9048***	-0.8911***	-0.9033***
	(0.211)	(0.201)	(0.207)	(0.196)	(0.206)	(0.133)	(0.131)	(0.136)	(0.128)	(0.135)
Equity Volatility	3.6910***	3.6767***	3.8342***	3.7759***	4.1541***	2.9469***	2.9290***	3.0243***	3.0154***	3.2863***
	(0.623)	(0.617)	(0.653)	(0.616)	(0.676)	(0.390)	(0.381)	(0.405)	(0.381)	(0.414)
Excess Return	-1.1919***	-1.1345***	-1.1133***	-1.1518***	-1.0922***	-0.7747***	-0.7264***	-0.7057***	-0.7392***	-0.6960***
	(0.180)	(0.180)	(0.186)	(0.177)	(0.182)	(0.110)	(0.112)	(0.116)	(0.111)	(0.114)
Liquidity	-0.1271	-0.1202	-0.0905	-0.1071	-0.1033	-0.0379	-0.0446	-0.0237	-0.0336	-0.0313
	(0.111)	(0.112)	(0.112)	(0.109)	(0.114)	(0.074)	(0.074)	(0.077)	(0.073)	(0.077)
Constant	13.6699***	13.6904***	13.5772***	13.4455***	13.2904***	11.2423***	11.1732***	11.4909***	11.1168***	11.3303***
	(3.015)	(2.872)	(2.932)	(2.799)	(2.950)	(1.887)	(1.852)	(1.899)	(1.795)	(1.902)
N	2,661	2,836	2,836	2,836	2,836	2,661	2,836	2,836	2,836	2,836
R^2	24.9876	26.9142	26.3712	27.8841	26.6135	43.6447	46.1649	44.5204	46.8006	45.1199
F-Test Heterogeneity	3.7418	3.8176	3.7958	3.8074	3.8548	3.7208	3.8346	3.8211	3.8258	3.8664
LM Test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Hausman Test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

5.4.4. Time-Varying Effect of Derivatives Use on the Probability of Default

In this section we are interested in examining whether the effect of derivative on a firm's probability of default is influenced by macroeconomic conditions. We interact our derivatives variables with the year dummies (see Equation [15]). This allows the coefficient on our derivatives dummy to vary by year. This analysis will show whether there is any variation in the impact of derivatives on the probability of default over-time and whether it is consistent with changes in macroeconomic circumstances. It is conceivable that firms classified as derivative users will hedge more intensively during periods of economic and financial downturn. If this is the case, then the impact of derivatives use on the probability of default should be greater during these periods and consequently we would expect a larger negative value for our derivatives coefficient at this time. Conversely, firms might undertake less hedging activity with derivatives during favourable macroeconomic conditions in which case we would expect a smaller difference in the probability of default between derivative user and non-user firms. It follows then, that we would expect the absolute value of the derivatives coefficient to fall when macroeconomic and financial market conditions are good.

The regression results are presented in Table 5-15. The results show that the derivative interaction coefficient has mixed sign and not always significantly different from zero. In column 1 of Table 5-15, the derivatives coefficient varies from 0.46% in 2004 to -1.62% in 2009. The results show that the derivatives coefficient is significantly negative in the period 2000 to 2001 and the period 2007 to 2009 and positive during the years 2005 to 2006. This variation in the impact of derivatives on the probability of default seems to follow closely the performance of the UK economy as indicated by the annual GDP growth rate (right-hand scale of Figure 5-4). Although the UK economy was not in recession during 2000 to 2001, there was an economic downturn in several major economies such as the United States and real GDP growth in the UK fell from a peak of 4.36% in the 2000 to 2.18% in 2001 and 2.3% in 2002.

During 2004 to 2006 period macroeconomic conditions were relatively beginning to improve and firms' financial positions improved as profitability increased. This led to a decline in corporate sector credit risks. During this period the coefficient on interaction term on derivatives is positive and significant for year 2005-2006. During 2007 to 2009 period the UK economy experienced a sharp decline and fell into a deep and prolonged recession. This was accompanied by a significant deterioration in credit market conditions, a hike in market-wide IR spreads and an increase in corporate bankruptcies. This economic downturn and recession led to an increase in corporate bankruptcies. Then, we argue that if one of the goals of use of derivatives is to lower the probability of default, then firms that use financial derivatives may have experienced significant benefits in the form of lower probability of default during these periods. Our results show that hedging with derivatives during these periods had a significant negative impact on default probabilities, whereas hedging with derivatives during favourable economic conditions had either a positive impact or very little effect on default probabilities. This is consistent with theory that hedging with derivatives is more valuable during economical and financial downtime.

We get qualitatively similar results when we interact year dummies with FC and IR derivatives. Overall, these findings suggest that there was noticeable difference in probability of default levels between derivative users and non-users firms over this period. These results are consistent with the fact that financial markets were crashed in year 2000 after the corporate corruptions and dotcom bubble and in year 2007 after the sub-prime mortgages. All of our results are highly significant for the year 2008, which is the heart of recent financial crisis. We find qualitatively similar effect of derivatives interaction term on EDF5YEAR.

Regarding the control variables, each of the control variables we use attracts the expected coefficient and majority of them are statistically significant. For example, firms with more leverage and more equity volatility have higher probability of default and firm that have low probability of default are more profitable, are larger, have more excess return and have more liquidity.

In Figure 5-4, we plot the yearly derivative coefficients using the results from Table 5-15 for EDF1YEAR. The figure shows significant variation over-time in the effect of derivatives on the probability of default irrespective of the type of derivative instruments used for hedging. It is noticeable from the figure that the effect of derivatives on the probability of default is negative during the heightened risk. The magnitude effect of derivatives increases depending on the level of economic and financial crisis. The magnitude effect is larger during 2008 and 2009 than it was in 2001-2002. We plot yearly derivatives coefficients for EDF5YEAR in Figure 5-5. The effect of derivatives on EDF5YEAR over the time follows similar patter but the effect is less in magnitude.

Table 5-15: Time-Varying Effects of Derivatives Use on the Probability of Default

The table presents estimates of equation [15]. The dependent variable is EDF1YEAR in panel A and EDF5YEAR in panel B. ***All Derivative Users*** *is a dummy variable set equal to 1 if a firm is a derivative user and 0 otherwise.* ***FC Derivatives Users (UB)*** *is a dummy variable set equal to 1 if a firm is a FC derivative user and 0 for non-users.* ***IR Derivatives Users (UB)*** *is a dummy variables set equal to 1 if a firm is a IR derivative user and 0 for non- users.* ***Leverage*** *is the ratio of total debt to market value of assets.* ***Profitability*** *is measured as return on invested capital, which calculated as the sum of pre-tax profits and total interest charges divided by invested capital.* ***Excess Return*** *is the annual return on the firm minus the value weighted FTSE all shares index annual return over the entire fiscal year.* ***Equity volatility*** *is expressed as square root of number of trading days multiplied by standard deviation of natural log of the daily price growth rate.* ***Firm Size*** *is a natural logarithm of total assets.* ***Liquidity*** *is the ratio of total current assets minus total stock & work in progress over total current liabilities. All specifications include annual GDP growth rate to control for macroeconomic conditions. GDP growth rate is sourced from the IMF official website.*[128] *Industry dummies are included across all specifications to control for industry-specific effects. Standard errors (in parenthesis) are adjusted for heteroskedasticity and clustering by firms. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels respectively.*

Variables	*Panel A: EDF1YEAR*			*Panel B: EDF5YEAR*		
Model	*All Derivative Users*	*FC Derivative Users (UB)*	*IR Derivative Users (UB)*	*All Derivative Users*	*FC Derivative Users (UB)*	*IR Derivative Users (UB)*
	FE	FE	FE	FE	FE	FE
Derivative Users	-0.6128**	-0.7156**	-0.9841**	-0.4588**	-0.5019**	-0.7007***
	(0.311)	(0.358)	(0.392)	(0.178)	(0.210)	(0.225)
Leverage	10.2776***	9.3681***	9.7571***	7.4051***	6.7936***	7.0126***
	(1.234)	(1.338)	(1.402)	(0.720)	(0.792)	(0.817)
Profitability	-1.1412*	-1.2287*	-1.0452	-0.8012**	-0.9159**	-0.7272*
	(0.634)	(0.681)	(0.704)	(0.394)	(0.423)	(0.429)
Firm Size	-1.1098***	-1.0160***	-1.1969***	-0.8743***	-0.8204***	-0.9602***
	(0.163)	(0.161)	(0.215)	(0.106)	(0.105)	(0.141)
Equity Volatility	4.8533***	4.8331***	4.9779***	3.6269***	3.5398***	3.7490***
	(0.597)	(0.665)	(0.756)	(0.367)	(0.410)	(0.456)
Excess Return	-1.0343***	-1.0644***	-1.0338***	-0.6695***	-0.6882***	-0.6717***
	(0.165)	(0.174)	(0.189)	(0.101)	(0.107)	(0.119)
Liquidity	-0.1408*	-0.1364*	-0.1176	-0.0929	-0.0934	-0.0427
	(0.079)	(0.082)	(0.111)	(0.058)	(0.061)	(0.076)
GDP Growth	-0.1145	-0.1236	-0.0632	-0.0319	-0.0384	-0.0109
	(0.9044)	(0.092)	(0.095)	(0.0526)	(0.054)	(0.058)
2000 Derivative*	-0.4931***	-0.5122***	-0.4745**	-0.2926***	-0.2960**	-0.2593**
	(0.182)	(0.190)	(0.196)	(0.110)	(0.116)	(0.119)
*2001 * Derivative*	-0.7346***	-0.7372***	-0.4977**	-0.2875**	-0.2713**	-0.1675
	(0.196)	(0.211)	(0.213)	(0.114)	(0.123)	(0.128)
*2002 * Derivative*	-0.0999	-0.0385	-0.0807	0.1486	0.2102	0.1245
	(0.252)	(0.274)	(0.268)	(0.152)	(0.166)	(0.161)
*2003 * Derivative*	-0.2115	-0.1983	-0.1073	-0.0145	-0.0010	0.0191
	(0.188)	(0.196)	(0.200)	(0.118)	(0.124)	(0.128)
*2004 * Derivative*	0.3163	0.3063	0.5481**	0.3247***	0.3224**	0.4295***
	(0.193)	(0.210)	(0.223)	(0.117)	(0.127)	(0.135)
*2005 * Derivative*	0.4626**	0.4627**	0.6242***	0.3179***	0.3104***	0.4216***
	(0.183)	(0.192)	(0.201)	(0.114)	(0.119)	(0.125)
*2006 * Derivative*	0.3665**	0.3146*	0.7590***	0.2301**	0.1885	0.4986***
	(0.185)	(0.188)	(0.217)	(0.117)	(0.119)	(0.136)
*2007 * Derivative*	-0.3617*	-0.2631	-0.0598	-0.2643**	-0.2166*	-0.0456
	(0.206)	(0.204)	(0.232)	(0.129)	(0.131)	(0.146)
*2008 * Derivative*	-1.5350***	-1.5412***	-1.2905**	-0.8265***	-0.8797***	-0.6677*
	(0.489)	(0.501)	(0.582)	(0.286)	(0.289)	(0.349)
*2009 * Derivative*	-1.6186**	-1.8236**	-1.0116	-0.6145	-0.7633	-0.2994
	(0.807)	(0.819)	(0.873)	(0.471)	(0.479)	(0.526)
*2010 * Derivative*	0.3596	0.1954	0.5793*	0.3625**	0.2368	0.5498***
	(0.293)	(0.263)	(0.330)	(0.181)	(0.165)	(0.206)
Constant	13.3885***	12.4905***	14.6759***	10.6917***	10.2319***	11.9396***
	(2.265)	(2.257)	(3.003)	(1.440)	(1.430)	(1.945)
N	3,422	3,062	2,835	3,422	3,062	2,835
R^2	0.5105	0.4846	0.5025	0.5929	0.5679	0.5870
F-Test Heterogeneity	3.8217	3.9100	3.8800	4.0352	4.1100	3.9300
LM Test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Hausman Test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

[128] *Available at the IMF website at http://www.imf.org/external/pubs/ft/weo/2013/02/weodata/index.aspx*

Taken together, these results suggest important time variation in the effect of derivative on the probability of default during different financial or economic conditions. In particular, our results suggest that derivatives are the most valuable during the time of market downturns. Our results also suggest that hedging with derivatives was more valuable in recent financial crisis than it was during 2000-2001.

Figure 5-4: Effects of Derivatives on EDF1YEAR Over-Time

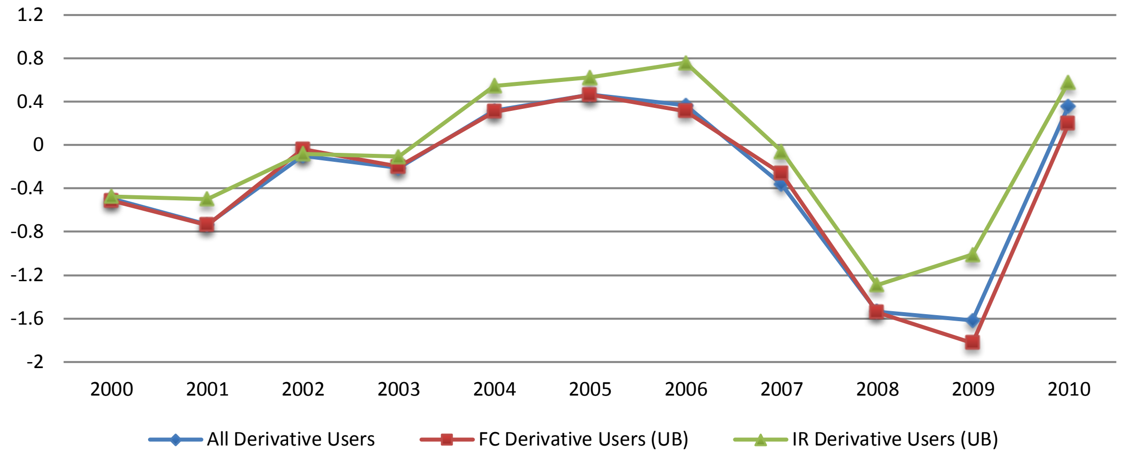
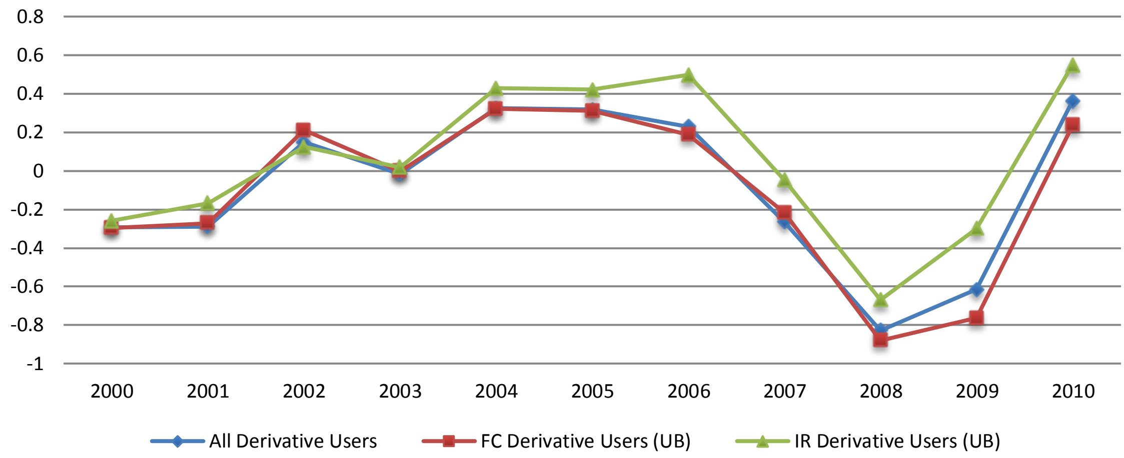


Figure 5-5: Effects of Derivatives on EDF5YEAR Over-Time



5.4.5. Effects of Derivative Use on The Probability of Default of Firms with Different Levels of Accounting-based Risk

The results above showed that derivatives have a greater (negative) impact on default probabilities during periods of economic downturn and heightened aggregate credit risk. We do this by interacting derivatives use with Z-score (see Equation [16]). We argue that firms that possess a lower level of credit worthiness measured before the effects of derivatives (that is, lower Z-score) should benefit more from derivatives use than firms that are financially strong (that is, higher Z-score). If this is the case, then the impact of derivatives use on the probability of default should be more negative for firms with lower Z-scores and less negative for firms with higher Z-scores.

As mentioned previously Z-score is an accounting-based measure of the likelihood of financial distress and as suggested by our univariate analysis it seems to exclude the effects of derivatives. Therefore we would argue that it can be considered as an appropriate measure of pre-derivative default risk. Firms with a high Z-score are considered financially healthy whilst firms with a low Z-score are less so. In equation [16], we expect the coefficient on our Z-score variable to be negative. All else being equal a financially healthy firm should have lower probability of default. We expect a positive coefficient on the interaction term between derivatives and Z-score. This is because at higher Z-scores we would expect the effects of derivatives on default probabilities to be lessened. Derivatives should be more beneficial for firms with higher pre-derivative distress risk (i.e. lower Z-score) and hence the interaction coefficient (derivatives dummy * Z-score) is expected to be positive which would imply a weakening of the association between Z-score and the probability of default.

The results of this analysis are presented in Table 5-16. Consistent with our expectations, we find a statistically significant negative effect of Z-score on the probability of default suggesting that firms exhibiting a high degree of creditworthiness have a lower probability of default. The coefficient on the interaction term between derivatives and Z-score is positive and statistically significant in both model 1 and model 4. This shows that the negative effect of derivatives on default probabilities is greater (smaller) at lower (higher) Z-scores (i.e. firms with a greater (smaller) risk of financial distress). The results in column 1 show that for a derivative user a one standard deviation increase in Z-score reduces the negative effect of derivatives on its post-derivatives default probability by 0.5556%. We repeat the analysis for FC and IR derivative users in columns 2 and 3 for one-year default probabilities and in columns 5 and 6 for five-year default probabilities and find qualitatively similar results. Majority of the control variables have expected sign and are statistically significant.

Table 5-16: Effect of Derivatives Use on The Probability of Default: Firms with Different Levels of Risk

*The table presents estimates from equation [16]. The dependent variable is **EDF1YEAR** in panel A and EDF5YEAR in panel B. **All Derivatives Users** is a dummy variable set equal to 1 if a firm is a derivative user and 0 otherwise. **FC Derivatives Users (UB)** is a dummy variables set equal to 1 if a firm is a FC derivative user and 0 for non- users. **IR Derivatives Users (UB)** is a dummy variables set equal to 1 if a firm is a IR derivative user and 0 for non- users. **Leverage** is the ratio of total debt to market value of assets. **Profitability** is measured as return on invested capital, which calculated as the sum of pre-tax profits and total interest charges divided by invested capital. **Excess Return** is the annual return on the firm minus the value weighted FTSE all shares index annual return over the entire fiscal year. **Equity volatility** is expressed as square root of number of trading days multiplied by standard deviation of natural log of the daily price growth rate. **Firm Size** is a natural logarithm of total assets. **Liquidity** is the ratio of total current assets minus total stock & work in progress over total current liabilities. All specifications include annual GDP growth rate to control for macroeconomic conditions. Annual GDP growth rate is sourced from the IMF official website.[129] Industry dummies are included across all specifications to control for industry-specific effects. Standard errors (in parenthesis) are adjusted for heteroskedasticity and clustering by firms. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels respectively.*

	Panel A: EDF1YEAR			Panel B: EDF5YEAR		
Variables	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE	(6) FE
All Derivative Users	-0.8755**			-0.5097**		
	(0.359)			(0.202)		
*All Derivative Users * Z-score*	0.5556**			0.3401**		
	(0.224)			(0.139)		
FC Derivative Users (UB)		-0.9632**			-0.5448**	
		(0.423)			(0.243)	
*FC Derivative Users (UB) * Z-score*		0.5747**			0.3569**	
		(0.241)			(0.150)	
IR Derivative Users (UB)			-1.0204**			-0.6263**
			(0.440)			(0.254)
*IR Derivative Users (UB) * Z-score*			0.6484***			0.4342***
			(0.244)			(0.153)
Z-score	-0.4525**	-0.4777**	-0.4799**	-0.3267***	-0.3378***	-0.3557***
	(0.191)	(0.203)	(0.196)	(0.123)	(0.130)	(0.125)
Leverage	10.0678***	9.1251***	9.5455***	7.2574***	6.6261***	6.8915***
	(1.223)	(1.338)	(1.366)	(0.712)	(0.790)	(0.791)
Profitability	-0.9078	-0.9484	-0.7386	-0.5312	-0.6288	-0.4241
	(0.707)	(0.760)	(0.766)	(0.438)	(0.473)	(0.451)
Firm Size	-1.0617***	-0.9599***	-1.1058***	-0.8264***	-0.7674***	-0.8801***
	(0.154)	(0.148)	(0.195)	(0.098)	(0.094)	(0.126)
Equity Volatility	4.8844***	4.8417***	4.9889***	3.6358***	3.5260***	3.7609***
	(0.600)	(0.666)	(0.752)	(0.367)	(0.408)	(0.454)
Excess Return	-1.0778***	-1.1048***	-1.0812***	-0.7046***	-0.7218***	-0.7091***
	(0.160)	(0.168)	(0.180)	(0.097)	(0.102)	(0.112)
Liquidity	-0.1383	-0.1327	-0.0910	-0.0813	-0.0847	-0.0156
	(0.092)	(0.097)	(0.118)	(0.067)	(0.070)	(0.079)
Constant	13.2057***	12.0264***	13.9521***	10.4156***	9.7627***	11.2714***
	(2.251)	(2.193)	(2.852)	(1.410)	(1.355)	(1.825)
N	3,408	3,050	2,826	3,408	3,050	2,826
R^2	0.5126	0.4875	0.5051	0.5974	0.5738	0.5926
F-Test Heterogeneity	3.7326	3.8323	3.8511	3.9486	4.0329	3.8917
LM Test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Hausman Test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

[129] *Available at the IMF website at http://www.imf.org/external/pubs/ft/weo/2013/02/weodata/index.aspx*

5.4.6. Controlling for Endogeneity

It is not possible to rule out the notion that the use of derivatives in the above regression analysis is endogenous. In our model, endogeneity might arise because of simultaneous causality. This occurs when the causality runs in both directions, that is, from the regressor(s) to the dependent variable and from the dependent variable to the regressor(s). In our case, the derivatives–probability of financial distress relationship is affected by a feedback loop such that the use of derivatives affects the probability of default but the probability of default also affects the decision to use derivatives. In effect, if derivatives are used for hedging then they could lower the probability of default but it is also the case that firms with a high probability of default are more likely to use derivatives for hedging purposes. However, we also need to recognize the role of leverage in this circular relationship. By reducing the likelihood of default, derivatives increase a firm's debt capacity (Stulz, 1996; Ross, 1997; Leland, 1998). It follows from this that any initial reduction in the probability of default could be offset by a return to the pre-derivative-use probability of default as firms take advantage of the additional debt capacity by increasing their holdings of debt. In effect, we have a circular relationship that creates an endogeneity problem between probability of default, leverage and derivatives. When there is simultaneous causality, the endogenous variables and the error term are correlated and OLS estimation picks up both forward and backward effects, thereby leading to bias and inconsistent coefficients.

As discussed earlier there is a problem of selection bias in studies that use observation data. For this study it means that firms are assigned or assign themselves to use derivatives is not typically ignorable and hence suggest that the use of derivatives is endogenous. Endogeneity also occurs when an explanatory variable is correlated with the error term and hence restricts from getting unbiased estimates from regression analysis (Wooldridge, 2002). We control for endogeneity using treatment effects and propensity score model.

5.4.6.1. Controlling for Self-Selection Bias: Treatment Effects Model

In selection equation [45] we model the decision to use derivatives as a function of instrumental variables and firm-specific variables that have been shown to be important determinants of derivative use previously. In determining our choice of instrumental variables we follow the literature (Géczy et al., 1997; Allayannis and Ofek, 2001; Muller and Verschoor, 2005; Bartram et al., 2011; Gay et al., 2011; Allayannis et al., 2012;

Magee, 2013; Marin, 2013). The first instrument that we use is the ratio of foreign sales to total sales. Géczy et al. (1997), Marin (2013), Gay et al. (2011), Allayannis et al. (2012) and Magee (2013) use foreign sales to total sales and find that its positively and significantly associated with use of derivatives. For second instrumental variable, we use capital expenditure to sales. This variable is a measure of growth. Several papers use research & development expenditure to sales as a measure of growth and as an instrument for derivative use (Géczy et al., 1997; Allayannis and Ofek, 2001; Gay et al., 2011; Magee, 2013; Marin, 2013). Géczy et al. (1997) and Allayannis and Ofek (2001) find significant and positive relation between derivatives use and their growth variable. The last instrumental variable that we use is the interest coverage ratio calculated as the ratio of EBIT to interest payment. Muller and Verschoor (2005) and Bartram et al. (2011) use interest coverage as an indicator for gross IR exposure. Muller and Verschoor (2005) find positive relation between EBIT/interest expense and firms use of FC derivatives.

5.4.6.2. Treatment Effects Results

Regression results from this treatment effects estimation on the effects of derivatives use constitute our main results and are presented in Table 5-17. The first conclusion that we can draw from the treatment effects regression is that we can reject the null hypothesis that the correlation between the error terms of the selection and outcome equations is zero. The χ^2 statistics shown at the bottom of the Table 5-17 are all significantly different than zero at least at 10% level of significance. Thus, we have strong empirical support for selection bias in our study and this also suggests that applying the treatment effects model is appropriate.

We present the selection equation results in odd columns and outcome equation results in even columns of Table 5-17. The selection equation results in column 1 of Table 5-17 uses derivative users as a dependent variable and reports that all the instruments for derivatives have expected sign and all are significantly associated with firms' decision to use derivatives. In particular, we find that firms with more capital expenditure to sales are more likely to use derivatives and firm with higher interest coverage ratio are less likely to use derivatives. Hedging theories argue that firms that have more growth options benefits from hedging as it helps resolve the problem of underinvestment (Myers, 1977; Bessembinder, 1991; Froot et al., 1993) and firm with high interest coverage ratio are financially healthy and hence needs less hedging with derivatives. The estimation results in column 2 of Table 5-17 shows the results of outcome equation where we use the predicted values of derivatives use from the selection equation and examine its effects on probability of default. The reported inverse mills ratio is positive and significant (0.2440, $p < 0.05$), which indicates the presence of omitted variable. This suggests that the unobserved information that leads to firms self-selecting themselves to use derivatives is also associated with a higher probability of default. We use LR test of independent equation to test the hypothesis that the correlation between the error terms of the selection and outcome equations is non-zero. Violation of this assumption can result in the estimation bias. We can reject the null hypothesis as $\chi^2 = 3.63$ ($p < 0.10$) at a 10% significance level and conclude that the ρ is not equal to zero, which suggests that the use of treatment effects model is appropriate as there is a self-selection bias.

The coefficient on all derivatives in outcome equation is negative and significant, which indicates that firms that are using derivatives have lower probability of default and less at risk of defaulting than non-users. This coefficient on all derivatives is net of observed selection bias as we use the predicted value from our selection equation. The coefficient value is -1.4926 and it is significant at 1% level, suggesting that other things being equal firms that use derivatives have a mean probability of default that is 1.4926 % lower than firms that do not use derivatives. For our other explanatory variables in the outcome regression, we find majority of them have expected signs and are highly significant. We find that firms with higher leverage and higher stock return volatility have more probability of default while larger, more profitable, more liquid and firms with excess return have lower probability of default.

Treatment effects model is also used for different FC and IR derivatives variables. The selection equation in column 3 of Table 5-17 is for FC derivative user firms where non-user firms include “other-users”. All instruments are significant at 1% level and have the predicted sign in the selection equation. The results suggest that firms with more foreign sales and capital expenditure to sales are more likely to use FC derivatives while firms with high interest coverage ratio are less likely to use FC derivatives. The result of LR test ($\chi^2 = 14.3132$, $p < 0.001$) suggests correlation between the error terms of the two equations. We find coefficient on FC derivatives is negative and significant suggesting that firms that use FC derivatives have 1.7373% lower probability of default than non-FC derivative user firms (Column 4, Table 5-17). When we remove the IR only derivative user firms form our sample of non-users, Column 6 of Table 5-17, we find that FC derivative user firms have 1.5080% lower probability of default than non-derivative users. Majority of the explanatory variables are highly significant and have predicted sign. Our results for the selection equation are significant for all the instruments (column 5, Table 5-17). The inverse mills ratio and the LR test of independent equations are highly significant.

Table 5-17: Treatment Effects Model: MLE

*This table presents results of treatment effects model estimated using maximum likelihood model. For each specification we report results from the selection equation, where **All Derivative Users, FC Derivatives Users (B), FC Derivative Users (UB), IR Derivative Users (B)** and **IR Derivative Users (UB)** are dummy dependent variables, which are separately regressed on firm-level factors and instruments. In the adjacent column, we report results of our outcome regression where the dependent variable is the one-year default probability (**EDF1YEAR**), which is regressed on the predicted values of Derivatives Use from the first stage regression and other firm-level factors. Instruments we use are 1) **Foreign Sales** as measured by the ratio of foreign sales to total sales; 2) **Interest Coverage** as measure by the ratio of Earnings before Interest and Taxes to total interest expense and 3) Growth as measured by the ratio of capital expenditure to total assets. Firm-level factors include **Leverage** is the ratio of total debt to market value of assets. **Profitability** is measured as return on invested capital, which is calculated as the sum of pre-tax profits and total interest charges divided by invested capital. **Excess Return** is the annual return on the firm minus the value weighted FTSE all shares index annual return over the entire fiscal year. **Equity Volatility** is expressed as square root of number of trading days multiplied by standard deviation of natural log of the daily price growth rate. **Firm Size** is a natural logarithm of total assets. **Liquidity** is the ratio of total current assets minus total stock & work in progress over total current liabilities. In parentheses are standard errors adjusted for heteroskedasticity (White (1980)) and clustering at the firm level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. The regressions also include year dummies.*

Equation	*Selection*	*Outcome*	*Selection*	*Outcome*	*Selection*	*Outcome*	*Selection*	*Outcome*	*Selection*	*Outcome*
VARIABLES	*Derivative Users*	*EDF1 YEAR*	*FC Derivative Users (B)*	*EDF1 YEAR*	*FC Derivative Users (UB)*	*EDF1 YEAR*	*IR Derivative Users (B)*	*EDF1 YEAR*	*IR Derivative Users (UB)*	*EDF1 YEAR*
Users		-1.4922***		-1.7373***		-1.5080***		-1.9680***		-1.8547***
		(0.336)		(0.300)		(0.334)		(0.332)		(0.332)
Foreign Sales			0.1630**		0.2501**					
			(0.001)		(0.001)					
Capital Expenditure / Sales	2.4695***		1.1825**		2.5844***		1.5433**		2.6951***	
	(0.876)		(0.597)		(0.899)		(0.621)		(1.027)	
Interest Coverage	-0.0067***		-0.0068***		-0.0069***		-0.0115***		-0.0128***	
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)	
Leverage	1.0835***	7.2623***	-0.2452	6.8862***	0.9661***	7.1071***	1.1712***	7.8360***	1.1895***	7.2699***
	(0.300)	(0.650)	(0.180)	(0.622)	(0.314)	(0.733)	(0.206)	(0.690)	(0.326)	(0.722)
Profitability	0.3352**	-1.4038***	0.5015***	-1.3758***	0.3308**	-1.3983***	0.3558**	-1.4929***	0.5949***	-1.4614***
	(0.165)	(0.464)	(0.139)	(0.468)	(0.167)	(0.487)	(0.157)	(0.466)	(0.196)	(0.526)
Firm Size	0.3393***	-0.3944***	0.2637***	-0.3592***	0.3521***	-0.3883***	0.3901***	-0.2835***	0.4229***	-0.3327***
	(0.029)	(0.038)	(0.020)	(0.043)	(0.030)	(0.039)	(0.022)	(0.051)	(0.033)	(0.043)
Equity Volatility	-0.5273***	5.4814***	0.0331	5.6065***	-0.5365***	5.4376***	-0.3696**	5.4230***	-0.4505**	5.6942***
	(0.178)	(0.456)	(0.153)	(0.469)	(0.186)	(0.504)	(0.171)	(0.457)	(0.211)	(0.525)
Excess Return	-0.0432	-1.6574***	-0.1005*	-1.6842***	-0.0503	-1.6228***	-0.0852	-1.6819***	-0.0405	-1.7349***
	(0.066)	(0.182)	(0.058)	(0.184)	(0.067)	(0.195)	(0.061)	(0.182)	(0.075)	(0.211)
Liquidity	-0.0240	-0.3634***	0.0004	-0.3523***	-0.0184	-0.3751***	-0.0937***	-0.4013***	-0.0875***	-0.4366***
	(0.025)	(0.052)	(0.024)	(0.051)	(0.026)	(0.054)	(0.031)	(0.053)	(0.034)	(0.070)
Constant	-2.8170***	4.7550***	-2.2541***	4.4175***	-3.1245***	4.6842***	-4.4930***	3.2303***	-4.0951***	4.2216***
	(0.419)	(0.662)	(0.313)	(0.645)	(0.430)	(0.683)	(0.324)	(0.700)	(0.490)	(0.747)
N	3,417	3,417	3,399	3,399	3,041	3,041	3,417	3,417	2,831	2,831
rho	0.0880	0.0880	0.2544	0.2544	0.0910	0.0910	0.2585	0.2585	0.1313	0.1313
χ^2	3.6313	3.6313	14.3132	14.3132	4.3080	4.3080	11.4584	11.4584	6.4093	6.4093
Inverse Mills	0.2440	0.2440	0.7129	0.7129	0.2500	0.2500	0.7258	0.7258	0.3656	0.3656
S.E. Inverse Mills	0.1295	0.1295	0.1894	0.1894	0.1223	0.1223	0.2153	0.2153	0.1466	0.1466

In Table 5-17, we also present treatment effects results for IR derivatives variables. In selection equation, we use capital expenditure to sales and interest coverage ratio as instruments. Both of the variables have predicted sign and are significant (column 7, Table 5-17). The coefficient on IR derivative (non-users include "other" users) in column 8 of Table 5-17, is negative and significant. This suggests that firms that use IR derivatives have a probability of default that is 1.9680% lower than firms that do not use IR derivatives. The inverse mills ratio and the LR test of independent equations are highly significant. We find similar results when we remove FC only derivative use firms from non-user sample, column 10 of Table 5-17. In the selection equation (column 9 of Table 5-17) we find that all instruments are significant and have predicted sign. The coefficient on IR derivative users in column 10 shows that firms that use IR derivatives have 1.8547% lower probability of default than non-derivative user firms. The inverse mills ratio and LR test indicates that running treatment effects model is appropriate.

5.4.7. Instrumental Variable Approach

In this section we use a continuous measure of derivatives use as opposed to a dummy variable. The data on notional values is available only for a smaller sample since not all the sample firms disclose the data on notional amount of derivatives use. As reported in Table 5-1, we have 1152 firm-year observations on notional amounts of derivatives use on FC and/or IR and/or CP. We calculated the extent of derivatives use variable as total notional values for FC and IR and CP scaled by total assets. This measure captures the size of firms derivatives programme.

We control for endogeneity using a two stage least square model (2SLS). We also employ the GMM's instrumental variables approach, as 2SLS is suboptimal in the presence of heteroskedasticity. In the first stage of both the models, we model our endogenous variables using instrumental variables.[130] The instruments capture the variation in the extent of derivatives use and leverage. In the second stage regression, the probability of default is estimated using the predicted values of extent of derivatives use and leverage from the first stage regression and the exogenous variables. The advantage of GMM is that it models parameters of the observed variables without making strong assumptions regarding the distributional properties of those variables and hence provides solution for

[130] *The first stage in instrumental variables estimation is to estimate the endogenous variables as a function of the exogenous variables in the second stage plus additional instruments.*

the problem when the statistical independence between error term and regressors is not satisfied.

In this section we control for the endogeneity between the probability of default, derivatives and leverage. We also recognize the role of leverage in this circular relationship. By reducing the likelihood of default, derivatives use increases a firm's debt capacity (Stulz, 1996; Ross, 1997; Leland, 1998). It follows from this that any initial reduction in the probability of default could be offset by a return to the pre-derivative usage probability of default as firms take advantage of the additional debt capacity by increasing their holdings of debt. This may indicate that derivatives helped firm in increasing debt capacity by keeping the same probability of default. In effect we have a circular relationship that creates an endogeneity problem between probability of default, leverage and derivative usage. A good instrumental variable is one that will affect the probability of default only through its impact on the extent of derivatives use and leverage and not directly by itself that suggests that a valid instrumental variable must be correlated with derivatives and leverage but uncorrelated with error term, ε_{it}.

5.4.7.1. Instrumental Variable Regression Results

Column 1 of Table 5-18 presents the results of OLS regression. Consistent with our expectations, the estimated coefficient on the extent of derivative use is negative but insignificant, suggesting that the extent of a firm's all derivative use does not affect its probability of default. However, due to the problem of simultaneity between derivatives, leverage and probability of default, these results are not surprising. If firms employ more leverage in their capital structure then firm will face high probability of financial distress and this will motivate firm to use derivatives to hedge. With the help of derivatives firm can lower its financial distress. This will help firm in borrowing more debt from the market. This relationship between derivatives and leverage suggests that they are endogenous and positively related. Due to this relationship it is difficult to observe a significant relationship between the probability of default and the extent of derivative use. Other results indicate that firms with more leverage in capital structure and firms with high asset volatility are more likely to default. There is a strong relation between profitability and probability of default and firm size as measured by total assets and probability of default. These findings are consistent with the theoretical prediction and earlier empirical studies. This study finds negative relation between excess return and probability of default.

The results suggest that probability of default is associated with the scale of the firm: the bigger the firm the lower probability that the firm will default. Similarly, more profitable firms have less probability of default. Firm with higher equity volatility have more chances of default.

Table 5-18: Effect of Extent of Derivatives on the Probability of Default

This table presents the results of OLS, 2SLS and GMM-IV regressions of the probability of default on the Extent of All derivatives use. ***EDF1YEAR*** *is the probability of default in 1-year time.* ***Extent of derivative Use*** *is calculated as sum of notional value of FC derivatives, IR derivative and CP derivatives divided by total assets.* ***Leverage*** *is the ratio of total debt to market value of equity plus total debt.* ***Profitability*** *is measured as return on invested capital, which is calculated as the sum of pre-tax profits and total interest charges divided by invested capital.* ***Excess Return*** *is the annual return on the firm minus the value weighted FTSE all shares index annual return over the entire fiscal year.* ***Equity volatility*** *is expressed as square root of number of trading days multiplied by standard deviation of natural log of the daily price growth rate.* ***Firm size*** *is a natural logarithm of total assets.* ***Liquidity*** *is the ratio of total current assets minus total stock & work in progress over total current liabilities. In parentheses are standard errors adjusted for heteroskedasticity (White (1980)) and firm clustering. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. The regressions also include year and industry dummies.*

Variables	*OLS*	*2SLS-IV*	*GMM-IV*
Extent Of Derivative Use	-0.2241	-1.7898**	-1.5298*
	(0.158)	(0.724)	(0.873)
Leverage	3.8063***	4.4074***	4.4201***
	(0.345)	(0.818)	(0.889)
Profitability	-2.6964***	-1.3721**	-1.4105*
	(0.788)	(0.612)	(0.828)
Excess Return	-0.9143***	-0.8226***	-0.7891***
	(0.113)	(0.127)	(0.165)
Equity Volatility	2.3430***	1.3878***	1.3855***
	(0.349)	(0.336)	(0.369)
Firm Size	-0.1811***	-0.4827***	-0.4840***
	(0.038)	(0.119)	(0.126)
Liquidity	-0.0215	-0.0094	0.0044
	(0.054)	(0.068)	(0.067)
Constant	2.1537***		
	(0.617)		
N	1,038	979	979
R^2	0.5776	0.4482	0.4677
F-Test	13.2612	15.1795	9.3652
Hausman Test		10.7179	6.8713
Hausman		0.0047	0.0322
Under-identification Test		51.1611	27.1643
Under-identification Test (P-value)		0.0000	0.0000
Sargan-Hansen J-Stat		3.3009	2.7591
Sargan-Hansen J-Stat (P-value)		0.1920	0.2517
Crag-Donald F-Stat		13.1652	13.1652

To control for the above-discussed issue of endogeneity, this study uses instrumental variable regression using 2SLS and GMM approach. A Hausman (1978) test is performed to determine whether extent of derivative use and leverage are jointly endogenous. This test is based on the difference between OLS estimator and instrumental variables estimator. The null hypothesis for the test states that an OLS estimator for the same equation would yield consistent estimates. This means that any endogeneity among the regressors would not have adverse effects on OLS estimates. A rejection of null hypothesis indicates that instrumental variables techniques are required. Our result rejects the null hypothesis of no endogeneity at the 1% level and suggests OLS regression generates inconsistent estimates and ignores the endogeneity of extent of derivative use and leverage with respect to probability of default and due to that potentially misleading.

Columns 2 and 3 present the 2SLS and GMM-IV results respectively. For the 2SLS regression, the extent of derivative use is negatively and significantly related to the probability of default at 5% level. The results suggest that a 1% increase in the extent of all derivatives use leads to an economically large reduction of 1.79% in EDF1YEAR. Except for liquidity, all other control variables are significant and have predicted sign. For the GMM-IV regression, the estimated coefficient on the extent of derivative use is still negative but significant at 10%. The results suggest that a 1% increase in the extent of all derivatives use lowers the probability of default by 1.53%. Smaller coefficient and significance is expected, as GMM is more robust than 2SLS. These results suggest that after controlling for endogenous derivative use and leverage, the extent of derivatives use is associated with economically lower probability of default.

5.4.7.2. Validity of Instrumental Variables

In this section, the validity of instrumental variables is discussed. A valid instrument must be uncorrelated with error term in the regression equation and it must be correlated with the endogenous explanatory variables in regression. That is, a valid instrumental variable is one that affects the probability of default through its impact on extent of derivative use and leverage and not directly by itself. To test the first condition, that is, the instrument must be uncorrelated with error term, this study conducts a Sargan-Hansen Test of over identifying restrictions. Under this test the joint null hypothesis is that the instruments are valid instruments, that is uncorrelated with error term and that the excluded instruments are correctly excluded from the estimated equation. The Sargan-Hansen statistics are small with a *p*-value of 0.1920 and 0.2517 respectively for 2SLS and GMM-IV regressions. Therefore, this study cannot reject the null hypothesis that the instrumental variables are uncorrelated with the error term.

To test the second condition, that is instrument must be correlated with the endogenous explanatory variables, this study employs Under-Identification test (LM statistic). Under this test that null hypothesis is that the equation is under-identified, that is excluded instruments are "irrelevant", meaning uncorrelated with endogenous regressors. The *p*-value of Under-Identification tests for both 2SLS and GMM-IV is 0.0000. Therefore, this study rejects the null hypothesis that the instrumental variables are uncorrelated with the endogenous variables. This suggests that that equation is identified and excluded instruments are correlated with endogenous regressors.

5.4.8. Propensity Score Matching

To control for the problem of endogeneity we have used a treatment effects specification and an instrumental variable technique. In this section we use PSM to control for endogeneity. Here we attempt to match derivative user firms with non-user firms based on their propensity score and then compare their respective default probabilities. We use PSM method to examine the impact of the use of derivatives (treatment variable) on the probability of default (our outcome variable). This method is an alternative way of reducing selection bias by matching on a single index propensity score and making derivative user firms and non-user firms as comparable as possible on the confounding variables. This examination will provide unbiased estimation effects of treatment, derivative use, on the outcome variable, default probability. To calculate a propensity score for each firm we employ variables that are deemed to influence the decision to use derivatives to create matched pairs of observations where the observed covariates on determinants for derivatives use are similar for derivative user firms (treated firms) and non-user firms (control firms). We use the Rosenbaum bounds method to test our results against bias from unobserved covariates.

There are several problems that affect the results of studies that use observational data. The first problem is the distribution on observed characteristics between treatment and control group. Majority of the studies that examines the use of derivatives, use a regression model where they regress measure of risk on dummy for derivatives and other control variables. Researchers then examine the coefficient on derivatives by saying ceteris paribus and hence assume the value of coefficient as the casual effect of the derivatives. However, the problem with simple regression analysis is that they cannot identify whether the observed characteristics used have any comparable overlap. Li (2013) argue that the findings of studies that use regression model with observational data could be misleading as they did not control for the overlap between treated and control group.

Assessing the impact of derivatives use is complex because of incomplete information. With observational data one can identify whether a firm uses derivatives or not and the probability of default conditional on derivatives use. However, the problem with making causal inference is how to identify the outcomes that are not observed. This means that if firm *i* used derivatives at time *t*, what would have happened if it had not used derivatives. Hence, the fundamental problem in estimating unbiased causal effects is constructing the unobserved counterfactuals for treated (derivative users) observations. With PSM counterfactuals can be reconstructed for observational data. Li (2013) shows that PSM reconstructs counter factual by adjusting covariates between treated and control group using observational data. PSM calculates counterfactuals by reducing bias due to lack of distribution overlap and bias due to different density weighting.

5.4.8.1. Propensity Score Estimation and Results

In Table 5-19, we present our results of the PSM analysis.[131] We have 3693 observations for derivative user firms and 571 observations for non-users. It was not possible to match all the derivative user firms with unique non-user firms, as the control group (non-user firms) is smaller than treated group (derivative user firms). In Table 5-19 we present the results of PSM for our two outcome variables EDF1YEAR and EDF5YEAR. The table reports the numbers of firms, caliper value, mean and median values for the derivative users (treated) and non-users (control firms), the difference in mean and median values and the Wilcoxon p-value. We can use the simple mean difference test to obtain an estimate of the average treatment effect on the treated as the propensity score-matching method removes the bias related to observable covariates. Our results show that the estimated effect from PSM supports our hypothesis on effects of derivatives use: firms that use derivatives have lower probability of default than non-users on matched basis.

In model 1 we use one-to-one matching without replacement to match a derivative user firm with a non-user firm. This is one of the most common and frequently used methods. In this matching method a firm from derivative user group is matched one by one with a

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[131] *The model to calculate propensity score is provided in section 3.5.9.1.1 on page no 67.*

firm from non-derivative user group without replacement that has closest propensity score. This method finds the pair of firms with the shortest distance of their propensity score. The result shows that we get a significant negative effect of the use of derivatives (treatment) on the user firms of -1.7442 for 1-year probability of default. That is the average EDF1YEAR for derivative user firms is around 1.74% lower than that of matched non-user firm (control group). For EDF5YEAR, we also get significant negative effect of the use of derivatives on the users of -1.1805 that shows that the average EDF5YEAR is 1.18% lower for users compared to non-users.

In model 1, a treated firm is matched against a control firm without limiting the difference between their propensity score and hence may lead to a bad match if the difference is huge. To control for this we introduce a tolerance level, caliper, on the difference between a treated and a control firms propensity scores. This limits the maximum propensity score distance for matching.[132] This reduces bad matches and increases the quality of matches. In model 2 and 3, we use one-to-one matching without replacement with caliper. We use two values of tolerance level. In model 2 we use 0.01 and in model 3 we follow Austin (2011) and calculate caliper of width equal to 0.2 of the standard deviation of the logit of the propensity score.[133] The numbers of firms matched are reduced as now a treated firm is matched with a control firm that is within the distance set by the tolerance level. The mean difference between a derivative user firm and a non-user firm is still statistically negative and suggest that derivative user (treated) firms have lower probability of default than non-users (control firms) and that the use of derivatives have statistically significant negative effect on both EDF1YEAR and EDF5YEAR for derivative user firms. In particular, the average EDF1YEAR for derivative users is 1.70% and 1.61% lower than non-users for models 2 and 3 and for the average EDF5YEAR this difference is 1.12% and 1.11% lower for derivative users.

Model 4 and model 5 we use radius and kernel matching estimation. The one-to-one matching discussed above uses only one observation from control group to match against treated group and because of this only few observations from control group are used. This

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[132] See for more details Caliendo and Kopeinig (2008)

[133] The standard deviation of the logit of the propensity score is calculated as $\sqrt{(\sigma_1^2 + \sigma_2^2)/2}$. Where σ_1^2 is the variance of logit of propensity score for derivative users and $\sigma_2^2$is the variance of logit of propensity score for non-users prior to matching.

limits the number of firms that are matched with control group and reduces the number of observations. Radius matching matches derivative user firms against all the non-user firms within the caliper value. Kernel method uses weighted averages of all the firms in the comparison group to calculate the counterfactual (Caliendo and Kopeinig, 2008). The benefit of radius and kernel matching over one-to-one matching is that they use more information and reduces the variance. The results of matching analysis show significant effect of the derivatives use on our outcome variable EDF1YEAR and EDF5YEAR. The result suggests that derivative user firms have significantly lower probability of default than non-user firms. The results show that derivative user firms have 1.83% and 2.10% lower EDF1YEAR and 1.24% and 1.41% lower EDF5YEAR than matched non-users under radius and kernel matching methods respectively.

Table 5-19: Propensity Score Matching Analysis

*This table presents the results of mean and median difference for our outcome variable **EDF1YEAR** and **EDF5YEAR** for **All Derivative User** and **Non-User** firms matched using propensity score. The table provides caliper size, number of observations, Mean for derivative users and non-users, difference in mean and t-test for significance. The propensity score for **Model 1** is calculated with common support and without replacement. The propensity score for **Model 2** is calculated with common support, without replacement and with a caliper of 0.01. The propensity score for **Model 3** is calculated with common support, without replacement and with a caliper of 0.2 of the standard deviation of the logit of the propensity score. The propensity score for **Model 4** is calculated with common support using radius matching with caliper of 0.2 of the standard deviation of the logit of the propensity score. The propensity score for **Model 5** is calculated with common support using kernel matching with bi-weight. The covariates that we use are **Z-score, Interest Coverage, Leverage, Liquidity, Firm Size, Market to book, Foreign Debt** and **Foreign Sales.***

Model	*N*	*Caliper*	*Users*		*Non-Users*		*Difference*		*Wilcoxon p-value*
			Mean	*Median*	*Mean*	*Median*	*Mean*[134]	*Median*	
					Panel A: EDF1YEAR				
1	418	-	0.6696	0.1160	2.4138	0.2807	-1.7442***	-0.1647	0.000
2	398	0.01	0.7391	0.1381	2.4427	0.2682	-1.7036***	-0.1301	0.001
3	414	0.032	0.7887	0.1274	2.3954	0.2682	-1.6067***	-0.1408	0.000
4	1731	0.032	1.0472	-	2.8825	-	-1.8353***	-	-
5	1731	Bi-weight	1.0472	-	3.1460	-	-2.0988***	-	-
					Panel B: EDF5YEAR				
1	418	-	0.8033	0.2561	1.9838	0.5201	-1.1805***	-0.2640	0.000
2	398	0.01	0.8634	0.3175	1.9860	0.5169	-1.1226***	-0.1994	0.004
3	414	0.032	0.8533	0.3001	1.9649	0.5169	-1.1116***	-0.2168	0.000
4	1731	0.032	1.0695	-	2.3105	-	-1.2409***	-	-
5	1731	Bi-weight	1.0695	-	2.4748	-	-1.4053***	-	-

[134] ****, ** and * are based on the t-test and shows the significance at 1%, 5% and 10% level respectively.*

5.4.8.2. Balancing Test

In Table 5-20 we report the balancing results for the covariates used in model 3 of Table 5-19. The table shows how the control sample is selected to match the treated sample so that they are directly comparable to the treated sample to estimate the effects of the treatment. The table presents before and after matching mean for the treated and control group, the SB statistics that represents the mean difference as a percentage of the average standard deviation between the groups, per cent reduction in bias, *t-tests* and *p-value* for the observed covariates. The *t-test* and the SB are the main tests to ensure the balance of the strata for the covariates.

Table 5-20: Balancing Test for Covariates

This table presents the balancing test results for the covariates that are used to calculate the propensity score before and after matching. ***Z-score*** *is Altman's Z-score for UK Firms;* ***Interest Coverage*** *is the ratio of earnings before interest and taxes to interest expenses on Debt;* ***Leverage*** *is the ratio of total debt to market value of assets;* ***Liquidity*** *is the ratio of total current assets minus total stock and work in progress over total current liabilities.* ***Firm Size*** *is a natural logarithm of total assets.* ***Market to Book*** *is the ratio of market values of assets to book value of assets;* ***FC Debt*** *is a dummy variable set is equal to '1' if a firm uses Foreign Debt and '0' otherwise;* ***Foreign Sales*** *is the ratio of foreign sales to total sales.*

Variables	*Sample*	*Mean*		*SB (%)*	*Reduction in SB (%)*	*T-Test*	*p > |t|*
		Users	*Non-Users*				
Z-score	Unmatched	3.0546	4.0885	-26.90		-4.47	0.000
	Matched	4.1902	4.0215	4.40	83.70	0.37	0.714
Interest Coverage	Unmatched	12.8790	30.0420	-55.70		-9.72	0.000
	Matched	30.8900	29.3660	4.90	91.10	0.41	0.682
Leverage	Unmatched	0.2279	0.1257	55.00		7.88	0.000
	Matched	0.1140	0.1269	-7.00	87.30	-0.78	0.433
Liquidity	Unmatched	1.0065	1.8312	-47.90		-9.94	0.000
	Matched	1.6166	1.7639	-8.60	82.10	-0.76	0.448
Firm Size	Unmatched	13.3900	11.5310	97.50		14.06	0.000
	Matched	11.4450	11.5930	-7.80	92.00	-0.69	0.488
Market to Book	Unmatched	1.5739	2.0336	-22.90		-3.70	0.000
	Matched	2.1582	2.0443	5.70	75.20	0.49	0.624
FC Debt	Unmatched	0.8068	0.4641	76.10		11.62	0.000
	Matched	0.3720	0.4589	-19.30	74.60	-1.80	0.073
Foreign Sales	Unmatched	57.1300	53.3200	11.20		1.55	0.122
	Matched	51.9200	53.4900	-4.60	58.70	-0.46	0.649

The *t-test* simply compares the mean difference between treated and control group for both before and after matching. The insignificant value of t-test indicates the mean difference is not statistically important. The results in Table 5-20 show that the *t-test* value is very small for all the covariates after matching. This suggests that after matching the mean difference for treated and control group is not significantly different. In the matched sample the *p-values* are higher than 0.05 for all the covariates. This ensures good comparison for outcome variable as there is no significant difference in covariates after matching. We calculate the SB for all the observed covariates.[135]

Our results in Table 5-20 show that before matching, many covariates had bias greater than 20%. According to Rosenbaum and Rubin (1985) the covariates between treatment and control group are out of balance when the absolute value of the standardized difference is greater than 20.0. After matching the derivative user firms and non-user firms on propensity score, the bias for covariates are reduced by at least 58%. The bias statistics are less than 20.0 for all covariates. This result confirms that we have achieved balance on all the covariates that are used to calculate the propensity score. This ensures that firms with the same propensity score values have a chance of being both derivative users (treated) and non-users (untreated). The process of matching created a high degree of covariate balance between the treatment and control group for the study.

5.4.8.3. Sensitivity Analysis and Hidden Bias Equivalent

Compared to a standard regression model the propensity score model provides more reliable and unbiased results by comparing treated firms with control firms that have a similar propensity score. Rosenbaum (1991) argues that under the situation of hidden bias where groups differ on unobserved characteristics that are not measured the groups are not comparable. This situation is hard to resolve as the hidden or unobserved variables are difficult to measure. If there are unobserved or hidden variables that affect treatment assignment (the decision to use derivatives) or outcome variable, then there is a problem of endogenous selection and under such circumstances the estimates obtained from PSM are inconsistent and the results are no longer unbiased. These unobserved variables might compromise the validity of inferring causality from observational data to which PSM method is not robust.

PSM allows sensitivity analysis on this selection bias and also estimates the extent to which this hidden bias may affect the inference about the effects of derivatives use. We perform a sensitivity analysis by looking at Rosenbaum bounds and hidden bias

[135] *See section 3.5.9.1.3 for more details.*

equivalents (Diprete and Gangl, 2004). This method determines the extent to which selection on unobserved variables needed in order to change the inferences calculated by the PSM. The results of the analysis are presented in Table 5-21. The table provides the value of gamma significant at 5% level. A gamma value indicates how much an unobserved variable is associated with a change in odds ratio of whether a firm is treated, for example the gamma value of 1.50 in Table 5-21 indicates that the unobserved variable that would increase the odds of using derivatives for the firm should have 50% hidden effect on derivative users than a firm that is a non-user.

Table 5-21: Sensitivity Analysis and Hidden Bias Equivalents

*This table presents the Rosenbaum (2002) bounds and Hidden Bias Equivalents for our first 3 models for outcome variable **EDF1YEAR** and **EDF5YEAR**[136]. The table provides the gamma values (the change in odds ratio) that are significant at 5% and the associated Hidden Bias Equivalents.*

Model	*Gamma*	*Z-score*	*Interest Coverage*	*Leverage*	*Liquidity*	*Firm Size*	*Market to Book*	*FC DEBT Dummy*	*Foreign Sales*
				Panel A: EDF1YEAR					
1	1.50	10.9862	-77.3198	0.5195	-13.7681	1.6976	15.7708	0.5049	192.00
2	1.30	7.1088	-50.0313	0.3361	-8.9089	1.0985	10.2048	0.3267	124.24
3	1.40	9.1168	-64.1633	0.4311	-11.4254	1.4087	13.0873	0.4189	159.33
				Panel B: EDF5YEAR					
1	1.40	9.1168	-64.1633	0.4311	-11.4254	1.4087	13.0873	0.4189	159.33
2	1.20	4.9401	-34.7677	0.2336	-6.1910	0.7633	7.0915	0.2270	86.33
3	1.40	9.1168	-64.1633	0.4311	-11.4254	1.4087	13.0873	0.4189	159.33

Table 5-21 also provide the magnitude of hidden bias for each covariate that would require us to revise our results for the effect of derivatives use on the probability of default. As we have negative estimated treatment effect, we use p-values of negative bounds to calculate the hidden bias. For model 1, the critical level of *gamma* is reached at a 1.50. To alter our conclusions, the unobserved or hidden bias would have to produce the effect of a difference of 10.98 in Z-score, which is double than the average Z-score value for whole sample, -77.3198 (more than 4 times the mean) in interest coverage, 0.5195 in leverage (more than double the mean), -13.76 in liquidity (more than 12 times the mean) and 15.7708 in market to book (more than 9 times) and 192% in foreign sales (more than 3 times). All these differences are very large suggesting that to overturn our results of risk reducing effect of derivatives the unobserved variables must have an effect that must be as large as the magnitude of changes in the covariates. For other models also the hidden bias

[136] Rosenbaum bounds can be calculated for only models with one-to-one matching without replacement.

affects needs to be large to overturn the significant effect that we find of derivatives use on the probability of default.

Diprete and Gangl (2004) and Becker and Caliendo (2007) argue that these sensitivity analysis is a worst case scenario. So a small gamma value does not show existence of heterogeneity and that treatment has no effect on outcome variable but it shows at what level the confidence interval for effect will include zero if a hidden bias caused the odds ratio to differ between the treatment and control group.

Overall, the results of PSM analysis show that derivative user firms have statistically and economically significant lower EDF1YEAR and EDF5YEAR than matched non-users. There are a considerable bias in the covariates prior to matching and a simple matching and a regression analysis that does not control for the difference in covariates would suffer from a biased estimation results. With the help of PSM method we remove a large portion of standardised bias. Our results for propensity score model are also robust to hidden bias.

5.4.9. Coarsened Exact Matching

In previous section we used PSM method to match derivative users with non-users firms. The drawback of PSM is that it improves balance between treated and control group for most of the covariates but at the same time leave some of the variables unbalanced and hence the balance of covariates needs to be checked and if the covariates are out of balance then PSM needs to be re-estimated. In this section we use CEM to match derivative user firms with non-user firms. We match derivative users and non-users on Z score, interest coverage, leverage, liquidity, firm size, market to book and foreign sales.[137]

5.4.9.1. Balance Statistics After CEM

In this section, we discuss imbalance in covariates before and after using CEM method. Particularly, we discuss Multivariate *L1* and univariate *L1*. *L1* is a an imbalance statistics proposed by Iacus, King and Porro (2011). The Multivariate *L1* statistic compares empirical histogram of all pre-treatment covariates between treated and control groups. This statistics ranges between 0 and 1; where 0 indicates perfect balance and 1 indicates perfect imbalance. Larger values of L1 indicate larger imbalance and smaller value

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[137] *This covariates are similar to the one we used to calculate propensity score in section 5.4.8. We did not use foreign debt with CEM as it resulted in a small matched sample.*

indicate smaller imbalance (Blackwell et al., 2009). The Univariate *L1* statistic compares empirical histogram of a pre-treatment covariate between treated and control groups.

In Table 5-22 we provide information on number of observations for both control and treated groups, Multivariate *L1* before and after CEM and univariate *L1* after CEM. CEM automatically prune the data by applying exact matching and removed observations that are not matched from the analysis. Because the method uses exact matching, the matching is results in fewer observations. With each additional continuous variable the matched observations reduces significantly as it will result in fewer observations matched.

Table 5-22: Balance of Control Variables after CEM

*This table provides the imbalance statistics for **All Derivative Users, FC Derivative Users (UB)** and **IR Derivative Users (UB)**. **All Derivatives Users** is a dummy variable set equal to 1 if a firm is a derivative user and 0 otherwise. **FC Derivatives Users (UB)** is a dummy variable set equal to 1 if a firm is a FC derivative user and 0 for non-users. **IR Derivatives Users (UB)** is a dummy variable set equal to 1 if a firm is an IR derivative user and 0 for non-users. The table provides number of observations in treated and control group, Multivariate L1 before & after CEM Matching and after matching Univariate L1.*

	CEM		
	All Derivative Users	*FC Derivative Users (UB)*	*IR Derivative users (UB)*
Treated	181	330	287
Control	101	237	197
Multivariate L1 Before	0.9989	0.9955	0.9945
Multivariate L1 After	0.6049	0.8297	0.8277
	Univariate L1		
Z-score	0.0718	0.1339	0.1443
Interest Coverage	0.0000	0.0061	0.0035
Leverage	0.0387	0.0227	0.0354
Liquidity	0.0746	0.0879	0.1283
Firm Size	0.0138	0.0333	0.0418
Market to Book	0.1206	0.0855	0.1069
Foreign Sales	0.0221	0.0354	0.0244

The results in Table 5-22 show that 181 derivative users firm-year-observations are matched against 101 non-user firm-year-observations. Prior to matching there is a perfect imbalance (Multivariate *L1* = 0.9989). Blackwell et al. (2009) argue that *L1* is not valuable on its own but works as a comparison for matching results. The Multivariate L1 is 0.6049 after matching. Compared with before matching multivariate *L1* this shows a substantial reduction after matching. Table 5-22 also provides the *L1* for each covariate after matching. We also apply CEM for FC derivative users and IR derivative users. These results are also reported in Table 5-22.

Figure 5-6: Univariate L1 Statistics Before and After CEM for All Derivative Users

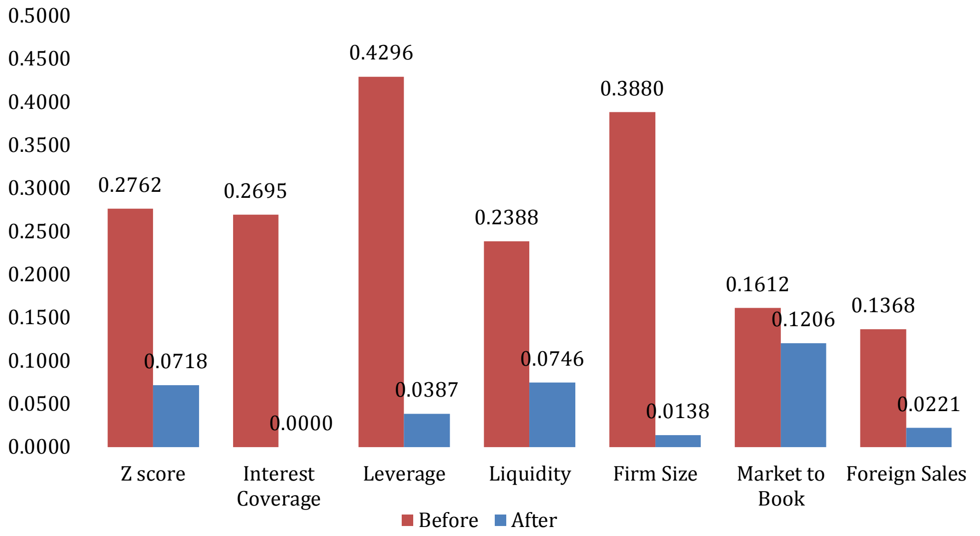

Figure 5-7: Univariate L1 Statistics Before and after CEM for FC Derivative Users

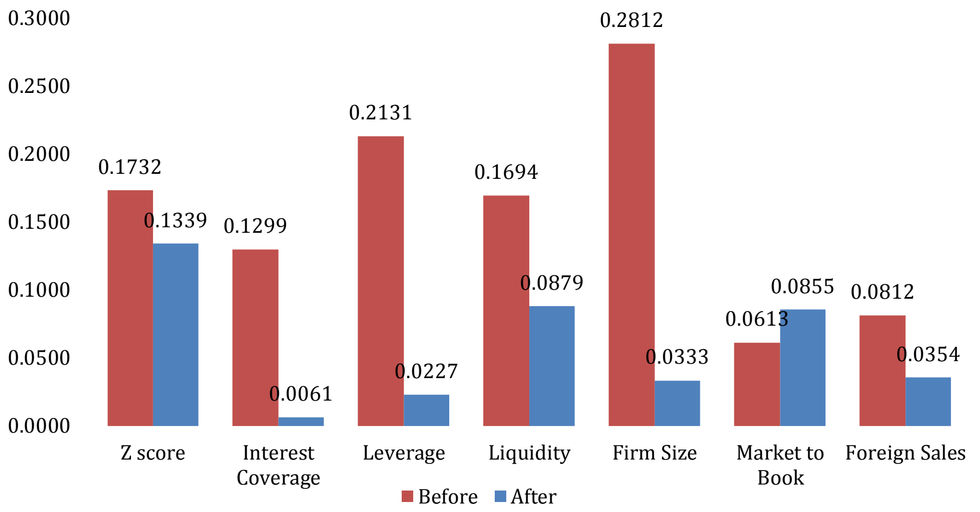

Figure 5-8: Univariate L1 Statistics Before and after CEM for IR Derivative Users

In Figure 5-6, we use univariate L1 imbalance statistics for before and after CEM matching. The derivative users and non-users in the unmatched sample are largely unbalanced than after matching. Prior to matching the L1 statistics for foreign sales is 0.1368 and after matching it is 0.0221. This shows that after using CEM derivatives users and non-users are more comparable on foreign sales. Derivative users and non-users have large imbalance prior to matching on firm size, liquidity, leverage, interest coverage and Z-score. However, after matching derivative users and non-users are more comparable on all these variables. There is a small change in before and after imbalance in market to book for derivative users and non-users.

In Figure 5-7 we present before and after CEM matching univariate L1 for FC derivative users. Prior to matching, highest imbalance between FC derivative users and non-FC derivative users is for firm size, leverage, liquidity and interest coverage. The imbalance is reduced after the matching except for market to book where the imbalance is increased after matching. Figure 5-8 show the imbalance results for before and after matching for IR derivative users. Similar to FC derivative users, the highest imbalance prior to matching is for firm size, leverage interest coverage and liquidity. The imbalance in all the covariates is reduced after matching using CEM. Overall, Figure 5-6, Figure 5-7 and Figure 5-8 shows that prior matching the covariates were not comparable between derivative users and non-users. However, after applying CEM the imbalance between derivative users and non-users reduced and hence allows the examination of impact of derivatives use on the EDF1YEAR and EDF5YEAR (outcome variables) on a list of comparable covariates.

5.4.9.2. Impact of Derivatives Use on the Probability of Default After CEM

In this section we estimate the causal effect of derivatives use on the probability of default after matching derivative users and non-users using CEM. We present results of this estimation in Table 5-23. We match users and non-users on three treatments (All Derivative Users, FC Derivative users and IR derivative users) and for two outcome variables (EDF1YEAR and EDF5YEAR). After matching derivative users and non-users using CEM, we run regression analysis of matched firms and apply CEM weights.[138]

[138] *We conducted parametric analysis after matching. We also included all of the covariates to account for any potentially remaining balances.*

Table 5-23: Impact Estimate of Derivative Use on The Probability of Default

This table provides the results of treatment effect on the ***EDF1YEAR*** *and* ***EDF5YEAR*** *after matching firms on CEM.* ***All Derivatives Users*** *is a dummy variable set equal to 1 if a firm is a derivative user and 0 otherwise.* ***FC Derivatives Users (UB)*** *is a dummy variable set equal to 1 if a firm is a FC derivative user and 0 for non-users.* ***IR Derivatives Users (UB)*** *is a dummy variable set equal to 1 if a firm is an IR derivative user and 0 for non-users. In parentheses are standard errors adjusted for heteroskedasticity (White (1980)) and firm clustering. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. The regressions also include year and industry dummies.*

Treatment	*EDF1YEAR*		*EDF5YEAR*	
	Const.	*Impact*	*Const.*	*Impact*
All Derivatives Users	19.0675***	-1.6279**	12.8979***	-1.0648**
	(7.0718)	(0.8523)	(4.3467)	(0.5238)
FC Derivative Users (UB)	10.8007***	0.0072	7.5200***	0.0872
	(2.5537)	(0.3330)	(1.6565)	(0.2160)
IR Derivative Users (UB)	12.9547***	-0.6872**	8.9819***	-0.4841**
	(3.1382)	(0.3672)	(2.0092)	(0.2350)

The results in Table 5-23 show that there is a significant (p-value <0.05) effect of derivatives use on the EDF1YEAR and EDF5YEAR. These suggest that firm's all derivatives use reduces the EDF1YEAR by 1.6279% and EDF5YEAR by 1.0648%. The detected impact of all derivative use is consistent with the results of PSM matching.[139] We repeat the analysis for FC and IR derivative users. We fail to find any impact of FC derivatives use on EDF1YEAR and EDF5YEAR. Similar to all derivatives use, we find significant negative impact of IR derivatives use on both EDF1YEAR and EDF5YEAR (p-value < 0.05). The results suggest that IR derivative use reduces EDF1YEAR by 0.6872% and EDF5YEAR by 0.4841%.

Overall, the results in this section provided further evidence of the significant negative effect of derivatives use on the probability of default. The results in this section showed that after matching derivative user firms with non-user firms on the CEM, we removed a large imbalance from the covariates. After matching, we run the analysis on data and find that all derivatives use and IR derivatives use have statistically significant negative impact on the EDF1YEAR and EDF5YEAR.

5.5. Summary of Research Findings

The main objective of this chapter was to examine the effects of derivative use on the probability of default for a large cross-section of UK non-financial firms during the period

[139] *See section 5.4.8.1*

1998 to 2010. This question is important in UK setting, as UK is creditor friendly country that makes the likelihood of bankruptcy, all else being equal, much greater, UK economy is more open and more exposed to foreign exchange risk and UK firms are one of the biggest users of derivatives. We examined the effects of all, FC and IR derivatives use on 1-year and 5-year probability of default and show that derivative users have statistically lower probabilities of default than non-users both in univariate and multivariate analysis.

We find that derivatives use lowers the probability of default for both one and five-year horizons, with a larger effect on near term default probabilities as measured by one-year expected default frequencies. Our regression analysis shows that the use of IR derivatives has a larger negative impact on default probabilities than FC derivatives. We find that the use of CP derivatives has a non-significant impact on default probabilities. When we look at combinations of derivatives used, we find that firms using both FC and IR derivatives and IR and CP derivatives generate the greatest reduction in the probability of default. The common factor in these instances is IR derivatives use. Financial distress is a direct result of a firms' inability to service the interest on its debt and payback debt when it matures and by using IR derivatives firms can directly manage this risk and in so doing more effectively reduce their probability of default. Our results also suggest that firms that use two types of derivatives for risk management benefits more as a result of larger reduction in the probability of default than one type of derivatives use. In this chapter, we interacted derivatives dummy with credit risk proxies and year dummies. The results of interaction with credit risk proxies suggest that derivatives use is associated with a significant reduction in the 1-year and 5-year probability of default during the period of elevated credit risk. The results of interaction between derivatives and year dummies show that derivatives use has larger negative effect on the probability of default during the period of economic crisis such as witnessed during the period of 2000-2001 and during recent financial crisis of 2007-2009. This analysis also reveals that derivatives were more beneficial during the period of recent financial crisis than the one before. In year 2008, the all derivative user firms have 1.54% (0.83%), the FC derivative users have 1.56% (1.02%) and IR derivative users have 1.39% (0.73%) lower 1-year (5-year) probability of default than non-users. We also interact derivatives dummy with Z-score. The positive coefficient on the interaction term suggests that the effect of derivatives on the probability of default is lessened and suggests that derivatives are more beneficial for firms with higher financial distress risk.

We control for the self-selection bias by using heckman treatment effects model and find that derivatives use has a statistically significant negative impact on the probability of default. We control for the problem of endogeneity by using instrumental variable. In instrumental variable model, we use a continuous measure of derivatives. The results of instrumental variables are consistent with our earlier results and suggest that extent of derivatives use is associated with a reduction in the probability of default. We also use PSM and CEM methods to control for the problem of endogeneity. In PSM, a derivative user firm is matched with a non-user firm based on their likelihood of using derivatives and in CEM a derivative user firms is matched with a non-user firm directly on the covariates. The mean difference test between a matched derivative user and non-user firm showed that derivative user firms have statistically and economically lower values of both 1-year and 5-year probability of default.

Overall, our results provide evidence consistent with the view that the use of derivatives by UK firms reduces their probability of default. This empirical evidence is consistent with the notion that UK firms on average are using derivatives for hedging rather than speculation.

Chapter 6. The Effects of FC Derivatives and FC Debt on FX Exposure

6.1. Introduction

The contemporary drive of globalisation has opened world markets for firms. Business operations are pursued in diverse markets and therefore they have become intensively competitive and highly risky. With the expansions, many difficulties may come. Organisations encounter fresh challenges and less surfaced areas of risk. These expansions have opened new sources of risk for firms e.g. foreign exchange (FX) risk, IR risk, CP risk etc. Firms have also created liabilities and assets overseas which also faces risk. These all affect the value of a firm. A sudden unfavourable change in the FX rate, IR and CP may have huge negative impact on the current and future cash flows of the firm. Such changes may negatively affect firm value, increase financial distress costs and may increase probability of bankruptcy.

To reduce the cash flow volatility and chances of bankruptcy as a result of unanticipated changes in FX rates, firms may use financial hedging and operational hedging. Financial hedging is implemented by using derivative instruments such as forwards, futures, swaps and options; whereas operational hedging is implemented by diversifying foreign operations across foreign countries to reduce FX exposure. The derivative instruments are used by offsetting the underlying value of foreign assets as much as possible so that a firm's stock return sensitivity to changes in FX rates is as low as possible. The cost of implementing a financial hedge is lower than the cost of implementing an operational hedge and hence smaller and financially constrained firms are more likely to use financial hedge to manage their FX exposure. While it is true that both financial hedge and operational hedge are implemented with the intention of lowering the FX, they both differ in terms of the type of FX risk that they hedge. Financial hedging techniques are more suitable to hedge short-term (transaction) exposure whereas operational hedge is more suitable in reducing long-term (operating) exposure. Chowdhry and Howe (1999) show that derivative instruments are used by firms at a greater extent to hedge short-term FX exposure and operational hedging to hedge long-term exposure.

UK firms are more exposed to FX rate changes compared to their US counterparts due to relatively open economy and more foreign sales as a proportion of total sales. The firms in our sample have an average ratio 57% of foreign sales to total sales. For a sample of US firms, Allayannis and Ofek (2001) find that the average foreign sales for their sample firms is approximately 20%. Elliott et al. (2003) report 44% of average foreign sales for their sample of 88 US firms. Kedia and Mozumdar (2003) report average foreign sales of 18.5% for a sample of 472 large US firms. For a sample of UK firms Muller and Verschoor (2008) report average foreign sales of 60.65%. A recent study by Zhou and Wang (2013) find 46.71% of average foreign sales of UK firms. These suggests that UK firms have more to lose if there is an unfavourable sudden change in FX rate due to higher FX exposure from their real foreign operations. UK firms actively use FC derivatives to manage their exposures. Demographic distribution of derivative usage shows that EU accounts for 66% of the global IR derivatives market and 60% of the global FC derivatives market. Out of that, London accounts for 39% and 44% of these respective global markets. The US has 24% and 15% of the value of global OTC derivatives market respectively[140].

The above discussion provides an important motivation for investigating the effects of FC derivatives use on FX exposure in the UK setting. Moreover, there are only couple of studies that examined the effects of derivatives use on FX exposure (Muller and Verschoor, 2008; Zhou and Wang, 2013). However, the effect of FC derivatives on FX exposure for UK firms is not clear. This study tries to fill this gap by examining the effects of FC derivatives use on FX exposure of a large sample of UK non-financial firms. Both Muller and Verschoor (2008) and Zhou and Wang (2013) examine the effects of FC derivatives on FX exposure using 1 year's data. Both studies provide weak results for the effect of FC derivatives use on FX exposure. The present study also contributes to the literature by investing the impact for a much larger period of 12 years starting from 1999 to year 2010.[141]

In this study, we examine the effects of FC derivatives use on FX exposure. We calculate FX exposure for UK firms in 3 ways 1) using Sterling broad effective exchange rate, 2) using lagged changes in Sterling broad effective exchange rate and 3) using Sterling/Euro and Sterling/USD bilateral exchange rates. If firms are using FC derivatives for hedging, then it should reduce the FX exposure of a firm whereas it should increase the FX exposure if derivatives are used for speculative purposes. To test the relationship between FC derivatives use and FX exposure, we include operating and financing decisions. We

[140] *Bank for International Settlements (2007)*

[141] *The sample period is 12 years when we use dummy variable as a proxy for FC derivatives use. However, the sample period is 9 years when we use notional values of FC derivatives.*

find that firms use FC derivatives to hedge unexpected changes in FX rates and not to speculate as we find that the use of FC derivatives, financing decision, reduces FX exposure. Our finding is consistent with previous studies that examined the relationship between FC derivatives use and FX exposure. (Nydahl, 1999; Allayannis, Ihrig, et al., 2001; Allayannis and Ofek, 2001; Nguyen and Faff, 2003; Zhou and Wang, 2013). Our results also indicate that the stock return is sensitive to not only the current changes but also to the lagged changes in exchange rates and that the use of FC derivatives also significantly reduces the sensitivity of stock return to the lagged changes in exchange rates.

Next, we examine the role of FC debt as a natural hedging instrument in reducing FX exposure of UK non-financial firms. Empirical results suggest that a large numbers of UK non-financial firms are use FC debt.[142] However, there are no studies that investigated the effect of FC debt use on FX exposure for UK firms. We try to fill this gap in literature by investigating the effect of FC debt on FX exposure for UK firms. We find results suggesting that firms' use of FC debt is associated with a reduction in FX exposure. This result is generally consistent with Keloharju and Niskanen (2001), Elliott et al. (2003), Doukas et al. (2003) and Kedia and Mozumdar (2003). The major contribution of this study is that we use not only percent of FC debt usage but also debt denominated in Euro and USD. This information of UK firms debt in different currencies allow us to do further analysis than previous studies on the importance of foreign debt in reducing risk. This makes our study more important for understanding foreign debt usage of UK firms and its effect in reducing FX exposure. We perform separate analysis of use of FC debt denominated in Euro and USD and examine its impact on FX exposure arising from changes in Sterling/Euro and Sterling/USD respectively. We find significant negative relationship between Euro debt and FX exposure arising from Sterling/Euro exchange rate changes suggesting that use of EU debt work as natural hedge for the exposure arising from Sterling/Euro exchange rate changes. We find no evidence that the US debt is associated with lower FX exposure arising from Sterling/USD exchange rate changes.

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[142] The average firm in our sample has 46% of FC debt usage. Judge (2006a) and Bartram et al. (2009) show that large number of UK firms use FC debt. Bartram et al. (2009) show that 85.6% of their UK sample uses FC debt whereas Judge (2006a) find that 65.8% of UK sample firms use FC debt. Clark and Judge (2008) show that out of 128 UK non-financial firms that hedge FX exposure 49.2% of firms hedge it with combined use of FC derivatives and FC debt, 25.8% of firms with only FC debt and 25% of firms used FC derivatives only.

After showing that FC debt can be used as a risk management instrument, we examine the effect of FC debt on the probability of default and Z-score. We argue that there are two opposite effects of FC debt use in relation to risk management: 1) Hedging effect - a reduction in cash flow volatility by matching foreign assets with foreign liabilities and hence, we argue FC debt should lower the probability of default and 2) Leverage effect –an increased level of debt from use of FC debt that may increase the probability of default due to increased interest payment. We find that firms that use FC debt have lower Z-score but not statistically different probability of default. Our insignificant results for FC debt on probability of default suggests that the leverage effect from the use of FC debt is neutralised by the hedging effect resulting in an overall insignificant effect of FC debt on the probability of default. These results combined with our earlier results suggest that FC debt can be used to manage FX exposure without increasing overall probability of default due to increased leverage.

This chapter is organized as follow: Section 6.2 provides variable description, Section 6.3 describes our methodology, Section 6.4 presents the empirical results and section 6.5 summarises research findings.

6.2. Variable Description

6.2.1. Measure of Foreign Exchange Exposure

In this chapter, we examine the effects of FC derivatives and FC debt on the FX exposure. We use equation [7] and calculate FX exposure using weekly and monthly data.[143] This is a proxy for the level of exchange rate risk. We calculate FX exposure in various ways:

- *Using a trade-weighted exchange rate index*
- *Using a lagged trade-weighted exchange rate index*
- *Using a bilateral Sterling/Euro exchange rate index*
- *Using a bilateral Sterling/USD exchange rate index*

The exchange rate exposure calculated using equation [7] measures the sensitivity of the stock return to the unanticipated changes in the above-mentioned exchange rates. The

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[143] We use three years return data surrounding the particular year to calculate monthly FX exposure. For example to calculate the FX exposure for year 2010, we used monthly return starting in 2009:01 to 2011:12.

calculated FX exposure could be either positive or negative. In empirical examination, we use raw, absolute, positive and negative values of FX exposure.[144]

6.2.2. Main Explanatory Variables

Following are the variables of interest in this chapter. All else being equal, if firms are using FC derivatives and FC debt for hedging then the FX exposure of user firms should decline after firm start using FC derivatives and FC debt. We employ both continuous and dummy measure of FC derivatives and FC debt as discussed below;

- *Continuous Measure of FC Derivatives and FC Debt*

  We use yearend outstanding notional values of FC derivatives as a continuous measure of FC derivatives use. We scale notional values of FC derivatives by total assets. This gives an extent of FC derivatives use and can differentiate between a firm with high FC derivative usage with a firm with low FC derivative usage.

  We also collected data on the percentage of firms debt denominated in FC. We specifically collect this information for 1) debt denominated in Euro 2) debt denominated in USD and 3) debt denominated in any other currency than Sterling. Based on this data, we calculate 1) FC debt percentage 2) EU debt percentage and 3) US debt percentage.

- *Dummy Measure of FC Derivatives and FC Debt*

  In this chapter, our measure of FC derivatives use is a dummy variable set equal to '1' if a firm uses FC derivatives and '0' for non-users.[145] We also investigate the effect of FC debt on the FX exposure. We create a FC debt dummy by setting it equal to '1' if a firm uses FC debt and '0' otherwise. We also create several categories of FC debt dummy based on the currency of the FC debt. We create EU debt dummy, which is set equal to '1' if a firm uses EU debt and '0' otherwise, and US debt dummy, which is set equal to '1' if a firm uses US debt and '0' otherwise.

  We also create following combination of FC derivatives and FC debt dummies 1) FC derivatives and FC debt dummy which is set equal to '1' if a firm uses both FC

[144] After initial multivariate analysis with raw and negative FX exposures, we restrict our empirical examination to absolute and positive FX exposures.

[145] We exclude "Other" users from the sample of non-users.

derivatives and FC debt and ‘0’ otherwise 2) FC derivatives and EU debt dummy which is set equal to ‘1’ if a firm uses both FC derivatives and EU debt and ‘0’ otherwise 3) FC derivatives and US debt dummy which is set equal to ‘1’ if a firm uses both FC derivatives and US debt and ‘0’ otherwise. For each of these three categories of dummy variables, we also create corresponding FC derivatives only, which is set equal to ‘1’ if a firm uses FC derivatives only and ‘0’ otherwise, FC debt only, which is set equal to ‘1’ if a firm uses FC debt only and ‘0’ otherwise, EU debt only, which is set equal to ‘1’ if a firm uses EU debt only and ‘0’ otherwise, and US debt only, which is set equal to ‘1’ if a firm uses US debt only and ‘0’ otherwise.

6.2.3. Control Variables

We use following control variables while examining the effects of FC derivatives and FC debt on the FX exposure.

- *Foreign Sales:* A foreign sale is a measure of firm’s exposure to foreign exchange exposure. Majority of the previous studies that investigated the effects of derivatives use on foreign exchange exposure incorporated foreign sales in their model (Allayannis, Brown, et al., 2001; Allayannis and Ofek, 2001; Keloharju and Niskanen, 2001; Nguyen and Faff, 2003; Muller and Verschoor, 2008; Zhou and Wang, 2013). We calculate this measure as a ratio of foreign sales divided by total sales.
- *Leverage:* We calculate leverage as the ratio of total debt to book value of assets minus book value of equity plus market value of equity. Smith and Stulz (1985) argue that by reducing the likelihood of default hedging reduces the expected costs of financial distress. This indicates that firms with high levels of debt are more likely to use derivatives and hence are less exposed to exchange rate risk. However, net of derivatives use leverage should increase the FX exposure. We expect a positive association between leverage and FX exposure.
- *Firm Size:* We use natural log of total assets as a measure for firm size. We expect that firm size will be negatively associated with FX exposure.
- *Liquidity:* We measure liquidity as ratio of total current assets minus total stock and work in progress over total current liabilities. Liquidity is also considered as a hedging substitute and hence firms with more liquidity may not use derivatives for

hedging. This suggests that firms with high levels of liquidity should have higher FX exposure.

- *Market to Book:* We calculate market to book as the ratio of market value of assets to book value of assets. We expect positive association market to book and FX exposure.

6.2.4. Summary Statistics

Panel A of Table 6-1 provides the summary statistics for FX exposure variables that we calculate using equation [7] for two periods weekly and yearly. We have total 4194 firm-year-observations for each weekly and monthly FX exposures. Around 51% of these observations are positive FX exposure. The mean value for whole sample suggests that firms have positive FX exposure for yearly FX exposure and negative for weekly FX exposure. When we look at positive and negative exposure, the results show that the positive FX exposures for weekly are less in magnitude than negative exposure while monthly exposure is milder for negative exposure than positive exposure. Overall, the results indicate that UK non-financial firms are more exposed to positive FX exposure.

In our sample of weekly FX exposure, we have 490 (11.6%, Positive – 46.93%, Negative - 53.06%) observations that are significant at 10% and 266 (6.34%, Positive – 46.61%, Negative - 53.38%) observations are significant at 5% level. The numbers of significant monthly exposures at 10% level are 617 (14.71% Positive – 57.69%, Negative – 42.31%) and 388 (9.25%, Positive – 63.14%, Negative – 38.86%) observations are significant at 5% level. There are more significant positive cases for monthly FX exposure than negative significant cases. Weekly significant cases are higher for negative exposure. These results indicate that sample firms are sensitive to both positive and negative FX exposures. Other studies also find similar percentage of firms exposed to exchange rate risk in their sample. Dominguez and Tesar (2006) find around 9% of firms are exposed to FX risk when they use currency of major trade partners to calculate FX exposure and 11% of firms are exposed to exchange rate risk when they use trade-weighted exchange rate. Nguyen and Faff (2003) report that 14.58% of their sample observations are significant for weekly FX exposure while 10.34% of monthly FX exposures are significant. Zhou and Wang (2013) find 9.46% of firms exposed to FX risk in their sample of UK non-financial firms for the year 1999. The numbers of significant firms in our study are similar to the above studies. These results suggest that UK non-financial firms are more exposed to positive exchange rate risk. These suggest that the appreciation of the pound will unfavourably affect the performance of the UK non-financial firms' than the depreciation of pound.

Table 6-1: Summary Statistics for Exposure to Fluctuations in Trade-Weighted Sterling Index

The table provides summary statistics for FX exposure calculated using equation [7], *derivatives variables and other determinants of FX exposure variables.* ***Extent of FC Derivatives*** *is the notional amount of FC derivatives scaled by the firm's total assets;* ***FC Derivatives*** *is a dummy variable that is set to '1' if a firm is FC derivatives users and '0' otherwise;* ***FC Debt*** *is a ratio of foreign debt to total debt;* ***Foreign Sales*** *is the ratio of foreign sales to total sales;* ***Leverage*** *is the ratio of total debt to market value of assets;* ***Liquidity*** *is the ratio of total current assets minus total stock and work in progress over total current liabilities;* ***Firm Size*** *is a natural logarithm of total assets;* ***Market to Book*** *is the ratio of market value of assets to book value of assets.*

Panel A: Summary Statistics for Exposure to Fluctuations in Trade-Weighted Sterling Index

Statistics	*Whole Sample*		*Positive Exposure*		*Negative Exposure*	
	Weekly	*Monthly*	*Weekly*	*Monthly*	*Weekly*	*Monthly*
Observations	4194	4194	2147	2221	2047	1973
Mean	-0.0583	0.2132	0.6858	1.1592	-0.8386	-0.8517
Median	0.0258	0.0716	0.5180	0.7500	-0.5640	-0.6441
Minimum	-3.7020	-3.2275	0.0006	0.0005	-0.0003	-0.0003
Maximum	2.8450	5.7536	2.8450	5.7536	-3.7020	-3.2275
Standard Deviation	1.0543	1.4266	0.6136	1.2089	0.8323	0.7347
Significant Expo -5%	266/6.34%	388/9.25%	124/5.77%	245/11.03%	142/6.93%	143/7.24%
Significant Expo -10%	490/11.68%	617/14.71%	230/10.71%	356/16.03%	260/12.70%	261/13.23%

Panel B: Summary Statistics for Derivatives and Determinants of FX Exposure Variables

Variables	*Observations*	*Mean*	*Median*	*Minimum*	*Maximum*	*Standard Deviation*
Extent of FC Derivatives	845	0.1387	0.0536	0.0000	2.4139	0.2988
FC Derivatives (Dummy)	2706	0.8684	1.0000	0.0000	1.0000	0.3381
FC Debt (% of Total Debt)	2966	0.4574	0.4529	0.0000	1.0000	0.3888
Foreign sales	2706	0.5761	0.5989	0.0000	1.0000	0.3383
Leverage	2706	0.2035	0.1675	0.0000	0.8920	0.1824
Liquidity	2706	1.2057	0.8800	0.0000	8.8000	1.3197
Firm Size	2706	13.0905	13.1766	0.0000	17.2529	2.0716
Market to Book	2706	1.7278	1.1626	0.2781	14.3325	1.9673

In panel B of Table 6-1, we present the summary statistics for the variables that we used in regression analysis. We have 845 firm-year-observations for notional values of FC derivatives. The mean value indicate that as a percentage of total assets an average firm use 13.87% of FC derivatives. Allayannis and Ofek (2001) for a sample of US firms find that the average firm in their sample use 3% of FC derivatives as a percentage of total sales. Allayannis, Ihrig, et al. (2001) report that the average use of FX derivatives among their sample user firms is 2.40% of total assets. For 88 US MNCs, Elliott et al. (2003) find that the average use of FC derivatives among user firms is 10.26% of total assets. Magee (2013) reports the derivative use of average user firms is 4.8% of total assets. Zhou and Wang (2013) report that the average fair value of FC derivative usage of their sample firms is 1.59% of total assets. These suggest that UK firms' higher extent of FC derivatives use compared to their US counterparts.

The mean value for FC derivatives dummy shows that 85.87% of firms in our sample report the use of FC derivatives. 42.6% of sample firm in Allayannis and Ofek (2001) report use of FC derivatives. Allayannis and Weston (2001) report that 37% of their sample firms use FC derivatives. Muller and Verschoor (2008) report 66.6% of their Belgian, German and Dutch firms sample firms use FC derivatives whereas 97.8% of their UK sample firms use FC derivatives. Clark and Judge (2008) report that 74.2% of 366 of their UK sample firms use FC derivatives. Bartram et al. (2009) report that 54.5% of 886 UK firms use FC derivatives compared with 37.7% of 2231 US firms. Magee (2013) reports that 67.3% of their US sample firms use FC derivatives. Zhou and Wang (2013) report that 75% of their initial sample firms use FC derivatives. These comparisons of percentage of FC derivative users between UK and US suggest that large numbers of UK firms are using FC derivatives.

The average foreign sale as a percentage of total sales of our sample firms is 57.16% suggesting pre-derivatives use FX exposure. Allayannis and Ofek (2001) report 19.80% of foreign sales as a percentage of total sales for their sample US firms. Allayannis and Weston (2001) report average foreign sales of 18% for a sample of large US MNCs. Elliott et al. (2003) report that the average foreign sales for their sample of US firms is 44.30%. Kedia and Mozumdar (2003) report that the average foreign sales of 18.5% of their 472 US firms. Nguyen and Faff (2003) report average foreign sales of 40% for a sample of Australian firms. Faff and Marshall (2005) report that the average US firm in their sample have foreign sales of 29.3%, the average foreign sales of UK firms is 41.8%. Nandy (2010) reports 64% of foreign sales for their sample of UK firms. Magee (2013) reports 33.20% of foreign sales for a 401 US firms. For a sample of Belgian, German and Dutch firms Muller and Verschoor (2008) find that the average foreign sales is 35.74% whereas the average foreign sales for UK firms is 60.65%. This indicates that UK firms are more exposed to FX risk than US firms due to their foreign operations. We also present descriptive statistics for other control variables. The table shows that the sample firms have average 20.35%

leverage. The mean liquidity of our sample firms is 1.2057. The average market to book ratio of our sample firm is 1.7278.

6.3. Methodology

The regression estimated using equation [17] would assess whether the use of derivatives increases, decreases or has no impact on the level of FX exposure. The coefficient on the *FC derivatives* variable is an important parameter in this case. If firms are using FC derivatives for hedging purpose then we expect a negative coefficient on FC derivatives indicating that the more a firm uses FC derivatives the less it is exposed to exchange rate risk assuming that FC derivatives can reduce the exchange rate risk. We expect that the use of FC derivatives should minimize the FX exposure for firms with positive exposure and should increase (decrease in absolute term) for firms with negative FX exposure. We expect a positive coefficient on foreign sales as we expect that an increase in foreign sales should increase FX exposure.

6.4. Empirical Analysis

In this section, we examine the effects of FC derivatives and FC debt on FX exposure and the probability of default in a multivariate framework. We use both continuous and dummy measure of derivatives and FC debt in the analysis. We calculate several measures of FX exposure based on various exchange rates.[146]

6.4.1. Effect of Foreign Currency Derivatives on FX Exposure

To examine the effect of FC derivatives use on FX exposure we use equation [17]. Consistent with Jorion (1990), Allayannis and Ofek (2001) and Nguyen and Faff (2003) we expect that a firms' FX exposure should be positively related to its ratio of foreign sales to total sales, as for a given exposure an increase in income from foreign operations should increase FX exposure. About FC derivatives, we expect that if firms use derivatives for hedging and assuming that FC derivatives are effective in hedging then it should lessen a firm's FX exposure.

Table 6-2 provides the regression results for equation [17] and examines the relationship between a firm's FC derivatives use and a firm's weekly and monthly FX exposure. The

[146] *See section 6.2.2 for more information*

main independent variable in the regression model is FC derivatives, which is a continuous measure of FC derivative use. In panel A of Table 6-2 we use raw values weekly and monthly values of FX exposure, which includes both positive and negative values of FX exposure, as our dependent variables. The results show a negative but insignificant relationship between weekly and monthly FX exposure and use of FC derivatives. For foreign sales, the relationship is negative and insignificant for weekly FX exposure and positive but insignificant for monthly FX exposure. Previous studies also find insignificant coefficient on FC derivatives when they use raw values of FX exposure (Allayannis and Ofek, 2001; Nguyen and Faff, 2003; Zhou and Wang, 2013). Allayannis and Ofek (2001) and Nguyen and Faff (2003) uses same model. Allayannis and Ofek (2001) uses monthly FX exposure and find that the coefficient on FC derivatives is negative but insignificant. Nguyen and Faff (2003) uses weekly and monthly FX exposure and find positive but insignificant coefficient on FC derivatives for weekly and monthly FX exposure. Zhou and Wang (2013) include firm size and incorporate a dummy variable for negatively exposed firms in the sample along with fair values of FC derivatives and ratio of foreign sales to total sales when they model for all FX exposure (raw values). They find negative coefficient on fair values of FC derivatives with stastically weak significance.

As our raw FX exposure variable includes both positive and negative observations, it is puzzling to interpret the coefficient on FC derivatives; as we expect a negative coefficient on FC derivatives when there is a positive FX exposure and positive coefficient when the FX exposure is negative indicating reduction in FX exposure. For an easier interpretation, we use the absolute values of FX exposure and re-examine the relationship between FX exposure and firm's use of FC derivatives[147]. If use of FC derivatives is motivated by hedging intentions then we expect the use of FC derivatives should reduce both positive and negative FX exposure in absolute values. Therefore, we expect that use of FC derivatives should be negatively related to absolute values of FX exposures. Panel B of Table 6-2 presents the results of absolute values of FX exposure. The coefficient on FC derivatives is negative but insignificant for both weekly and monthly FX exposures.

Table 6-2: The Effect of Foreign Currency Derivatives Use on FX Exposure

The table provides regression results of effects of Extent of FC Derivatives on FX exposure using equation [17]. The dependent variable is $\hat{\boldsymbol{\beta}}_{\boldsymbol{2it}}$ estimated using equation [7]; ***Extent of FC Derivatives*** *is the notional amount of FC derivatives scaled by the firm's total assets;* ***Foreign Sales*** *is the ratio of foreign sales to total*

[147] *Allayannis and Ofek (2001) and Nguyen and Faff (2003) also uses absolute values of FX exposures*

*sales. In panel A, we use raw values of FX exposure as a dependent variable. In panel B, we use absolute values of FX exposure as a dependent variable. In panel C, we use only positive values of FX exposure as a dependent variable. In panel D, we use only negative values FX exposures as a dependent variable. In parentheses are standard errors adjusted for heteroskedasticity (White (1980)) and clustering at the firm level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. The regressions also include year and industry dummies.*

	Panel A		***Panel B***	
	Raw Values of Betas		*Absolute Values of Betas*	
Variables	Weekly	Monthly	Weekly	Monthly
Extent of FC Derivatives	-0.0782	-0.1802	-0.1187	-0.0803
	(0.088)	(0.153)	(0.075)	(0.093)
Foreign Sales	-0.0809	0.2406	0.0047	0.3268***
	(0.085)	(0.159)	(0.069)	(0.124)
Constant	0.0774	0.2125	0.6834***	0.5418**
	(0.242)	(0.303)	(0.163)	(0.232)
N	825	825	825	825
Adj. R^2	0.0524	0.0421	0.0408	0.0615
F-Value	2.7876	2.9085	2.4445	2.5353
	Panel C		***Panel D***	
	Positive Values of Betas		*Negative Values of Betas*	
Variables	Weekly	Monthly	Weekly	Monthly
Extent of FC Derivatives	-0.1960***	-0.0654	0.0055	0.0348
	(0.057)	(0.169)	(0.156)	(0.082)
Foreign Sales	0.0244	0.4736**	0.0184	-0.1593*
	(0.082)	(0.193)	(0.119)	(0.086)
Constant	0.3876***	0.6199	-0.4486***	-0.3118**
	(0.130)	(0.788)	(0.162)	(0.130)
N	488	454	337	371
Adj. R^2	0.0730	0.0743	0.0515	0.1214
F-Value	3.0989	1.7056	1.8445	2.9303

Allayannis and Ofek (2001) find significant negative coefficient on FC derivatives when they use absolute value of monthly FX exposure. Nguyen and Faff (2003) find significant negative impact of FC derivatives on monthly FX exposure and insignificant positive coefficient on FC derivatives when they use weekly FX exposure. We find significant positive effect of foreign sales on absolute monthly FX exposures. These results suggest that for a given FX exposure the revenue from foreign sales makes the FX exposure larger. These indicate that the FX exposure of net-exporting firms is appears to be increasing with increase in ratio of foreign sales to total sales. For monthly FX exposure Nguyen and Faff (2003) find positive but insignificant coefficient on ratio of foreign sales to total sales and for weekly FX exposure they find negative and significant coefficient. This indicates that higher ratio of foreign sales to total sales is associated with lower FX risk whereas Allayannis and Ofek (2001) find positive and significant coefficient on foreign sales indicating that foreign sales increases FX exposure.

As reported above more than half of our observations have negative FX exposure and hence it is important that we model positively and negatively exposed firms separately. To further address the issue and examine the effects of FC derivatives use on FX exposure we separately run regression with positive and negative values of FX exposures using equation [17] separately.

Panel C of Table 6-2 presents regression results where we use positive FX exposures. For positive FX exposures, the negative coefficient on FC derivatives would indicate reduction in exchange rate risk and hence we expect negative coefficient on FC derivatives. As per our expectations, we find use of FC derivatives has statistically negative impact on weekly FX exposures that suggests that firms' use of FC derivatives reduces the FX exposure. The results are statistically significant at 1% level. The results indicate that a 1% increase in FC derivatives use reduces the weekly FX exposure by an average 0.1960 units in magnitude. Allayannis and Ofek (2001) also find statistically negative coefficient on FC derivatives.[148]

Nguyen and Faff (2003) find negative relationship between FX exposures and FC derivatives.[149] Muller and Verschoor (2008) find FC derivatives reduce weekly and monthly FX exposure, however insignificant. Their finding suggests that the use of FC derivatives by European firms does not significantly reduce the FX exposure. Zhou and Wang (2013) find negative but insignificant impact on weekly positive FX exposures. Similar to Nguyen and Faff (2003) and Zhou and Wang (2013), we find positive but insignificant relationship between weekly FX exposure and ratio of foreign sales to total sales. We find significant positive impact of foreign sales on FX exposure.

Finally, panel D of Table 6-2 presents the results of negative FX exposures. For negative FX exposures, the positive coefficient on FC derivatives would indicate reduction in FX exposure and would indicate that hedging is the motive for derivatives use. As expected, we find positive coefficient on FC derivatives use however insignificant. Our results

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[148] *Allayannis and Ofek (2001) and Zhou and Wang (2013) measured effective exchange rate index as units of home currency per unit of basket of foreign currencies. Our measure of the effective exchange rate is measured in similar way and hence the positive and negative exchange exposures for net exporters and net importers are the same.*

[149] *Nguyen and Faff (2003) and Muller and Verschoor (2008) measure effective exchange rate index as units of FC per unit of home currency. Therefore, a decrease in the index suggests that home currency is depreciating. In their study a net has negative exposure where as a net importer have positive exposure. In our study a net exporter has a positive exposure where as a net importer has a negative exposure. Hence, we compare their results of negative exposure with our positive exposures.*

suggest that neither ratio of foreign sales to total sales nor FC derivatives have any explanation power in explaining the variation in weekly FX exposure. However, we find that for a given FX exposure the revenue from foreign sales makes the FX exposure larger.[150] Nguyen and Faff (2003) find insignificant coefficient on FC derivatives when they use weekly FX exposure and significant when they use monthly FX exposure. Muller and Verschoor (2008) find insignificant results for net-importers. Zhou and Wang (2013) uses negative FX exposures and find positive but insignificant impact of FC derivatives use on their weekly FX exposures. The insignificant results observed for monthly FX exposure indicate that longer horizon FX exposure captures the effect of economic exposure that is difficult to hedge with derivatives. Nguyen and Faff (2003) find no relationship between long horizon exposure and FC derivatives.

In Table 6-3, we re-estimate the relationship between FX exposure and FC derivatives, as in Table 6-2, using a dummy variable as a proxy for FC derivatives use instead of notional values of FC derivatives for absolute and positive FX exposures. Henceforth, we restrict our analysis to only absolute values of FX exposures and firms with positive FX exposures.[151] The FC derivatives dummy variable is set equal to '1' if a firm disclosed that it uses FC derivatives and '0' otherwise. The problem with notional values of FC derivatives is that not all the firms disclose it and hence we lose firms that do not report this quantitative information. In FC derivatives dummy variable, we include all the firms that mention quantitative and qualitative use of derivatives and hence we have more observations. As expected the coefficients on FC derivatives dummy in both panel A and B of Table 6-3 are negative and statistically significant for both weekly and monthly FX exposures. These results suggest that FC derivative user firms have lower FX exposures than non-FC derivative user firms. As expected, the coefficient on ratio of foreign sales to total sales is positive but insignificant.

Table 6-3: The Effects of Foreign Currency Derivatives Use on FX Exposure

*The table provides regression results of effects of FC Derivatives use on FX exposure using equation [17]. The dependent variable is $\widehat{\boldsymbol{\beta}}_{\boldsymbol{2it}}$ estimated using equation [7]; **FC Derivatives** is a dummy variable that is set to '1' if a firm is FC derivatives users and '0' otherwise; **Foreign Sales** is the ratio of foreign sales to total*

[150] *For negative exposure the revenue from foreign sales makes the negative exposure larger in absolute terms and in relative terms its taking it away farther from zero making it larger negative number.*

[151] *Allayannis and Ofek (2001) argue that foreign sales create positive FX exposure and in the absence of imports data it would be better to use positive FX exposure to examine the effects of FC derivatives use otherwise it will create problem of omitted variable.*

*sales. In panel A, we use absolute values of FX exposure as a dependent variable. In panel B, we use only positive values of FX exposure. In parentheses are standard errors adjusted for heteroskedasticity (White (1980)) and clustering at the firm level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. The regressions also include year and industry dummies.*

Variables	***Panel A***		***Panel B***	
	Absolute Values of Betas		*Positive Values of Betas*	
	Weekly	Monthly	Weekly	Monthly
FC Derivatives	-0.1355**	-0.2292***	-0.1255**	-0.2730***
	(0.054)	(0.066)	(0.061)	(0.095)
Foreign Sales	0.0473	0.0093	0.0081	0.1258
	(0.038)	(0.051)	(0.048)	(0.080)
Constant	0.5261***	0.7214***	0.9905***	1.1782***
	(0.093)	(0.099)	(0.117)	(0.183)
N	3,552	3,573	1,668	1,602
Adj. R^2	0.1930	0.1208	0.1064	0.1141
F-Value	21.8155	16.0465	10.4394	6.2092

6.4.2. Controlling for Incentives of Derivatives Use

The regression results are estimated using equation [18] and presented in Table 6-4. In panel A and B we use notional values of FC derivatives and in panel C and D we use a dummy variable for FC derivatives use. The regression results in panel A show insignificant mixed effect of FC derivatives use on absolute values of weekly and monthly FX exposures. When we examine the effect of FC derivatives on firms with positive FX exposures in panel B we find significant negative effect of FC derivatives on weekly FX exposure suggesting that use of FC derivatives lowers weekly FX exposures of firms with positive FX exposure. The results indicate that a 1% increase in FC derivatives use reduces weekly FX exposure by an average 0.1757 units. The risk reducing effect of FC derivatives is absent for monthly positive FX exposure. Muller and Verschoor (2008) uses similar models and examine the relationship between FC derivatives and FX exposure. The authors fail to find any significant reduction in FX exposure from FC derivatives use in their OLS model. However, when they use WLS they find significant reduction in both positive and negatives monthly FX exposures. We find that FX exposure increases with the use of leverage. This is consistent with Chow and Chen (1998) who find that firms with high leverage ratio have more FX exposure. Nguyen and Faff (2003) examine similar model using absolute values of monthly FX exposure and find positive coefficient on leverage, however insignificant. Muller and Verschoor (2008) also find significant positive effect of leverage on monthly FX exposure.

Table 6-4: FC Derivatives Effect on FX Exposure: Controlling for Incentives for FC Derivatives

This table presents the regression results for equation [18]. *In panel A and B, we use* ***Extent of FC derivatives*** *and in panel C and D, we use* ***FC derivatives dummy****. In both models the dependent variable is* $\widehat{\boldsymbol{\beta}}_{\mathbf{2it}}$ *estimated using equation [7]; Extent of FC Derivatives is the notional value of FC derivatives scaled by the firm's total assets;* ***FC Derivatives dummy*** *is a variable that is set to '1' if a firm is FC derivatives users* *and '0' otherwise;* ***Foreign Sales*** *is the ratio of foreign sales to total sales;* ***Leverage*** *is the ratio of total debt to market value of assets;* ***Liquidity*** *is the ratio of total current assets minus total stock and work in progress over total current liabilities;* ***Firm Size*** *is a natural logarithm of total assets;* ***Market to Book*** *is the ratio of market value of assets to book value of assets. In parentheses are standard errors adjusted for heteroskedasticity (White (1980)) and clustering at the firm level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. The regressions also include year and industry dummies.*

Variables	***Panel A:*** *Absolute Values*		***Panel B:*** *Positive Values*	
	Weekly	*Monthly*	*Weekly*	*Monthly*
Extent of FC Derivatives	-0.0641	0.0032	-0.1757***	0.1071
	(0.063)	(0.101)	(0.048)	(0.142)
Foreign Sales	-0.0169	0.2795**	0.0154	0.4040**
	(0.062)	(0.113)	(0.074)	(0.170)
Leverage	0.6063***	1.2649***	0.3246*	1.6384***
	(0.180)	(0.356)	(0.173)	(0.479)
Liquidity	0.0595*	0.0695	0.0639	0.1073
	(0.036)	(0.049)	(0.039)	(0.070)
Firm Size	-0.0752***	-0.1745***	-0.0911***	-0.2455***
	(0.014)	(0.028)	(0.018)	(0.043)
Market to Book	0.0155	0.1055***	0.0298	0.1584***
	(0.020)	(0.037)	(0.041)	(0.049)
Constant	1.3863***	3.1037***	1.8028***	2.9024***
	(0.267)	(0.542)	(0.368)	(0.779)
N	808	808	474	443
Adj. R^2	0.1307	0.1883	0.1671	0.2237
F-Value	3.4704	6.5925	4.3757	5.4264
Variables	***Panel C:*** *Absolute Values*		***Panel D:*** *Positive Values*	
	Weekly	*Monthly*	*Weekly*	*Monthly*
FC Derivatives (Dummy)	-0.0968*	-0.2149***	-0.1314**	-0.2837***
	(0.054)	(0.068)	(0.063)	(0.095)
Foreign Sales	0.0139	-0.0081	-0.0266	0.1108
	(0.038)	(0.051)	(0.048)	(0.077)
Leverage	0.8012***	0.8088***	0.5730***	1.0171***
	(0.116)	(0.156)	(0.135)	(0.216)
Liquidity	0.0257	0.0201	0.0236	-0.0098
	(0.016)	(0.021)	(0.023)	(0.025)
Firm Size	-0.0681***	-0.0576***	-0.0502***	-0.0530***
	(0.013)	(0.014)	(0.012)	(0.020)
Market to Book	0.0017	0.0211*	0.0128	0.0261*
	(0.009)	(0.011)	(0.012)	(0.014)
Constant	1.2287***	1.3652***	1.5530***	1.3860***
	(0.217)	(0.220)	(0.204)	(0.305)
N	3,270	3,248	1,517	1,480
Adj. R^2	0.2493	0.1557	0.1623	0.1625
F-Value	23.6251	14.8553	11.3874	6.1747

The coefficient on firm size is negative and statistically significant at 1% indicating that larger firms have less FX exposure and provides support for the economies of scale in use of derivatives hypothesis. Larger firms are more likely to hedge as they may already have human resource and financial capital to effectively enter into financial derivatives market.

Hagelin and Pramborg (2004) argue that larger firms may have lower inherent exposure due to their ability to use operational hedges. Nguyen and Faff (2003) also use firm size in their model to determine FX exposure of Australian firms and find significant negative coefficient on firm size. In contrast, Zhou and Wang (2013) find positive association between firm size and sub-sample of firms that have positive FX exposure. This suggests that FX exposures increase with firm size, which is in contrast to other studies and theoretical expectations. One possible explanation for this behaviour of firm size could be that larger firms have lower costs of financial distress and hence they may have less need to hedge. However, as we discussed earlier larger firms are more likely to use derivatives and as a result should have lower FX exposures if derivatives have risk reducing impact. Larger firms also benefits from international diversification and operational hedging, which reduces FX exposure. Hagelin and Pramborg (2004) and Muller and Verschoor (2008) find significant negative relationship between firm size on FX exposure.

In panel C and D, we re-estimate equation [18] using a binary variable for FC derivatives use. As expected, the regression results suggest that the FC derivative users have lower FX exposures for both weekly and monthly and for both absolute and positive FX exposures than non-users suggesting reduction in FX exposure as a result of FC derivatives use. We find that the monthly FX exposure increases with the ratio of foreign sales to total sales. The other control variables in the model attract expected signs. In particular, we find that FX exposure increases with leverage and reduces with firm size.

6.4.3. The Effect of Foreign Currency Derivatives use on Lagged FX Exposure

Part A of Table 6-5 presents the descriptive statistics for $\beta_{3i}STR_{t-1}$ calculated for both weekly and monthly exposures using equation [19]. The table shows that 3.92% (1.88%) and 6.74% (3.76%) of sample firms are significantly exposed to weekly and monthly FX exposure at 10% (5%) significance level, respectively. The numbers of significant exposure are less compare to Table 6-1, where FX exposures are calculated as the current changes in Sterling effective exchange rate index. These suggest that the stock prices of majority of UK firms incorporate changes in FX rate without any time delay. However, exchange rate changes affect stock return of few sample firms with time delay. For firms with positive FX exposure 8.35% and 14.47% of the firms have significant exposure to weekly and monthly lagged FX exposures, respectively.[152] Overall, this indicates that there are firms in our sample that are affected by changes in the lagged Sterling exchange rate index.

Part B of Table 6-5 presents the results of regression where FX exposure is calculated using the lagged changes in Sterling exchange rate index. Similar to Hagelin and Pramborg (2004), the results in panel A of Table 6-5 shows that FC derivatives use has significant negative impact on $\beta_{2i}STR_{t-1}$ for weekly and monthly FX exposure. This suggests that use of FC derivatives significantly reduce sensitivity of stock return to time delayed FX rate changes. The results indicate that a 1% increase in FC derivatives use reduces the sensitivity of stock return volatility to time delayed weekly (monthly) exchange rate changes by 0.1061 (0.1881) units. Panel B of Table 6-5 uses FC derivatives dummy as a measure of firms derivatives use. As expected, the results show that the coefficients on FC derivatives dummy are negative and statistically significant for weekly and monthly return horizons. These suggest that FC derivative user firms have 0.0968 (0.2149) units lower sensitivity of stock return volatility to time delayed weekly (monthly) exchange rate changes. Together results in panel A and B of Table 6-5 indicates that the use of FC derivatives reduces the sensitivity of stock return to the lagged changes in the trade-weighted Sterling exchange rate index.

Table 6-5: The Effect of FC Derivatives Use on Absolute Value of Lagged FX Exposure

This table provides summary statistics for $\boldsymbol{\beta_{3i}STR_{t-1}}$ *in Part A and regression results for equation* [18] *using* $\boldsymbol{\beta_{3i}STR_{t-1}}$ *as dependent variable in Part B. In both panel A and B of Part B, we use absolute values of* $\boldsymbol{\beta_{2i}STR_{t-1}}$, *estimated using equation* [19], *as the dependent variable. In panel A, we* ***Extent of FC Derivatives*** *and in panel B, we use* ***FC derivatives dummy*** *as main explanatory variable.* ***Extent of FC Derivatives*** *is the notional value of FC derivatives scaled by firm's total assets;* ***FC derivatives dummy*** *is a variable that is set to '1' if a firm is FC derivatives users and '0' otherwise;* ***Foreign Sales*** *is the ratio of foreign sales to total sales; Leverage is the ratio of total debt to market value of assets;* ***Liquidity*** *is the ratio of total current assets minus total stock and work in progress over total current liabilities;* ***Firm Size*** *is a natural logarithm of total assets;* ***Market to Book*** *is the ratio of market value of assets to book value of assets. In parentheses are standard errors adjusted for heteroskedasticity (White (1980)) and clustering at the firm level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. The regressions also include year and industry dummies.*

Part A	*Whole Sample*		*Positive Exposure*	
Statistics	*Weekly*	*Monthly*	*Weekly*	*Monthly*
Observations	4464	4464	2059	2059
Mean	-0.1550	-0.0672	0.6771	0.9523
Median	-0.0792	-0.0880	0.5018	0.6928

[152] *The number of significant lagged FX exposures for negatively exposed firms are very few and hence we do not report the results.*

Minimum	-4.0802	-3.7525	0.0005	0.0011
Maximum	2.6078	3.8093	2.6078	3.8093
Standard Deviation	1.0872	1.2725	0.6076	0.8728
Significant Expo -5%	84/1.88%	168/3.76%	83/4.03%	166/8.06%
Significant Expo -10%	175/3.92%	301/6.74%	172/8.35%	298/14.47%

Part B	*Panel A: Extent of FC Derivatives*		*Panel B: FC Derivatives Dummy*	
Variables	*Weekly*	*Monthly*	*Weekly*	*Monthly*
FC Derivatives	-0.1061*	-0.1881**	-0.0968*	-0.2149***
	(0.058)	(0.087)	(0.054)	(0.068)
Foreign Sales	-0.0190	0.0431	0.0139	-0.0081
	(0.060)	(0.091)	(0.038)	(0.051)
Leverage	0.9464***	0.9847***	0.8012***	0.8088***
	(0.145)	(0.220)	(0.116)	(0.156)
Liquidity	0.0483**	0.0500	0.0257	0.0201
	(0.020)	(0.034)	(0.016)	(0.021)
Firm Size	-0.0429***	-0.0542***	-0.0681***	-0.0576***
	(0.015)	(0.016)	(0.013)	(0.014)
Market to Book	0.0139	-0.0605**	0.0017	0.0211*
	(0.017)	(0.029)	(0.009)	(0.011)
Constant	1.3838***	1.3853***	1.2287***	1.3652***
	(0.318)	(0.363)	(0.217)	(0.220)
N	824	825	3,270	3,248
Adj. R^2	0.2748	0.1760	0.2493	0.1557
F-Value	7.2979	6.9900	23.6251	14.8553

6.4.4. The Effect of FC Derivatives use on Exposure to the Euro and the USD Exchange Rates

We use two individual exchange rates Sterling/Euro and Sterling/USD to test the robustness of our results, as these two currencies are the two most important currencies in which UK trade. A report from Office for National Statistics (2013) shows that UK exports 50% of its services to EU, 28% services to US, 16% to Asia and rest to Australia, Oceania and Africa. The report also shows that UK imports 51% of services from EU, 26% of services from US, 19% services from Asia and rest from Australia, Oceania and Africa. These suggest that UK firms have twice as much export to EU than to US and three times to that of Asia. In respect to imports of UK, the data shows that import from EU is double to that of US and close to three times that of Asia. Overall, these suggest that UK firms are more exposed to Euro and USD and the exposure to Euro is double to that of USD. As EU and US play major role in export-import activity of UK, we calculate FX exposure of UK firms using Sterling/Euro and Sterling/USD bilateral exchange rates. The shortcoming of using a trade-weighted index for all firms is that not all the firms in our sample have the similar type of trade with other countries as the weights applied in calculating trade-weighted index and hence may not be relevant for such firms. Again, there would be firms in the sample that would not be affected by Europe and US exchange rates.[153] The results of this analysis are presented in *Table 6-6*.

Part A of *Table 6-6* reports the descriptive statistics for monthly Sterling/Euro and Sterling/USD FX exposures. It reports that 4.82% and 5.35% of the sample firms have significant exposure to Sterling/Euro and Sterling/USD respectively.154 This suggests that even though UK firms have more import-export with EU, UK firms are more exposed to the changes in bilateral Sterling/USD exchange rate. The mean Sterling/Euro and Sterling/USD exposure values suggest that the average UK firm has negative exchange rate exposure.

In panel A of *Table 6-6* we present regression results where we use notional values of FC derivatives as an explanatory variable. We find negative but insignificant relationship between FC derivatives use and sensitivity of firms' stock return volatility to changes in Sterling/Euro exchange rate whereas the relation between the FC derivatives use and the sensitivity of stock return volatility to FX rate movements in Sterling/USD is positive and insignificant. Muller and Verschoor (2008) calculate FX exposure for their European and UK firms using bilateral US exchange rate against Euro and Sterling. The authors also fail to find any significant relationship between FC derivatives use and USD FX exposure.[155] We find that firm' real foreign operation, ratio of foreign sales to total sales, significantly increases firms' stock return sensitivity to changes Sterling/Euro exchange rate. For other determinants of FX exposure, we find that leverage increases exposure whereas firm size is negatively associated with reduction in both Sterling/Euro and Sterling/USD FX exposures.

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[153] Jong et al. (2006) show that the use of trade-weighted currency index and individual exchange rates works as compliments.

[154] Significant exposures at 10%. The percentages of observations that are significant at 5% level are 2.26% and 2.67% respectively for Sterling/Euro and Sterling/USD exposures.

[155] Muller and Verschoor (2008) find significant results when they use WLS for firms with monthly negative USD FX exposures. They fail to find any significant effect of FC derivatives use on either weekly USD FX exposure or firms with positive USD FX exposures even when they use WLS.

Table 6-6: The Effects of FC Derivatives Use on Exposure to The Euro and USD Exchange Rates

This table provides summary statistics for STREURO and STRUSD FX exposures in Part A and regression results for equation [18] in Part B. In both panel A and B of Part B, the dependent variable is absolute values of $\hat{\beta}_{2it}$ estimated using following equation $R_{it} = \beta_{0i} + \beta_{1i}R_{mt} + \beta_{2i}EXR_t + \varepsilon_{it}$ where Rit is the rate of return on the ith firm's common stock in period t; Rmt is the rate of return on the market portfolio in period t; EXRt is the rate of return on 1) Sterling/Euro exchange rate and 2) Sterling/USD exchange rate. In panel A, we use Extent of FC derivatives and in panel B, we use FC derivatives dummy. ***Extent of FC Derivatives*** *is the notional values of FC derivatives scaled by a firm's total assets;* ***FC Derivatives dummy*** *is a variable that is set to '1' if a firm is FC derivatives users and '0' otherwise;* ***Foreign Sales*** *is the ratio of foreign sales to total sales;* ***Leverage*** *is the ratio of total debt to market value of assets;* ***Liquidity*** *is the ratio of total current assets minus total stock and work in progress over total current liabilities;* ***Firm Size*** *is a natural logarithm of total assets;* ***Market to Book*** *is the ratio of market value of assets to book value of assets. In parentheses are standard errors adjusted for heteroskedasticity (White (1980)) and clustering at the firm-level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. The regressions also include year and industry dummies.*

Part A	*Whole Sample*	
Statistics	*STREURO*	*STRUSD*
Observations	4564	4562
Mean	-0.2736	-0.0320
Median	-0.1684	-0.0043
Minimum	-4.1266	-3.1584
Maximum	2.3347	2.6847
Standard Deviation	1.1035	0.9602
Significant Expo -5%	103/2.26%	122/2.67%
Significant Expo -10%	220/4.82%	244/5.35%

Part B	*Panel A: FC Derivatives (Notional)*		*Panel B: FC Derivatives (Dummy)*	
Variables	*STREURO (1)*	*STRUSD (2)*	*STREURO (3)*	*STRUSD (4)*
FC Derivatives	-0.1162	0.0262	-0.1773**	-0.1514***
	(0.090)	(0.053)	(0.079)	(0.057)
Foreign Sales	0.2701***	0.0711	0.0439	0.0093
	(0.085)	(0.055)	(0.052)	(0.041)
Leverage	1.2430***	0.5889***	0.9420***	0.6032***
	(0.286)	(0.177)	(0.153)	(0.104)
Liquidity	0.0671	0.0163	0.0404*	0.0089
	(0.048)	(0.021)	(0.021)	(0.016)
Firm Size	-0.0774**	-0.0535***	-0.0882***	-0.0645***
	(0.033)	(0.017)	(0.021)	(0.013)
Market to Book	0.0085	-0.0328	0.0292**	0.0102
	(0.043)	(0.021)	(0.012)	(0.010)
Constant	1.1942**	1.6651***	1.8114***	1.8912***
	(0.523)	(0.377)	(0.290)	(0.205)
N	828	827	3,279	3,277
Adj. R^2	0.1714	0.1277	0.1490	0.1775
F-Value	4.3813	2.6462	7.8189	14.2645

In panel B of *Table 6-6* we use FC derivatives dummy as the proxy for FC derivatives use. We find negative and statistically significant coefficient on FC derivatives dummy for both Sterling/Euro and Sterling/USD FX exposure. These results indicate that FC derivative user firms have 0.1773 unit's lower Sterling/Euro exposure and 0.1514 units lower Sterling/USD exposure than non-users. We find leverage has positive and significant impact on both Sterling/Euro and Sterling/USD FX exposure. Firm size has negative and significant impact on both FX exposures. As expected, we find that liquidity has positive coefficient for both FX exposure while significant for Sterling/USD FX exposure.

6.4.5. The Effect of FC Derivatives and FC Debt on FX Exposure

In this section, We estimate equation [20] and [21] using WLS. The regression results are provided in *Table 6-7*. In panel A of *Table 6-7*, we use absolute value of monthly $\hat{\beta}_{2i}$, which is calculated using Sterling broad effective exchange rate, as a dependent variable. Our regression results show risk reducing effect of FC derivatives and FC debt. In particular, the results show that the combined use of FC derivatives and FC debt, the use of FC derivatives only and the use of FC debt only have significant negative impact on weekly and monthly FX exposures. These suggest that users of either of the financial instruments have lower FX exposure than non-users. Allayannis, Ihrig, et al. (2001) also find negative relationship between combine use of FC derivatives & FX exposure and FC debt & FX exposure.[156] Hagelin and Pramborg (2004) find negative and significant impact of the combined use of FC derivatives and FC debt, the use of FC derivatives only and the use of FC debt only on FX exposure. Chiang and Lin (2005) also examine the joint effect and find that FC derivatives have significant negative impact on FX exposure; whereas they find that the use FC debt increases FX exposure. Nguyen and Faff (2006) find negative but significant impact of FC debt on FX exposure for firms in industrial sector, positive but insignificant impact of FC debt on FX exposure for firms in resources sector and negative but insignificant impact for the combined sample. As expected and consistent with previous studies we find significant positive impact of ratio of foreign sales to total sales on FX exposure. These suggest that for a given FX exposure an increase in FX revenue increases FX exposure. This finding is consistent with Hagelin and Pramborg (2004)[157] who also find positive and significant coefficient on their proxy for foreign exposure and in contrast to Nguyen and Faff (2006) who find negative and significant impact of ratio of foreign sales to total sales on FX exposure for all firms and firms in resources sector. For firms in industrial sector they find positive but insignificant coefficient. In column 2, we

[156] Allayannis, Ihrig, et al. (2001) use a use a dummy variable for either use of FC derivatives or FC debt and use it to examine the effect of risk management on FX exposure.

[157] Hagelin and Pramborg (2004) use NE, calculated as difference between percentage of foreign revenue and percentage of foreign cost, as a proxy for firms' net foreign exposure.

use equation [21] where we control for determinants of FX exposures. We get similar results even after controlling for the determinants of FX exposures. Among other control variables, we find leverage has positive and significant impact on FX exposure.

In panel B of *Table 6-7*, we use absolute value of monthly $\hat{\beta}_{2i}$ calculated using Sterling/Euro bilateral exchange rate as a dependent variable. The results of equation [20] presented in column 3, show that the combined use of FC derivatives and Euro debt, the use of FC derivatives only and the use of Euro debt only has significant negative impact on Sterling/Euro FX exposure. We find significant positive coefficient on foreign sales suggesting foreign sales increases Sterling/Euro FX exposure. The regression results of equation [21] presented in column 4, show that results consistent with our previous results and suggest that the use of financial instruments is associated with a reduction in Sterling/Euro FX exposure for a user firm.

In panel C of *Table 6-7*, we use absolute value of monthly $\hat{\beta}_{2i}$ calculated using Sterling/USD bilateral exchange rate as a dependent variable. The results in column 5 show significant negative impact of combined use of FC derivatives and US debt on Sterling/USD FX exposure. We also find significant negative impact of FC derivatives on Sterling/USD FX exposure. These results suggest that the use FC derivatives on its own and together with US debt is associated with a reduction in Sterling/USD FX exposure. However, we fail to find any significant association between Sterling/USD FX exposure and US debt. This suggests that the use of USD debt has no effect on Sterling/USD FX exposure. When we control for determinants of FX exposure, we find that use of USD debt on its own or together with FC derivatives has no significant effect on FX exposure arising from changes in Sterling/USD rates.

Overall, the results of this section show that the use of FC debt is an important part of risk management for UK non-financial firms as the use of FC debt is associated with reduction in FX exposure. The results also suggest that for UK non-financial firms the debt denominated in Euro is more valuable as its use reduces FX exposure arising from unanticipated movement in Sterling/Euro; whereas USD debt has no significant effect on FX exposure arising from unanticipated movement in Sterling/USD exchange rate.

Table 6-7: The Effect of FC Derivatives and FC Debt on FX Exposure (WLS)

This table provides WLS regression results. In columns 1, 3 and 5 we use equation [20] and in columns 2, 4 and 6 we use equation [21]. In panel A, the dependent variable is absolute values of monthly $\hat{\beta}_{2it}$ estimated using Sterling broad index using equation [7]; In panel B, the dependent variable is absolute values of monthly $\hat{\beta}_{2it}$ estimated using Sterling/Euro bilateral exchange rate using equation [7]; In panel C, the dependent variable is absolute values of monthly $\hat{\beta}_{2it}$ estimated using Sterling/USD bilateral exchange rate using equation [7]; ***FC Derivatives and FC Debt*** *is dummy set equal to '1' if a firm uses both FC derivatives and FC debt and '0' otherwise;* ***FC Derivatives only*** *is a dummy set equal to '1' if a firm uses FC derivatives but not FC debt and '0' otherwise;* ***FC Debt only*** *is a dummy set equal to '1' if a firm uses FC debt but not FC derivatives and '0' otherwise;* ***Foreign Sales*** *is the ratio of foreign sales to total sales;* ***Leverage*** *is the ratio of total debt to market value of assets;* ***Liquidity*** *is the ratio of total current assets minus total stock and work in progress over total current liabilities;* ***Firm Size*** *is a natural logarithm of total assets;* ***Market to Book*** *is the ratio of market value of assets to book value of assets. In parentheses are standard errors adjusted for heteroskedasticity (White (1980)). ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. The regressions also include year and industry dummies.*

Variables	*Panel A: Broad Index*		*Panel B: Sterling/Euro*		*Panel C: Sterling/USD*	
	1	*2*	*3*	*4*	*5*	*6*
FC Derivatives and FC Debt Dummy	-1.5682***	-0.5879***				
	(0.143)	(0.122)				
FC Derivatives Only Dummy	-1.9330***	-1.0791***				
	(0.179)	(0.148)				
FC Debt Only Dummy	-1.6811***	-1.0173***				
	(0.279)	(0.251)				
FC Derivatives and EU Debt Dummy			-0.4826**	-0.2880*		
			(0.202)	(0.153)		
FC Derivatives Only Dummy			-0.5764***	-0.4228***		
			(0.188)	(0.140)		
EU Debt Only Dummy			-0.4330*	-0.4380**		
			(0.232)	(0.188)		
FC Derivatives and US Debt Dummy					-0.2608***	-0.1161
					(0.076)	(0.071)
FC Derivatives Only Dummy					-0.2222***	-0.1293*
					(0.078)	(0.072)
US Debt Only Dummy					-0.0393	-0.0224
					(0.112)	(0.106)
Foreign Sales	1.0081***	0.6534***	0.1775*	0.0840	0.0869*	0.0484
	(0.122)	(0.136)	(0.106)	(0.081)	(0.045)	(0.042)
Leverage		2.7858***		1.6331***		0.6470***
		(0.266)		(0.236)		(0.103)
Liquidity		-0.0625		0.0553**		0.0047
		(0.051)		(0.026)		(0.015)
Firm Size		-0.4266***		-0.1597***		-0.0983***
		(0.034)		(0.023)		(0.010)
Market to Book		0.0566		0.0663***		0.0098
		(0.039)		(0.016)		(0.013)
Constant	1.6188***	6.3101***	1.3296***	2.8470***	1.2658***	2.3619***
	(0.226)	(0.518)	(0.228)	(0.302)	(0.100)	(0.171)
N	2,536	2,414	2,537	2,414	2,535	2,412
Adj. R^2	0.7634	0.7828	0.1263	0.2417	0.1182	0.1809
F-Value	293.6095	135.1687	6.9130	10.6988	11.8303	15.9477

6.4.6. The Effect of Extent of FC Debt on FX Exposure

We have also collected data on percentage of debt denominated in FC and use it to examine the effect of extent of FC debt use on FX exposure. In Table 6-8 we use equations [22] and [23] to investigate the impact of percentage of FC debt on exchange rate exposure.

We expect a negative relationship between FC debt and FX exposure. We use dummy variable for FC derivatives use to control for other interpretation of coefficient on FC debt.

Table 6-8: The Effect of FC Debt on FX Exposure

This table provides WLS regression results. In panel A we use equation [22] and in panel B we use equation [23]. In both models the dependent variable is absolute values of $\hat{\beta}_{2it}$ estimated using equation [7]; ***FC Derivatives*** *is a dummy set equal to '1' if a firm uses FC derivatives and '0' otherwise;* ***FC Debt*** *is a ratio of foreign debt to total debt;* ***Foreign Sales*** *is the ratio of foreign sales to total sales;* ***Leverage*** *is the ratio of total debt to market value of assets;* ***Liquidity*** *is the ratio of total current assets minus total stock and work in progress over total current liabilities;* ***Firm Size*** *is a natural logarithm of total assets;* ***Market to Book*** *is the ratio of market value of assets to book value of assets. In parentheses are standard errors adjusted for heteroskedasticity (White (1980)). ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. The regressions also include year and industry dummies.*

Variables	*Panel A*		*Panel B*	
	Weekly	*Monthly*	*Weekly*	*Monthly*
FC Derivatives	-0.1547***	-0.2667***	-0.1242**	-0.2351**
	(0.050)	(0.075)	(0.053)	(0.116)
FC Debt (% of Total Debt)	-0.0096	-0.0814*	0.0076	-0.1808**
	(0.039)	(0.048)	(0.040)	(0.077)
Foreign Sales	0.0268	0.1141**	0.0106	0.0138
	(0.040)	(0.052)	(0.041)	(0.073)
Leverage			0.6743***	1.1414***
			(0.112)	(0.202)
Liquidity			0.0088	0.0743**
			(0.018)	(0.034)
Firm Size			-0.0525***	-0.0222
			(0.010)	(0.020)
Market to Book			0.0030	0.0342*
			(0.012)	(0.019)
Constant	0.8483***	1.2940***	1.3981***	1.4417***
	(0.075)	(0.110)	(0.156)	(0.335)
N	2,550	2,535	2,425	2,415
Adj. R^2	0.1498	0.0786	0.1893	0.2291
F-Value	11.8692	9.2043	12.6780	10.1751

The empirical results, presented in Table 6-8, show a significant negative relationship between firms' use of FC debt and monthly FX exposure. The results are consistent with our expectation that FC debt acts as a hedging instrument, as we find that the use of FC debt significantly reduces the monthly FX exposure.[158] We find mixed effect of FC debt use on weekly FX exposure. Our results are consistent with Elliott et al. (2003) who also find that firms use FC debt to hedge FX exposure. Doukas et al. (2003) also find that the FX exposure of Japanese firms declines as the firms engage in raising FC debt to manage

[158] *It is important to note that FC debt can work as hedging instrument only for those firms that have cash inflow from foreign operations and if firms can match cash inflow with cash outflow.*

FX exposure. The authors use debt to assets ratio as a measure for FC debt. However, debt to assets ratio may not be good proxy for FC debt as it is a measure of leverage. On the other hand, our measure is more suitable to investigate the effect of FC debt, as it is an actual measure of firms' use of FC debt. Our results are opposite to Chiang and Lin (2005) who find positive and significant coefficient on FC debt. Nguyen and Faff (2006) also investigate the effects of FC debt on FX exposure for Australian firms and fail to find any significant impact of either FC debt or FC derivatives on long-term FX exposure.

We also find significant negative coefficient on FC dummy variable for both weekly and monthly FX exposure. Consistent with our earlier results, these results suggest that FC derivative user firms have lower FX exposure than non-user firms. We find positive and in some cases significant coefficient for foreign sales. Consistent with other studies we find FX exposure increases with leverage and reduces with firm size. Overall, the results suggest that FC debt is effective in lowering monthly FX exposure.

Overall, our results from this section suggest that either the combined use of FC derivatives and FC debt or FC derivatives only or FC debt only has significant negative impact on both weekly and monthly FX exposure. These results are consistent with our expectations and suggest that these financial instruments are used for hedging purposes. Our results on FC debt support the intuition that FC debt can also work as risk management tool for firms to manage their FX exposure. We also provide anecdotal evidence from the annual reports of our sample firms where they mention that they use FC debt as a natural hedging tool.[159] Collectively, we suggest that FC debt is also an integral part of risk management for non-financial firms that can be used to hedge FX exposure besides FC derivatives.

6.4.7. The Effect of Foreign Debt on The Probability of Default

In previous section, we show that the use of FC debt reduces FX exposure for the user firms and provide anecdotal evidence showing that firms use FC debt as a risk management instrument. Many previous studies also report that firms use FC debt for hedging (Berkman and Bradbury, 1996; Allayannis and Ofek, 2001; Keloharju and Niskanen, 2001; Elliott et al., 2003; Kedia and Mozumdar, 2003; Hagelin and Pramborg,

[159] *See appendix for more details*

2004; Aabo, 2006). As established above that FC debt is an instrument for hedging, in this section we investigate the impact of FC debt on probability of default along with FC derivatives. Probability of default is a measure of firms' probability of encountering financial distress and it is estimated using Merton's (1974) option pricing model.[160] In simple terms the probability of default measures the likelihood that the market value of a firm's assets will be less than the book value of its liabilities by the time the debt matures. Firms' probability of default increases if a firm does not have sufficient capital resource to pay off its liabilities. Firms' probability of default may also increase with volatile cash flow as it may reduce the value of firms' assets. One of the reasons for cash flow volatility is FX exposure. If firms can manage their FX exposure with FC debt then firms can reduce its cash flow volatility and hence reduce probability of default. This suggests that FC debt can also be used to hedge probability of default. However, the use of FC debt may also result in higher probability of default. In unreported univariate results, we find that firms that use FC debt have significantly higher leverage than firms that do not use FC debt, which indicates that FC debt user firms should have higher probability of default due to more leverage than non-FC debt user firms should. It follows that there are two effects behind FC debt, leverage effect and hedging effect, pushing it into opposite direction. If the hedging effect of FC debt was larger, then we would expect negative relationship between FC debt and probability of default and if the leverage effect of FC debt was larger, then we would expect significant positive relationship between FC debt and probability of default. We use equation [24] to investigate the effects of FC debt on probability of default.

The empirical results presented in column 1 of Table 6-9 show that the use of FC derivatives lowers (has a significant impact on the) the probability of default. In addition, the combined effect of FC derivatives and FC debt has a significant negative impact on the probability of default. Moreover, the impact of FC derivatives and FC debt on the probability of default (-0.9641) is not significantly different to that generated by FC derivatives only (-1.0826). However, we fail to find any significant impact of FC debt on the probability of default. Collectively, these results imply that FC debt is not having an adverse effect on firm default probabilities. Therefore, this suggests that the leverage

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[160] *We source this data from Moody's.*

effect[161] on default probabilities from the use of FC debt is neutralised by the hedging effect[162] on default probabilities resulting in an overall insignificant effect. We get similar results in panel B when we use long-term default probabilities. When we use the amount of FC debt firms use (FC debt as a % of total debt) in our specification (models 2, 3, 5 and 6) we also find that FC debt use has no significant effect on default probabilities. These results support the notion that the two effects generated by the use of FC debt cancel each other out.

In panel C, we examine the impact of FC derivatives and FC debt on Z-score, an accounting-based measure of distress risk. A higher Z-score implies a lower distress risk. In column 7 our results show that the combined use of FC derivatives and FC debt has no significant impact on Z-score, whereas for firms that use FC derivatives only, the impact on Z-score is positive, suggesting that derivatives use lowers the risk of default. For firms using FC debt the coefficient is negative but insignificant suggesting that the hedging and leverage effects (of FC debt) neutralise each other. The results in columns 8 and 9 suggest that firms using more FC debt have significantly lower Z-score, which implies that the leverage effect of FC debt outweighs the hedging effect. Our results suggest that the hedging effect of the use of derivatives is statistically weaker when we use Z-score; which may be because it is a pre-derivative use measure and it does not fully incorporate the effects of derivatives; whereas the leverage effect from FC debt use will be fully reflected in a firm's balance sheet and is therefore more likely to be picked up by the Z-score measure.

Overall, our results suggest that firms that use FC debt likely to have lower Z-score but not different probability of default. These results combined with our earlier results suggest that FC debt can be used to manage FX exposure without increasing overall probability of default due to increased leverage. This finding is important as the average firm in our sample has 46% of FC debt usage. Judge (2006a) and Bartram et al. (2009) show that large number of UK firms use FC debt. Bartram et al. (2009) show that 85.6% of their UK

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[161] Clark and Judge (2009) show firms use of FC debt for hedging also increases the possibility of increased leverage if the FC strengthens against home currency. They find that firms with high leverage use currency swap to match their foreign assets with foreign liabilities instead of issuing new debt.

[162] Many previous studies find that firms use FC debt for hedging and its use reduces FX exposure (Allayannis, Brown, et al., 2001; Allayannis and Ofek, 2001; Keloharju and Niskanen, 2001; Elliott et al., 2003; Kedia and Mozumdar, 2003; Hagelin and Pramborg, 2004; Bartram et al., 2009)

sample uses FC debt whereas Judge (2006a) finds that 65.8% of UK sample firms use FC debt. The advantage of using FC debt as opposed to domestic debt is that FC debt also works as hedge for FX exposure by matching foreign assets with foreign liabilities and FC debt is also cheaper to obtain than domestic debt (Keloharju and Niskanen, 2001). Our results suggest that the combined use of FC derivatives and FC debt and FC derivatives only is associated with reduction in probability of default.

Table 6-9: Effects of FC Derivatives and FC Debt on the Probability of Default and Z-score

This table provides regression results of equation [24] *using OLS model.* ***EDF1YEAR*** *is the probability of default in 1-year time;* ***EDF5YEAR*** *is the probability of default in 5-years time;* ***Z-score*** *is a Altman's Z-score calculated for UK firms;* ***FC Derivatives*** *and* ***FC Debt*** *is a dummy set equal to '1' if a firm uses both FC derivatives and FC debt and '0' otherwise;* ***FC Derivatives Only*** *is a dummy set equal to '1' if a firm uses FC derivatives but not FC debt and '0' otherwise;* ***FC Debt Only*** *is a dummy set equal to '1' if a firm uses foreign debt but not FC derivatives and '0' otherwise;* ***Leverage*** *is the ratio of total debt to market value of assets.* ***Profitability*** *is measured as return on invested capital, which is calculated as the sum of pre-tax profits and total interest charges divided by invested capital.* ***Excess Return*** *is the annual return on the firm minus the value weighted FTSE all shares index annual return over the entire fiscal year.* ***Equity Volatility*** *is expressed as square root of number of trading days multiplied by standard deviation of natural log of the daily price growth rate.* ***Firm Size*** *is a natural logarithm of total assets.* ***Liquidity*** *is the ratio of total current assets minus total stock and work in progress over total current liabilities. In parentheses are standard errors adjusted for heteroskedasticity (White (1980)) and clustering at the firm level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. The regressions also include year and industry dummies.*

Variables	*Panel A: EDF1YEAR*			*Panel B: EDF5YEAR*			*Panel C: Z-score*		
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
FC Derivatives and FC Debt Dummy (A)	-0.9641**			-0.6074**			0.1064		
	(0.408)			(0.247)			(1.092)		
FC Derivatives Only Dummy (B)	-1.0826**			-0.7404***			2.5058*		
	(0.430)			(0.273)			(1.319)		
FC Debt Only Dummy (C)	0.1608			-0.0091			-1.8374		
	(0.701)			(0.426)			(1.919)		
FC Derivatives Dummy		-1.0968***			-0.6617***			1.8463*	
		(0.380)			(0.233)			(1.110)	
FC Debt (% of Total Debt)		0.1318	-0.0209		0.1346	0.0420		-1.5755*	-1.8382**
		(0.196)	(0.174)		(0.129)	(0.113)		(0.889)	(0.840)
Leverage	6.1364***	6.1559***	6.1206***	4.7645***	4.7806***	4.8439***	-2.8516	-3.3092*	-2.1842
	(1.187)	(1.191)	(1.063)	(0.690)	(0.691)	(0.616)	(1.906)	(1.907)	(1.795)
Profitability	-1.3167**	-1.3273**	-1.6033***	-0.9416**	-0.9431**	-1.0648***	21.9865***	22.1690***	22.3059***
	(0.628)	(0.631)	(0.613)	(0.415)	(0.417)	(0.404)	(2.460)	(2.451)	(2.380)
Firm Size	-0.3995***	-0.4015***	-0.4421***	-0.3291***	-0.3303***	-0.3557***	-0.1613	-0.1780	0.0155
	(0.072)	(0.073)	(0.082)	(0.046)	(0.046)	(0.051)	(0.237)	(0.230)	(0.235)
Equity Volatility	6.1077***	6.1029***	6.1529***	4.4721***	4.4662***	4.5210***	-4.8281***	-4.7452**	-4.4321***
	(0.748)	(0.748)	(0.690)	(0.464)	(0.465)	(0.432)	(1.855)	(1.867)	(1.686)
Excess Return	-1.9716***	-1.9747***	-2.0483***	-1.3303***	-1.3340***	-1.3680***	0.1162	0.1458	0.2649
	(0.252)	(0.252)	(0.226)	(0.148)	(0.149)	(0.134)	(0.549)	(0.553)	(0.522)
Liquidity	-0.3360***	-0.3376***	-0.2949***	-0.1997***	-0.2032***	-0.1762***	2.6151***	2.6294***	2.7793***
	(0.097)	(0.096)	(0.085)	(0.067)	(0.067)	(0.060)	(0.685)	(0.691)	(0.668)
Constant	4.0141***	4.0727***	3.6989***	3.4778***	3.4473***	3.1945***	7.6019*	7.4529*	6.1425
	(1.088)	(1.099)	(1.050)	(0.696)	(0.698)	(0.670)	(3.968)	(3.930)	(3.787)
N	2,256	2,255	2,526	2,256	2,255	2,526	2,332	2,331	2,602
Adj. R^2	0.5402	0.5402	0.5439	0.6218	0.6218	0.6255	0.3468	0.3436	0.3400
Equality Test: A=B	0.5463			0.3251			0.0142		
A=C	0.0618			0.1033			0.2563		`

B=C	0.0473	0.0594	0.0371

6.5. Summary of Research Findings

In this chapter, we examine the impact of FC derivatives and FC debt on the exchange rate exposure of UK firms. We also examine the impact of these instruments on the likelihood of default. We first investigate the use of FC derivatives on FX exposure using models similar to Allayannis and Ofek (2001) and Nguyen and Faff (2003). We use continuous and dummy measures as a proxy for firms' use of FC derivatives. Consistent with previous studies and theories of hedging, we find that use of FC derivatives use is associated with reduction in FX exposure. Furthermore, our results show that the unexpected changes in FX rates significantly affect stock return of around 4% to 6% (8% to 15% for observations with positive exposures) of observations with time delay. However, FC derivatives are effective in reducing FX exposure arising from time delayed exchange rate changes. Additionally, we calculate Sterling/Euro and Sterling/USD FX exposures, as Europe and US are major trading partners for UK firms and hence the stock return sensitivity of UK firms may have higher association with changes to Sterling/Euro and Sterling/USD. We show that use of FC derivatives reduces FX exposure arising from both Sterling/Euro and Sterling/USD. However, the empirical results in relation to the effects of FC derivatives use with Sterling/USD are slightly weaker.

Next, we investigate the role for FC debt, as a natural hedge, in reducing FX exposure. The extent of FC debt usage is associated with reduction in monthly FX exposure. In analysis where we use dummy variable for FC debt usage, the results show significant negative association between FC debt dummy and FX exposure. Our results also show that debt denominated in Euro is appear to be associated with reduction in FX exposure arising from changes in Sterling/Euro exchange rates. However, the debt denominated in USD does not appear to be associated with a reduction in FX exposure arising from changes in Sterling/USD exchange rate. Overall, the results suggest that firm's use of FC debt supports hedging motives.

After establishing that firms use FC debt for hedging, we investigate the effect of FC debt on the 1-year and 5-year probability of default and on Z-score. We show that there are 2 effects behind the use of FC debt 1) leverage effect 2) hedging effect. We fail to find any significant effect of FC debt on either 1-year or 5-year probability of default suggesting that hedging effect neutralised the leverage effect of FC debt usage. When we use Z-score, which we argue is a pre-hedging measure of probability of default, we observe a significant negative impact of FC debt on Z-score indicating a pre-hedging risk-increasing effect. Overall, our results suggest that firms that use FC debt are likely to have lower Z-score implying greater pre-hedging default risk but not different probability of default which suggests similar post hedging default probabilities between FC debt users and non-users. These results combined with our earlier results suggest that FC debt can be used to manage FX exposure without increasing overall probability of default.

Chapter 7. Conclusion

7.1. Introduction

This thesis examined the effects of derivatives use on measures of financial risk for UK non-financial firms using a large unbalanced panel data for the period 1999-2010. This research is important in light of the role played by derivatives during the recent financial crisis, the introduction of the European Market Infrastructure Regulation and more recently the prospect of the introduction of the FTT. The extant empirical literature on this subject and particularly in the context of the UK is inconclusive on several important questions. This thesis was undertaken to answer three research questions:

- *Does the use of derivatives reduce equity price risk?*
- *Is the use of derivatives associated with a reduction in the probability of default?*
- *Do the use of FC derivatives and FC debt lower the exchange rate exposure?*

An understanding of the effects of derivatives use on UK non-financial firms financial risk is an important area of investigation given that the use of financial derivatives by UK non financial firms is increasing and if the use is not associated with hedging, then it would increase the financial risk of user firms and could potentially have serious consequences for financial stability in the UK. It is also important to investigate this issue in the UK setting as the bankruptcy code in the UK is creditor friendly which makes financial distress potentially more costly in the UK, all else being equal.

7.2. Empirical Findings

The empirical work in this thesis was organized in three chapters the findings of which are briefly summarized below.

7.2.1. Does the use of derivatives reduce equity price risk?

Chapter 4 empirically investigated the effects of derivatives use on several measures of equity price risk for a large sample of UK non-financial firms. The impact of all derivatives, FC derivatives and IR derivatives use on total risk, market risk and idiosyncratic risk was examined for the period from 1999 to 2010. In this chapter both continuous and dummy measures of derivatives were employed unlike previous studies that relied on dummy indicators of derivative usage. The empirical results of Chapter 4 showed that UK non-financial firms use of derivatives lowered equity price risk. The results demonstrated that all derivative and IR derivative user firms have lower total risk and idiosyncratic risk than non-users. FC derivative users have lower total risk but not different market risk or idiosyncratic risk suggesting that IR derivatives have a greater risk reducing effect than FC derivatives. Moreover, the results of Chapter 4 suggested that the important issue is not just whether firms use derivatives or not, but also the extent of derivatives used. The results showed that the extent of all derivatives, FC derivatives and IR derivatives is associated with an economically significant reduction in total risk, market risk and idiosyncratic risk. These results are consistent with the results of Guay (1999) and Bartram (2006) but contradictory to that of Hentschel and Kothari (2001), Bartram (2006) (results with UK sample) and Nguyen and Faff (2010).

Furthermore, the investigation of the nonlinear effect of derivatives demonstrated an inverted U-shaped relationship between derivatives and total risk and idiosyncratic risk. This indicated that low extent of derivatives use as well as high extent of derivatives use is associated with a reduction in total and idiosyncratic risk; whereas medium extent of derivatives use has no effect on these risks. The extent of FC derivatives of more than 80% is associated with a reduction in total risk, market risk and idiosyncratic risk and indicates that the low extent of FC derivatives is not useful enough for implementing an effective risk reducing strategy. The extent of IR derivatives of < 40% is associated with a reduction in total and idiosyncratic risk. Consistent with Nguyen and Faff (2010), the results showed that not all the levels of derivatives use is associated with a reduction in the firm risk measures. These results are contrary to the results of Hentschel and Kothari (2001).

An examination of the effect of derivatives over-time on total risk showed that derivatives were effective in reducing total risk during the period 2004 to 2009, but had no effect on total risk in the years 2001, 2003 and 2010 and increased total risk in year 2000. The highest negative effect of derivatives was in the years 2005 and 2006. The negative over-time effect of derivatives on idiosyncratic risk was stronger and negative for year 2002 to 2010. Contrary to our earlier results, the over-time effect of derivatives showed positive effect on market risk. The over-time effects of FC and IR derivatives on total risk and idiosyncratic risk produce qualitatively similar results.

In this chapter the endogeneity problem, due to simultaneity bias, was controlled using the propensity score method (PSM) method. Derivative users and non-users firms were matched on their likelihood of using derivatives, propensity score. The simple mean and median difference between matched derivative users and non-users reduce unbiased estimation effect of derivatives use on the firm risk and showed that compared to matched non-users, derivative users firms have lower total risk and idiosyncratic risk. The comparison of matched FC derivative users and non-users and matched IR derivative users and non-users reveal lower total and idiosyncratic risk for user firms. These results are consistent with those presented by Bartram et al. (2011).

The combined results of Chapter 4 showed that UK non-financial firms use derivatives for risk reduction and that the important issue is not whether firms use derivatives or not, but the extent of derivatives that firms use.

7.2.2. Is the use of derivatives associated with a reduction in the probability of default?

Chapter 5 provided an examination of the effects of derivatives use on the 1-year (short-term) and 5-year (long-term) probability of default. The probability of default was proxied by the expected default frequency (EDF), sourced from Moody's Analytics. The advantage of this measure of firm risk is that it uses volatility of a firm's assets and the possibility of a firm's value declining to the degree that the firm will not be able to service its debt, to calculate probability of default. Surprisingly, not all the studies that investigated the effects of derivatives on the probability of default examine the effects of IR derivatives on the probability of default. Chapter 5 extends the extant literature on the effects of derivatives on the probability of default by investigating the effects of all derivatives, FC derivatives and IR derivatives during the period when one would expect significant benefits from derivatives.

The empirical analysis revealed that the use of all derivatives, FC derivatives and IR derivatives is associated with a reduction in both 1-year and 5-year probability of default. These results are consistent with findings of Boyer and Marin (2013) and Magee (2013). Moreover, the risk reduction effect of derivatives is greater for the short-term probability of default than the long-term probability of default, consistent with the notion that derivatives are better suited to manage short-term rather than long-term financial risk. The results also showed that the inclusion of “other” users in the sample of non-users underestimates the actual effect of derivatives on the probability of default. Consistent with hedging theories, the results showed that two types of derivatives use have higher risk reduction effect on the probability of default than one type of derivatives use. Further investigation revealed that in one type of derivatives use, FC and IR derivatives use is associated with a reduction in the probability of default; whereas, the use of CP derivatives has no effect on the probability of default. The results also revealed that the combination of IR & FC and IR & CP is associated with a reduction in the probability of default and also highlight that IR derivatives have greater negative effect on the probability of default than FC derivatives.

Chapter 5 also examined the importance of derivatives during a period of heightened credit risk, financial crisis and for firms with different levels of accounting-based risk. The interaction of derivatives with credit risk conditions showed that derivatives are most beneficial to the firms during periods of higher financial and credit risk measured by variables such as aggregate corporate capital gearing and the corporate default spread. When we interacted our derivatives dummy with year dummies we found that derivatives were highly beneficial during periods of economic slowdown such as the years 2000-2001 and during the recent financial crisis of 2007-2009. Derivatives use was more beneficial during the recent financial crisis of 2007-2009 than the economic crisis of 2000-2001. Derivatives use during the period of favourable economic conditions either increased or had no effect on the probability of default. The results indicated that the effect of derivatives on the probability of default is time varying. The interaction of derivatives with Z-score, accounting-based measure of risk, revealed that derivatives are more beneficial for firms with lower pre-derivatives Z-score, firms with greater risk of financial distress, than firms with higher pre-derivatives Z-score. The separate investigation of FC and IR derivatives use revealed similar benefits for user firms.

The problem of simultaneity between the extent of derivatives use, probability of default and leverage was addressed using 2SLS and GMM-IV methods. The results of instrumental variable analysis supported the risk reducing effect of derivatives. Several tests of instruments validity suggested that the instruments used possessed properties required by valid instruments. Endogeneity and self-selection bias problems were also controlled using matching methods. In particular, propensity score (PSM) and coarsened exact matching (CEM) methods were used. In the PSM method derivatives users and non-users are matched on a single score based on their likelihood of using derivatives and in CEM method covariates are first coarsened and then derivative users are exactly matched with non-users on the coarsened data. Several matching algorithms were used to match derivative users with non-users on the estimated propensity score. The results of PSM showed that derivative users had lower average probabilities of default than matched non-users across various matching algorithms for both short-term and long-term default probabilities. These results are similar to Bartram et al. (2011). The results were robust to hidden bias as suggested by sensitivity analysis. The CEM removes the imbalance from the data and makes the derivative users and non-users firms more comparable. The results of imbalance before and after matching showed a large reduction in imbalance improving the data for better estimation effect of derivatives use. The results showed significant negative effect of derivatives use on the probability of default after matching derivative users and non-users using CEM. Furthermore, the results of treatment effect, which is also used for controlling the self-selection bias, confirmed the negative effect of derivatives on the probability of default.

The results in Chapter 5 provided strong evidence that the use of derivatives by UK non-financial firms is associated with a reduction in the probability of default. The empirical analysis also showed that IR derivatives use had a greater risk reducing effect on the probability of default than FC derivatives use. The effect of derivatives use is also time varying with significant risk reduction during periods of economic and financial crisis. The results also showed that derivatives were more beneficial to firms that had higher pre-derivative financial distress risk measured by Z-score and during periods of heightened credit risk conditions.

7.2.3. Do the use of FC derivatives and FC debt lower the exchange rate exposure?

Chapter 6 investigated the effects of FC derivatives on FX exposure for a large sample of UK non-financial firms for the period 1999-2010. This chapter also sought to investigate whether FC debt could be used as a hedging tool by examining the effects of FC debt on FX exposure, the probability of default and Z-score. The use of FC derivatives and FC debt was measured using both a continuous and a dummy measure. The analysis in Chapter 4 and Chapter 5 showed that UK non-financial firms are largely exposed to foreign exchange exposure due to higher foreign sales, foreign income and foreign assets. Unlike previous studies FX exposure was calculated in several ways and the effects of FC derivatives was examined on each of them. Firm's FX exposures were calculated using a trade-weighted Sterling index, lagged trade-weighted Sterling index, bilateral Sterling/Euro exchange rates and bilateral Sterling/USD exchange rates.

The analysis showed that a number of UK non-financial firms were significantly exposed to FX exposure. The majority of firms had positive FX exposure which suggested that an appreciation of the pound would unfavorably affect a firms cash flow than a depreciation of pound. The results showed a relatively weak effect of the extent of FC derivatives on contemporaneous FX exposure. When the examination was repeated with a decision to use FC derivatives, the results showed a strong negative effect of FC derivatives on contemporaneous FX exposure suggesting a reduction in FX exposure consistent with findings of Allayannis and Ofek (2001). The examination of lagged FX exposure revealed that the stock returns of a small number of UK non-financial firms were sensitive to lagged changes in FX exposure. The stock return of these firms takes time to react to the changes in FX exposure. The analysis revealed that the use of FC derivatives lowers the sensitivity of stock return to lagged changes in FX rates. Stock return sensitivity to Sterling/Euro and Sterling/USD was calculated after looking at the UK export-import data. Few sample firms are significantly exposed to FX exposures arising from the unanticipated changes in Sterling/Euro and Sterling/USD. However, the decision to use of FC derivatives lowers the stock return sensitivity of UK firms to unanticipated changes in Sterling/Euro and Sterling/USD.

Evidence from annual reports suggested that many UK non-financial firms used FC debt as a risk management instrument. The role of FC debt as a risk management instrument was examined along with FC derivatives. The analysis revealed that firms that used FC derivatives and FC debt, FC derivatives only and FC debt only benefited from lower FX exposures arising from unanticipated changes in the Sterling trade-weighted index. Also firms that used FC derivatives and EU debt, FC derivatives only and EU debt only benefitted from lower FX exposure arising from unanticipated changes in the Sterling/Euro bilateral exchange rate. Furthermore, the results showed that the use of US debt along with FC derivatives lowered FX exposure arising from unanticipated changes in the Sterling/USD bilateral exchange rate. However, the use of US debt only had no effect on FX exposure. Analysis that used a continuous measure of FC debt showed that FC debt is more effective in hedging long-term FX exposure than short-term FX exposure.

After showing that FC debt lowered FX exposure and therefore was an effective risk management instrument, further investigation was carried out to examine the effects of FC debt on the probability of default and Z-score. We argued that there were two financial risk effects of using FC debt, these being a leverage effect which increased financial risk and a hedging effect which reduced financial risk. The empirical results showed that the use of FC debt had no effect on the probability of default on its own but if used with FC derivatives then it lowered the probability of default. Combined, these results suggested that there is no adverse effect of FC debt on the probability of default and suggested that the leverage effect of FC debt is neutralised by the hedging effect. The effect of FC debt on Z-score, deemed to be a pre-derivative measure of distress risk, showed that FC debt users had lower Z-scores and hence increased firm distress risk suggesting that leverage effect of FC debt suppressed the hedging effect. Overall, the results highlighted the importance of FC debt in risk management and showed that FC debt can be used to manage FX exposure without increasing overall probability of default due to increased leverage.

Overall, this thesis provided a comprehensive analysis of the effects of derivatives on financial risk measures for UK non-financial firms and showed that UK non-financial firms use of derivatives lowered firm financial risk which is consistent with UK firms using derivatives for hedging and not for speculation.

7.3. Contribution of Thesis to Existing Knowledge

The main contribution of this thesis to the existing body of knowledge is the new evidence on the effects of derivatives use on firm financial risk measures. This thesis not only showed the effects of derivatives on UK non-financial firms risks but also identified the type of instruments that reduced firms' risk, the time period when derivatives are the most beneficial and firms to which derivatives will benefit the most. Various stakeholders such as employees, investors, creditors and regulators have become increasingly concerned about how UK non-financial firms use. The empirical analysis of this thesis provides comprehensive analysis of the effects of derivatives on UK non-financial firms' risks and fills an important gap in the literature.

The wider empirical work on the effects of derivatives on firm risk is carried out mainly using samples of US firms (Guay, 1999; Hentschel and Kothari, 2001; Bartram, 2006; Nguyen and Faff, 2010; Bartram et al., 2011; Boyer and Marin, 2013; Magee, 2013). This shows that very little is known about the impact of derivatives usage on firm risk for UK non-financial firms. This thesis argues that UK firms have greater incentives to use derivatives for risk reduction than say US firms in part due the creditor friendly bankruptcy code in the UK and hence provides a good rationale for examining the effects of derivatives use. The results of this thesis show that UK non-financial firms' use of derivatives lowers firm risk and suggests that UK firms use derivatives for hedging and not for speculation. In this way the thesis makes a strong contribution to the existing corporate hedging literature.

This thesis is the first to investigate the effects of derivatives on the firm risk during the period of economic and financial crisis and contributed to the body of knowledge. Understanding the effects of derivatives during the period of financial crisis is important, given the role played by derivatives during the recent financial crisis. This thesis also contributed to the hedging literature by showing that derivatives are the most beneficial during the period of heightened credit risk conditions and the most beneficial to firms that have higher pre-derivative distress risk.

Moreover, this thesis contributed to the literature that examines the effects of FC derivatives on FX exposure. The thesis showed that FC debt is an important part of risk management for UK non-financial firms and the use of FC debt is associated with a reduction in FX exposure. The thesis was the first to show that there are two financial risk effects behind FC debt use, a leverage effect and a hedging effect. This thesis contributed to the hedging literature by examining the effects of EU debt and US debt on the FX exposure arising from Sterling/Euro and Sterling/USD exchange rates. Finally, the thesis also contributed to hedging literature by showing the effect of FC debt use on the probability of default and Z-score.

This thesis also contributed to the current debate governing the introduction of European Market Infrastructure Regulation and the prospect of the introduction of the FTT. The results of this thesis showed that UK non-financial firms use of derivatives is consistent with hedging motives and hence UK non-financial firms should be exempted from the new regulations and permitted to use OTC derivatives without any impediments, as they do not pose any threat to financial stability.

7.4. Limitations of the Study

The main assumption of this thesis is that markets are rational and market prices reflect all the available public information. Although this study provides important findings with regards to firms' use of derivatives, it also encountered some limitations that should be acknowledged.

It is important to remind that this thesis only investigated the effects of derivatives on the UK non-financial firms and with reference to other setting, it may produce different results and hence external validity is considered a limitation of this study.

This thesis suffers from the data limitation with regards to derivatives. The data on firms' use of derivatives is manually collected from annual reports and in the absence of uniform disclosure requirement different firms disclose the information on the derivatives use differently. This could have resulted in misclassification of some firms. However, this would not bias our results significantly as the misclassification of users and non-users would have similar occurrence. Due to unavailability of import data, this thesis could not investigate the effects of FC derivatives on the negative FX exposure without facing the omitted variable bias.

This thesis uses two broad categories of derivatives, FC derivatives and IR derivatives, and based on that shows the effects of derivatives on the firm risk. This thesis assumes uniform effect for the instruments that are available under broad categories of FC and IR derivatives. However, the broad categories of derivative can be subcategories into the type of derivative instrument such as forwards, swaps, caps, collars and options for which separate effects are not examined.

The problem of simultaneity bias and omitted variable bias are controlled with instrumental variables. The instruments are used based on the empirical literature and necessary tests are employed to check for the validity of the instruments. However, concerns remain over whether the instruments are uncorrelated with error term.

7.5. Recommendation for Further Research

Although this thesis provided a comprehensive examination of the effects of derivatives on the firm financial risks it can be extended for further research. The limitations of the study show that a further analysis could be conducted using detailed information on various types of derivative instruments under FC and IR derivatives. This will show what particular types of instruments are more effective in reducing risk.

While examining the effects of FC derivatives on FX exposure, the thesis highlights the importance of operational hedging, which can also lower the FX exposure. However, data on operational hedging is not readily available and further research can be done by collecting this data. Further research should also calculate FX exposure using different methods showed in empirical research.

7.6. Conclusion

In light of the recent financial crisis, derivatives market has come under greater regulatory scrutiny and new imposed and proposed regulations are likely to increase the cost of using derivatives for non-financial firms. The empirical examination presented in this thesis shows that use of derivatives by UK non-financial firms is associated with a reduction in firm risk. The risk reduction benefits of derivatives are shown to be higher during the recent financial crisis and heightened credit risk and also for firms with higher pre-derivative distress risk. Due to the increased cost of using derivatives, non-financial firms may not be able to hedge their risk and hence would be more exposed to risk. This shows that any intervention in derivatives market that would result in non-financial firms using fewer derivatives due to increased cost may not be warranted.

Appendix

"In order to minimize the Group's exposure to exchange rate fluctuations, the currencies of its major income and expenditure flows are matched, where at all possible, thereby creating a natural hedge against such fluctuations."(Abbot Group, Annual Report 2006, pg no. 23)

"Where appropriate, borrowings are effectively arranged in currencies so as to provide a natural hedge against the investments in overseas net assets." (Davis Service Group Plc, Annual Report 2009, pg no.81)

"The group invests in property acquired in a currency other than pounds Sterling. In such situations, it is the group's policy to take out loans in the same currency to act as a natural hedge against currency fluctuations."(Grainger Plc, Annul report 2007, pg no. 111)

"The Group's objective in managing its structural currency exposures from its foreign currency expenditure is to maintain a low cost of borrowings, which provides a natural hedge against currency depreciation. "Genemedix Group, Annual Report 2005, pg no. 50)

"Group policies on foreign currency risk affecting cash flow, profits and net assets are maintained to minimize exposures to the Group by using a combination of natural hedge positions and derivative instruments where appropriate"(First Group Plc, Annual Report 2010, pg no. 26)

"A small proportion of continuing revenues are denominated in Euros. A surplus of Euros has been generated over the last two financial years, however, a natural hedge is now in place with Euro sales matching Euro purchases" (Filtronic Plc, Annual Report 2010, pg no.63)

"The group finances overseas company investments partly through the use of foreign currency borrowings in order to provide a natural hedge of foreign currency risk arising on translation of the group's foreign currency subsidiaries."(Spectris Plc, Annual Report 2010, pg no 62)

"The group does endeavor to match foreign currency borrowings to investments in order to provide a natural hedge for the translation of the net assets of overseas subsidiaries."(Euromoney Plc, Annual Report 2010, pg no 17)

"The Group faces currency exposure from exchange rate fluctuations against Sterling. Balance sheet exposures are hedged to the extent that overseas liabilities, including borrowings, provide a natural hedge."(EMI Group Plc, Annual Report, pg no 21)

"*The majority of Emap's debt is in Euros due to the lower cost of borrowing. The interest arising on the Euro debt also acts as a natural hedge for the operating profits of our French business when these are translated into Sterling"(Emap Plc, Annual Report 2005, pg no. 12)*

"The Group's policy is to use Euro-denominated debt as a natural hedge against the translation of Euro-denominated assets."(Christian Salvation Plc, Annual Report 2007, pg no. 18)

"The majority of the Group's operating expenses are in Sterling along with smaller elements in US dollars and Australian dollars. Where possible, anticipated foreign currency operating expenses are matched to foreign currency revenues. The excess exposure over and above this natural hedge, to the extent that cash flows are predictable, is managed using forward contracts"(BTG Plc, Annual Report 2010, pg no. 100)

"We are exposed to exchange rate transaction risk on foreign currency sales and purchases as we believe that active currency hedging does not provide long-term benefits to our shareholders. Because a majority of our sales are denominated in US dollars, and the US dollar plays a dominant role in our business, we borrow and hold surplus cash predominantly in US dollars to provide a natural hedge."(BHP Billiton Plc, Annual Report 2010, pg no 105)

"100% of our debt at 30 April 2010 was drawn in dollars providing a substantial but partial natural hedge against Sunbelt's dollar-based net assets."(Ahstead Group Plc, Annual Report 2010, pg no. 29)

"The Group is subject to a cross-border transactional currency exposure in respect of trading outside each operating company's functional currency. Where possible, currency receivables and payables are matched, creating a natural hedge. A proportion of any surplus cross-border transactional exposure is hedged using appropriate derivative instruments"(Anite Plc, Annual Report 2010, pg no. 29)

“The Group’s policy is to borrow locally wherever possible to act as a natural hedge against the translation risk arising from its net investments overseas.”(Aegis Group Plc, Annual Report 2009, pg no. 65)

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