Arbitrage Opportunities and Feedback Trading in Emissions and Energy Markets

Abstract

This paper extends Sentana and Wadhwani (SW 1992) model to study the presence of feedback trading in emissions and energy markets and the extent to which such behaviour is linked to the level of arbitrage opportunities. Applying our augmented models to the carbon emission and major energy markets in Europe, we find evidence of feedback trading in coal and electricity markets, but not in carbon market where the institutional investors dominate. This finding is consistent with the notion that institutional investors are less susceptible to pursuing feedback-style investment strategies. In further analysis, our results show that the intensity of feedback trading is significantly related to the level of arbitrage opportunities, and that the significance of such relationship depends on the market regimes.

Keywords: Feedback trading; Arbitrage opportunities; Emissions and energy markets; Conditional volatility

JEL Classification: G1, G12, G17

1. Introduction

Economists have long debated the impact of feedback traders on equilibrium market prices, especially after the dramatic rises and falls of stock markets in recent years.[1] Some argue that their existence is destabilising, causing inefficiency and instability in asset prices (Black, 1986).[2] However, it has also been recognised that the presence of trend-following investors can be beneficial as they provide market participants with liquidity (De Long et al. 1990). Numerous papers have been devoted to the study of feedback trading activities in global markets. The literature has focused primarily on positive feedback strategy whereby investors buy (sell) when prices rise (fall) i.e., chasing the trend. Evidence of this type of behaviour is found in both individual and institutional investors (Nofsinger and Sias, 1999) and also in a wide variety of markets; see, for example, Sentana and Wadhwani (1992) for evidence of feedback trading in the U.S. stock market, Antoniou et al. (2005) for the G-7 stock markets, Laopodis (2005) for foreign exchange markets, Salm and Schuppli (2010) for index futures markets, and Chau et al. (2011) for exchange-traded fund (ETF) markets. When it comes to commodity markets, however, there is no clearly identified evidence of the feedback trading, despite the increasing use of commodities as an investment tool by the fund industry.[3]

In recent years, with the historically low interest rates and meltdowns of financial markets, many institutional investors and portfolio managers have turned to commodity markets as a way of meeting their investment objectives and, to a lesser extent, as a means of controlling

[1] A positive (negative) feedback strategy is a simple trading rule whereby investors buy (sell) after a price rise and sell (buy) after a price fall, i.e., trend-following strategies.

[2] It should be noted that feedback trading need not be irrational or noise trading in the sense of Black (1986). It is consistent with, for example, portfolio insurance strategies and stop-loss orders. Nonetheless, as Shleifer (2000) points out, the interaction of feedback traders and rational investors could lead to price movements that are not warranted by their fundamental values.

[3] A notable exception is the recent work of Cifarelli and Paladino (2010) who finds evidence of feedback trading in the crude oil market. However, as Koutmos (2012) argues, the use of low frequency data such as the weekly data employed by Cifarelli and Paladino (2010) is inadequate to study the short-run feedback trading activity.

risk.[4] The World Bank (2012, p.70) estimates that "*Investment fund activity in commodities is currently at 330 US$ billion (as of 2012:Q1)…9 times higher than a decade ago, when this activity started becoming a popular investment vehicle within the financial community.*" Despite the growing popularity of commodity markets in strategic asset allocation, scarce evidence exists in the extant literature on the trading behaviour of commodity investors, and in particular we can identify a little research examining the presence of feedback (trend-following) behaviour in these important markets.[5] This is somewhat surprising given the nature and design of commodity futures markets (i.e., the low cost of trading, absence of short-sales constraints, and high leverage opportunity) can appeal to several feedback-style investment strategies such as portfolio insurance, short selling, and margin trading.[6]

Previous empirical investigations have generally assumed the behaviour of feedback traders is, ceteris paribus, invariant to the level of arbitrage opportunities in financial markets. However, it is widely recognised that arbitrage activities and rational speculation are among the most significant factors contributing to feedback trading (Cutler et al. 1990; De Long et al. 1990) and there is growing evidence that the arbitrage opportunities - as measured by the spot-futures basis or convenience yield - have a predictive value in future price variations (Khoury and Yourougou, 1991; Knetsch, 2007; Gorton et al. 2013), it seems overly restrictive to assume that the behaviour of feedback traders is unaffected by the level of arbitrage opportunities.

[4] Indeed, the potential risk-diversification benefits of investing in commodity markets should offer broad appeal across investor types, see Bodie and Rosansky (1980) and Baker and Filbeck (2013).

[5] The majority of previous studies investigate the benefits of including commodities as a separate asset class (Campbell et al. 2003), the trends in commodity price forecasting (Gerlow et al. 1993), and the profitability of technical trading rules such as momentum and contrarian strategies (Wang and Yu, 2004; Miffre and Rallis, 2007; Marshall et al. 2008). In contrast, empirical evidence concerning the presence of feedback trading in commodity markets is limited.

[6] For instance, Cutler et al. (1990) argues that margin call-induced selling after a series of negative returns is one of the main reasons for positive feedback trading. Therefore, it is not uncommon to observe the margin call-motivated feedback trading activities in commodity futures markets.

Against this backdrop, we seek to examine in this paper the presence of feedback trading in commodity markets and the extent to which such behaviour is linked to the level of arbitrage opportunities using a daily dataset of four major energy markets in Europe (coal, electricity, natural gas and crude oil) and the more recently launched carbon emission market. The carbon emission market was opened in 2005 to reduce the emission of greenhouse gases. The market is built on a "cap-and-trade" system launched by the European Union whereby only firms in certain industries can receive free allocation of carbon assets and individuals cannot claim carbon assets from emission reduction. As a result, almost all the participants in carbon markets are identified as institutional investors.[7] This provides us with a unique opportunity of investigating the relation between institutional investors and feedback trading. In addition, the carbon market price was generally trending downward with periods of high volatility and illiquidity. This allows us to test the hypothesis that feedback traders may be responsible, at least in part, for the declining prices. Antoniou et al (2005, p.230) finds that "*positive feedback trading is more acute at high levels of volatility*", confirming the view that feedback traders had a destabilizing influence on market prices. Similar findings are reported by Dean and Faff (2008) for the Australian bond and equity markets.[8]

More specifically, building on Sentana and Wadhwani (1992, hereafter SW) feedback trading model, we aim to address the following questions:

- Is feedback trading significant in commodity markets? Particularly, whether the investors (mostly institutions) in carbon emissions market engage in feedback-style activities?

- Whether and to what extent arbitrage opportunities affect the intensity of feedback trading?

[7] According to the European Union Emission Trading Scheme Transaction Log published in November, 2012, less than 6% of total accounts are personal holding accounts (2050 out of a total of 34492 accounts), suggesting that the vast majority of participants in the European carbon markets are institutional investors.

[8] Furthermore, given that it is still a relatively new market (opened in 2005), it is natural to expect that the carbon market may attract noise traders in general and positive feedback 'trend-chasing' traders in particular. Bohl and Siklos (2008, p.1380), for example, finds that "*there is evidence of more pronounced positive feedback trading strategies in emerging markets relative to mature ones*."

- Does the relation between arbitrage opportunities and feedback trading vary across market regimes?

The empirical evidence gathered in this paper has a broad appeal to those who have invested (or considering investing) in commodities, and bears practical significance for portfolio managers and commodity traders relying on trend-chasing investment strategies. Our results are also of direct relevance to regulators and policymakers in formulating effective policies to tackle uncertainty caused by speculative trading, especially during the turbulent periods. Taken together, our study contributes to the literature in a number of ways. First, we complement the recent research of Cifarelli and Paladino (2010) who documents a significant feedback trading in crude oil market. However, as Koutmos (2012) suggests, the low frequency data such as the weekly data used by Cifarelli and Paladino (2010) is insufficient for the study of short-run feedback trading strategies. One of our goals is, therefore, to address the inadequacy of using weekly data in analysing feedback trading activities and to provide robustness check of the results by Cifarelli and Paladino (2010) with a daily dataset. Moreover, we extend their investigation to other energy markets (including coal, electricity and natural gas markets) to provide new evidence of feedback trading. Second, to the best of our knowledge, this paper also represents the first attempt to study the trading behaviour of market participants in the newly opened carbon emission market. As the carbon emission markets are quickly developing to an alternative asset class for investors, discovering the trading behaviour of investors in these markets has a broad appeal in finance.[9] Additionally, since the vast majority of investors in carbon market are institutional investors, the results obtained could be particularly relevant in providing a deeper understanding of institutional investors' trading philosophy and strategy.

[9] The European carbon emission market is worth around $150 billion in 2011, which is 20 times than in 2005. It is nowadays a sizable market which attracting increasing amount of investments (Charles, et al. 2011).

Third, and more importantly, this paper adds to the growing number of studies in examining the influence of arbitrage opportunities on investor trading behaviour. Arbitrage, one form of rational speculation, has been seen as a key driver for feedback trading (De Long et al., 1990). Arbitrage opportunities may also be considered by traders as a signal to trade. This study extends the standard feedback trading model by allowing arbitrage opportunities to affect the demand of feedback traders, in both additive and multiplicative ways. The results of our analysis are important in understanding the speculative behaviour of commodity futures markets investors, where arbitrage and hedging are believed to be the main motives of transaction. In addition, we estimate our augmented feedback trading models in different market regimes, i.e. bull and bear markets, to examine whether the degree of feedback trading and the effect of arbitrage opportunities vary across market conditions. Finally, unlike many previous studies which assume a particular conditional variance specification, this paper conducts a detailed specification test to identify an appropriate model for each market.

The main findings of our investigation can be summarised as follows. First, our results show that feedback trading is significant in coal and electricity markets, but not in carbon, natural gas and crude oil markets. As the vast majority of investors in carbon emissions markets are institutions, the results do not support the notion that institutional investors contribute to feedback trading, in contrast to the findings of Nofsinger and Sias (1999). Moreover, the results of our augmented feedback trading models suggest that arbitrage opportunities have a significant influence on feedback traders' demand in electricity and natural gas markets. This finding is consistent with the view that the behaviour of feedback traders tend to vary depending on the level of arbitrage opportunities in these markets. Additional analysis indicates that the response of feedback trader to past return or arbitrage opportunities depends on market regimes. Overall, our results are robust to the alternative measures of arbitrage opportunities including spot-futures basis and the convenience yield.

The remainder of this paper is organised as follows. Section 2 briefly reviews the related literature and outlines alternative feedback trading models used in the ensuing investigation. The data and model selection results are provided in Section 3. Section 4 presents and analyses the main empirical results, and Section 5 discusses the robustness checks. Section 6 concludes the paper.

2. Research background

2.1 Related literature

Whether noise trader in general and feedback trader in particular affects stock prices is a question of long-standing interest to economists. Shiller (1984), for instance, argues that social norms or fashions can influence asset price movements. Black (1986) introduces the concept of noise traders and offers a formal definition of ‘noise trading’ as trading on noise (or non-information) as if it were information. SW develops a heterogeneous trader model to demonstrate that trading between rational arbitrageurs and feedback traders gives bubble-like patterns. Positive feedback traders reinforced by arbitrageurs’ jumping on the bandwagon leads to positive autocorrelation of returns at short horizons. Eventual return of prices to fundamentals, accelerated by arbitrage, entails a negative autocorrelation of returns at long horizons. Since news result in price changes that are reinforced by positive feedback traders, stock prices overreact to news and exhibit excessive volatility of a destabilising fashion. Moreover, SW finds the interesting result that returns switch from being positively autocorrelated to negatively autocorrelated as volatility increases, predicting a negative relationship between volatility and autocorrelation.

In subsequent investigations, and consistent with the existence of positive feedback traders, a negative relationship between autocorrelation and volatility has also been found to be the feature of returns in both mature and emerging stock markets (Bohl and Siklos, 2008), foreign exchange markets (Laopodis, 2005), index futures markets (Salm and Schuppli, 2010), ETF markets (Chau et al., 2011), and crude oil market (Cifarelli and Paladino, 2010). In addition, a growing number of studies have attempted to extend the feedback trading model. For instance, Faff et al. (2005) modifies the standard feedback trading model by introducing a cross-market feedback trader, whose demand function is also sensitive to the price movement in the foreign markets. Chau et al. (2011) considers the effect of investor sentiment on the feedback traders' demand function and develops an augmented model with sentiment. Koutmos (2012) incorporates the role of an additional group of investors i.e., the fundamental traders, in the determination of stock return dynamics. More recently, Chau and Deesomsak (2014) finds a significant feedback trading in the major stock exchanges of G-7 countries and the intensity of feedback trading is linked to the overall macroeconomic conditions.

Nonetheless, the aforementioned literature does not take into consideration the potential impact of arbitrage opportunities on feedback trading behaviour. Feedback trading can be the result of various motivations. De Long et al. (1990) argues that rational speculation and arbitrage are among the most important factors contributing to feedback trading. Interpreted within the context of futures markets, spot-futures arbitrage is a trading strategy that rational investors pursue to profit from the deviation of futures price from its underlying spot price (Chung, 1991). This is also the central mechanism in maintaining the linkage between two markets (MacKinlay and Ramaswamy, 1988) and to contribute to price discovery (Garbade and Silber, 1983). When spot-futures basis (a widely used signal for arbitrage opportunity) increases beyond a threshold level, arbitragers can simultaneously buy futures and sell the underlying asset to benefit from these price deviations (Kumar and Seppi, 1994). Intuitively, to the extent that the presence of arbitrage opportunities motivates more investors to trade, the level of feedback trading is also expected to increase as a result of enhanced rational speculation and arbitrage activities. While the profitability of arbitrage (Chung, 1991) and spot-futures mispricing (McMillian and Philip, 2012) have been extensively studied, the issue of whether arbitrage opportunities affect feedback trading activities is yet to be explored.

Furthermore, in recent years the commodity markets have become increasingly important in tactical asset allocation. The trading strategies of commodity investors attract considerable attention in academic research. Miffre and Rallis (2007) shows that both momentum and contrarian strategies are profitable in commodity markets. Marshall et al. (2008) suggests that certain technical trading rules can generate abnormal returns in commodity markets. However, to date, there exists a limited research on feedback trading strategy in commodities. Cifarelli and Paladino (2010) examines feedback trading in the U.S. crude oil markets using weekly data, but the vast of majority existing research utilises either daily or intraday prices. There is a benefit of using a high frequency dataset because feedback traders usually adopt short-run computerised strategies to capture the observed trends which tend to vanish quickly (Koutmos, 2012). The use of weekly data may fail to detect these feedback trading activities.

Motivated by the forgoing discussion, we seek to examine in this paper the existence of feedback trading in commodity futures markets and the extent to which such behaviour is linked to the level of arbitrage opportunities. Numerous studies have investigated the links between arbitrage opportunities (as measured by spot-futures basis and/or convenience yield) and hedging (Lien and Yang, 2008; Millios and Six, 2011), and there have been a number of empirical investigations concerned with the predicative power of basis for futures returns, both theoretically (Khoury and Martel, 1989) and empirically (Khoury and Yourougou, 1991). However, to our knowledge, there has been no empirical investigation on the question of whether (and how) arbitrage opportunities influence feedback traders' investment decisions. In this paper we make several extensions to SW's model to allow the behaviour of feedback trader to vary depending on the level of arbitrage opportunities. We investigate the statistical support for our new feedback models using a daily dataset on emission and energy markets. To establish the background for the ensuing analysis, we briefly discuss in the next section the SW model of feedback trading and introduce our extended versions of this model.

2.2 Feedback trading models

2.2.1 SW's feedback trading model

Several feedback trading models have been proposed in the literature carrying different implications for the autocorrelation pattern of returns. For example, the feedback models developed by Shiller (1984) and Cutler et al. (1990) imply positive autocorrelation of returns. However, as Shiller (1989) points out, the interaction of rational investors and feedback traders can give rise to negligible, even negative autocorrelation. Recent research suggests that the autocorrelation pattern of stock returns is more complex than commonly believed and, consistent with the existence of positive feedback traders, autocorrelation and volatility are also found to be inversely related (Antoniou et al. 2005).

The approach adopted by Sentana and Wadhwani (1992) is based on the assumption that investors are heterogeneous in the sense that some investors ('smart-money') follow expected utility maximising behaviour, whereas others follow feedback trading (trend-following) strategies. Specifically, the demand for shares by the first group (rational expected utility maximisers) is given by:

$$S_t = \frac{E_{t-1}(R_t) - \alpha}{\mu_t} \tag{1}$$

where S_t is the fraction of shares that 'smart money' investors hold, $E_{t-1}(R_t)$ is the expected return at time t based on the information available at time *t-1*, α is the rate of return on a risk-free asset, and μ_t is the risk premium when all the shares are held by this group of investors. Assuming a positive risk aversion for rational investors, the risk premium can be modelled as:

$$\mu_t = \mu(\sigma_t^2) \tag{2}$$

where σ_t^2 is the conditional variance of returns at time t and $\mu(.)$ is an increasing function. As the risk associated with returns increases, investors require a higher risk premium. It follows that, when all the shares are held by ‘smart money’ and the market is in equilibrium (i.e., $S_t = 1$), Equation (1) is equivalent to the Intertemporal Capital Asset Pricing Model (ICAPM):

$$E_{t-1}(R_t) - \alpha = \mu(\sigma_t^2) \tag{3}$$

The other group of investors (feedback traders) do not base their investment decisions on fundamentals but rather react to previous price changes. Their demand function is given as:

$$F_t = \gamma R_{t-1} \tag{4}$$

where R_{t-1} is the ex-post stock return at time $t-1$ and γ is the marginal response of feedback traders to previous returns. Positive feedback trading strategy is a bet that past performance will continue into the future and thus buy after a price rise and sell after a price fall ($\gamma > 0$). On the contrary, negative feedback traders buy (sell) when price is falling (increasing) to reflect their belief that trends will soon reverse ($\gamma < 0$). In equilibrium all shares must be held:

$$S_t + F_t = 1 \tag{5}$$

Substituting (1), (2) & (4) into (5) and rearranging gives:

$$E_{t-1}(R_t) - \alpha = \mu(\sigma_t^2) - \gamma\mu(\sigma_t^2)R_{t-1} \tag{6}$$

Assuming that the ‘smart-money’ investors have rational expectation, i.e.,

$$R_t = E_{t-1}(R_t) + \varepsilon_t \tag{7}$$

where ε_t is an independently and identically distributed error term. Equation (6) can then be reformulated as:

$$R_t = \alpha + \mu(\sigma_t^2) - \gamma\mu(\sigma_t^2)R_{t-1} + \varepsilon_t \tag{8}$$

The term $-\gamma\mu(\sigma_t^2)R_{t-1}$ in Equation (8) implies that the presence of positive (negative) feedback trading will induce negative (positive) autocorrelation in returns, and the higher the volatility the more negative the autocorrelation. However, Equation (8) does not consider the return autocorrelation caused by non-synchronous trading and other market imperfections. Allowing for these possibilities and taking a linear form of risk premium, SW assumes the following empirical version of feedback trading model:

$$R_t = \alpha + \rho\sigma_t^2 + (\gamma_0 + \gamma_1\sigma_t^2)R_{t-1} + \varepsilon_t \tag{9}$$

where γ_0 is the coefficient of first order autocorrelation induced by market imperfections and $\gamma_1=-\gamma\mu$. Thus, the presence of positive (negative) feedback trading implies that γ_1 is negative (positive) and statistically significant. Hereafter this model is referred to as baseline Model I.

2.2.2 Feedback trading with arbitrage opportunities

It is clear from Equation (4) and the baseline Model I that, the demand of feedback traders depends solely on previous price changes. Yet, an increasing number of studies show a strong linkage between the level of arbitrage opportunities and the trading behaviour of investors. Kumar and Seppi (1994) and Miller et al. (1994) indicate that the dynamics of basis or convenience yield can provide a useful signal for the existence of arbitrage opportunities. When the basis increases beyond a threshold level, rational speculators (or feedback traders) can exploit these opportunities by simultaneously trading in the spot and futures markets. Lien and Yang (2008) also demonstrates the importance of incorporating the changes of basis into hedging decision. They show that the spot-futures basis significantly affects the optimal hedge ratio estimation and hedging performance. A more recent study by Mellios and Six (2011) finds that the demand for hedging is highly associated with convenience yield.

Motivated by the above literature, in this paper we extend the model proposed by SW in order to examine whether arbitrage opportunities affect the intensity of feedback trading. For simplicity, as in SW, we assume there are two distinct groups of investors: 'smart money' investors and feedback traders, and let the demand for shares by smart money investors be given by Equation (1). However, we allow the demand for shares by feedback traders depends not only on the past returns but also on the observed level of arbitrage opportunities in the markets (as proxied by the lagged basis). Consider first extending the baseline Model I so that the demand by feedback traders depends in an additive way on the level of arbitrage opportunities:

$$F_t = \gamma R_{t-1} + \delta B_{t-1} \tag{10}$$

where B_{t-1} is the lagged basis, given $B_t = \ln(S_t / F_{t,T})$ and δ is a coefficient measuring the sensitivity of feedback traders to arbitrage opportunities (as captured by the lagged basis). Substituting (1), (2) & (10) into (5) and rearranging gives:

$$E_{t-1}(R_t) - \alpha = \mu(\sigma_t^2) - \gamma\mu(\sigma_t^2) R_{t-1} - \delta\mu(\sigma_t^2) B_{t-1} \tag{11}$$

Assuming the rational expectation and taking $\gamma_2 = -\delta\mu$ produces the empirical version of our augmented feedback trading model (Model II):

$$R_t = \alpha + \rho\sigma_t^2 + (\gamma_0 + \gamma_1\sigma_t^2) R_{t-1} + \gamma_2 B_{t-1}\sigma_t^2 + \varepsilon_t \tag{12}$$

It is interesting to note that return in period t depends additively on the measure of arbitrage opportunities B_{t-1} and the extent of this dependence varies with conditional volatility σ_t^2.

In Model II, the reaction of feedback traders to price changes is not in itself dependent on the level of arbitrage opportunities, although their overall demand is. As an alternative we also consider a demand function that is affected by arbitrage proxies in a multiplicative way:

$$F_t = (\gamma + \delta B_{t-1}) R_{t\text{-}1} \tag{13}$$

where B_{t-1} is defined as before. Substituting (1), (2) & (13) into (5) and rearranging gives:

$$E_{t-1}(R_t) - \alpha = \mu(\sigma_t^2) - (\gamma + \delta B_{t\text{-}1})\mu(\sigma_t^2) R_{t-1} \tag{14}$$

Following the empirical approximation of SW and taking γ_2=-$\delta\mu$ again produces the empirical version of our second augmented model (Model III):

$$R_t = \alpha + \rho\sigma_t^2 + (\gamma_0 + \gamma_1\sigma_t^2 + \gamma_2 B_{t-1}\sigma_t^2) R_{t-1} + \varepsilon_t \tag{15}$$

2.2.3 Conditional volatility specifications

Completion of the feedback trading Models (I)-(III) requires the conditional variance of returns σ_t^2 to be well-specified. Since it is well established that stock returns are conditionally heteroscedastic, many studies approximate the conditional volatility with a generalised autoregressive conditional heteroscedastic (GARCH)-type specification. SW assumes the exponential GARCH (EGARCH) in their study, but increasing number of researchers (Antoniou et al., 2005; Chau et al., 2011) are adopting an alternative asymmetric GARCH model proposed by Glosten et al. (1993) to capture the asymmetric effect in the conditional variance process. Cappiello et al. (2006) warns that if the GARCH model is not well-specified, the estimation results would no longer be consistent.[10] Therefore, in order to select the most appropriate model for the ensuing analysis, we conduct extensive tests to see which conditional volatility equation seems to fit our data the best. We compare three most popular volatility models in our specification tests:

[10] The search and application of an appropriate GARCH model is also important to ensure that 'non-convergence' problem is reduced to minimal. Most univariate GARCH models should encounter few convergence problems if the model is correctly specified and fits data reasonably well (Alexander, 2001).

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \qquad \text{[GARCH]} \qquad (16)$$

$$\ln \sigma_t^2 = \alpha_0 + \alpha_1 G_{t-1} + \beta \sigma_{t-1}^2 ; \quad G_{t-1} = \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{2}{\pi}} + \delta \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \qquad \text{[EGARCH]} \qquad (17)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \delta I_{t-1} \varepsilon_{t-1}^2 \qquad \text{[GJR-GARCH]} \qquad (18)$$

where σ_t^2 is the conditional variance at time t, ε_{t-1} is the innovation at time $t-1$ and I_{t-1} is a dummy variable which takes a value of one in response to bad news ($\varepsilon_{t-1}<0$) and zero otherwise. The 'best-performing' model is selected for each series using several criteria, including the log-likelihood function (Log L), heteroscedasticity-adjusted mean squared error (HMSE) and Akaike Information Criterion (AIC).

Most studies dealing with stock returns use the normal density function. However, the standardised residuals obtained from GARCH models that assume normality appear to be leptokurtic, rendering standard t-tests unreliable. Following Antoniou et al. (2005), this paper employs a more general density function i.e., the Generalised Error Distribution (GED) to allow for fat tails. Its density function is given by:

$$f(\mu_t, \sigma_t, \nu) = \frac{\nu}{2}[\Gamma(3/\nu)]^{1/2}[\Gamma(1/\nu)]^{-3/2}(1/\sigma_t)\exp(-[\Gamma(3/\nu)/\Gamma(1/\nu)]^{\nu/2} \,|\, \varepsilon_t \,|\, \sigma_t) \qquad (19)$$

where $\Gamma(.)$ is the gamma function and v is a scale parameter (or the degree of freedom) to be estimated endogenously. When v=2, GED yields normal distribution and for v=1 it yields the Laplace distribution.[11]

[11] For robustness, we also estimated our empirical models using the normal density function. The results are essentially the same as those presented in Section 4. In the interest of brevity, results of this robustness check are not reported but available from the authors on request.

3. Data and methodology

Our sample includes the daily spot and futures prices of carbon emission allowances and four major energy markets within the European Union, namely coal, electricity, natural gas and crude oil. In particular, the following futures contracts listed in the Intercontinental Exchange (ICE) and their reference spot prices are collected and analysed: EU Emission Allowance (EUA) futures (carbon emission); Rotterdam coal futures (coal); UK electricity futures (electricity); UK natural gas futures (natural gas); Brent crude oil futures (crude oil).[12] The starting date for each commodity varies due to the data availability: 03/03/2008 (carbon), 17/07/2006 (coal), 27/12/2006 (electricity), 06/02//2003 (natural gas), 08/09/2003 (crude oil). The end date is 30/09/2012 for all commodities. All data were obtained from DataStream and are expressed in the currency of each market's home country. To construct a continuous series of futures prices, we rollover the futures contracts on the first day of new trading month, for all available traded months. For the estimation of implied convenience yields, we follow Heaney (2002)'s approach and use the 3-month mid-rate of Euro-currency (London) USD, Euro and GBP as estimates of the risk-free rate.

[TABLE 1 about here]

The summary statistics of daily futures returns ($R_t = \ln(\mathrm{P}_t / \mathrm{P}_{t-1}) \cdot 100\%$) are presented in Panel A of Table 1. It is evident that coal and crude oil returns are negatively skewed while carbon, electricity and natural gas returns are positively skewed. All five series are highly leptokurtic and exhibit departures from normality (as implied by Jarque-Bera test statistics). Ljung-Box statistics show a clear evidence of serial correlation in all returns except carbon,

[12] These futures contracts have been widely used in the literature as proxies for each relevant commodity market. See, for example, Daskalakis et al. (2009) for carbon emission market, Borger et al.(2009) for coal market, Bunn and Gianfreda (2010) for electricity market, Hochradl and Rammerstorfer (2012) for natural gas market, and Ellen and Zwinkels (2010) for crude oil market.

and in all squared returns apart from natural gas. Significant ARCH effect is also found in carbon, coal, electricity and crude oil return series. The JOINT test of Engle and Ng (1993) for testing asymmetries in conditional volatility indicates significant asymmetries in all cases. Overall, the statistical nature of return distribution supports the use of a generalised autoregressive conditional heteroscedasticity (GARCH)-type model for the variance process. All five commodity markets are positively correlated, particularly between electricity and natural gas (Panel B of Table 1).

To gauge an initial idea on the degree of feedback trading in commodity markets, we estimate a simple autoregressive model of order five, AR(5). The results reported in Panel C of Table 1 show that there are significant autocorrelations and the coefficients are mostly negative. The interaction between feedback traders and rational investors can however give rise to return patterns that are more complex than a simple autoregressive model can capture (Chau et al. 2011). It is therefore imperative and informative to investigate the significance of feedback trading in these markets and whether the intensity of such trading behaviour varies depending on the level of arbitrage opportunities.

[TABLE 2 about here]

Summary statistics of the spot-futures basis and convenience yield are given in Table 2. The mean of all spot-futures bases are reasonably close to zero; however their absolute values are generally smaller than that of convenience yield. It is evident that convenience yields of these commodities are generally more volatile than their basis. There is also some evidence of skewness and excess kurtosis, contributing to the clear departures from normality.

[TABLE 3 about here]

Table 3 reports the specification test results for GARCH volatility models. The search and application of an appropriate GARCH model specification is important to ensure that non-convergence problem is reduced to minimal (Alexander, 2001). We therefore compare three popular volatility models and select the most appropriate specification on the basis of log-likelihood function (Log L), heteroscedasticity-adjusted mean squared error (HMSE) and Akaike Information Criterion (AIC). The 'best-performing' conditional variance equation for each market is presented in the last column; EGARCH for carbon, electricity, and natural gas; GJR-GARCH for coal and crude oil. Consistent with the JOINT test results given in Table 1, asymmetric models seem to fit our data better than the symmetric model in all cases. This in turn implies that the conditional variance is an asymmetric function of past squared residuals, i.e., past negative innovations increase volatility more than past positive innovations.[13]

4. Results and discussion

4.1 Feedback trading in emissions and energy markets

In Table 4 we present the estimation results of the original SW model (baseline Model I). At first glance we notice that the coefficients describing the conditional variance process, α_0, α_1, and β are all highly significant, indicating that the current volatility is a function of last period's squared innovation and last period's volatility. This is further confirmed by the overwhelmingly significant (at the 5% level) β coefficients, reflecting significant temporal dependencies and persistence in the conditional volatility process. Additionally, volatility also appears highly asymmetric as illustrated by the significance of δ (with an exception of coal market). This is perhaps not surprising given our model selection results reported in

[13] Despite the lack of a conclusive theory, most of the studies of financial returns also document the negative relationship between return and volatility. Several hypotheses have been proposed in the literature to explain the asymmetric volatility phenomenon e.g., the leverage effect and the volatility feedback effect.

Table 3 and that the volatility asymmetry phenomenon (i.e., responses to bad news lead to greater volatility than do responses to good news) has been widely documented in the literature.[14] A number of hypotheses have been proposed to explain this phenomenon such as the leverage effect and the volatility feedback effect. Interestingly, a study by Antoniou et al. (2005) argues that the reaction of positive feedback traders to bad news is usually greater than it is to good news, resulting in asymmetric volatility (at least in part). To examine whether this is the case, we consider next the estimates of parameters γ_0 and γ_1 in the conditional mean equation to test the presence of feedback trading in our sample markets.

[TABLE 4 about here]

As shown in Panel A of Table 4, the constant component of return autocorrelation (γ_0) is positive and significant for coal and electricity at 5% level, and for natural gas at 10% level, showing positive first-order autocorrelation. These are consistent with our autoregressive regression results reported in Table 1. Non-synchronous trading and market frictions can cause positive autocorrelation in ex-post return, especially in relatively high frequency data. The existence of positive (negative) feedback trading, on the other hand, induces negative (positive) autocorrelation that increases, in absolute terms, with the level of volatility. In this respect it is interesting to see that, with the exception of carbon and natural gas, γ_1 is significant (at the 10 % level at least) showing evidence of feedback trading and their influence tend to be greater in the periods of high volatility. This is not surprising given the design and market operation of commodity futures (i.e., the low cost of trading, absence of short-sales constraints, and high leverage opportunity) appeal to many trend-following strategies such as portfolio insurance, short selling, and margin trading. A large body of research documents that feedback-style trading strategies earn significant abnormal returns in

[14] The estimated scale parameter v in the GED function is significant and below 2 in all cases showing that all the error terms are not normally distributed and confirms the use of density functions with thicker tails, such as GED distribution. For v=2, the GED reduces to the standard normal distribution.

a variety of commodity markets; see, for example, Miffre and Rallis (2007) for evidence regarding momentum strategies, Wang and Yu (2004) for contrarian strategies, and Cifarelli and Paladino (2010) for evidence of positive feedback trading in the U.S. crude oil market.

In contrast, the insignificance of γ_1 in the carbon and natural gas markets implies that there is no significant feedback trading in these markets and investors do not base their investment decisions solely on previous price changes. As the vast majority of investors in carbon market are institutions, our results support the notion that institutional investors are less susceptible to behaviourally biased trading than retail investors, but are in contrast with the evidence of Nofsinger and Sias (1999) who concludes that institutional investors positive-feedback trade more than individual investors.[15] The insignificant feedback trading parameter found in oil and gas markets may be attributable to their unique market design and operation causing these markets less susceptible to feedback trading activities.[16] Relatively low trading volume in coal and electricity markets could also be a contributing factor because there is a greater likelihood that disequilibrium price will be persisted in an illiquid market attracting feedback traders to profit from the price deviation. Nonetheless, the absence of base feedback trading does not preclude the possibility of feedback trading conditional on the level of arbitrage opportunities. To investigate this possibility, we now turn to the focus of this paper and consider the effect of observed arbitrage opportunities over the presence and/or intensity of feedback trading.

4.2 The effect of arbitrage opportunities on feedback trading

[15] It is also worth of noting that an array of diagnostics tests performed on the standardised residuals show no serious misspecification of the model (Panel C of Table 4).

[16] For instance, one can argue that electricity is more prone to innovation than other markets and thus attracts relatively more significant feedback trading. A further examination of the reasons why feedback trading is found in coal and electricity, and not in oil and gas, is worthy of a study but is beyond the scope of the current paper.

In this section, we examine the influence of arbitrage opportunities on feedback trading. To that end, we use spot-futures basis as a proxy for the level of arbitrage opportunities (as in Sofianos, 1993; Kumar and Seppi, 1994) and run a set of regressions described in Models II and III to investigate whether arbitrage opportunities affect feedback trader's demand.[17]

[TABLE 5 about here]

Consider first the estimation results of Model II (Equation 12) where we allow the level of arbitrage opportunities (as measured by the lagged basis) to additively affect the demand for shares by feedback traders. In this model, a positive γ_2 (where γ_2=-$\delta\mu$) suggests that feedback traders sell futures when spot price is higher than futures price in the last period while a negative γ_2 implies that they long futures when the lagged basis is positive. The results given in Table 5 show coefficients in the conditional variance equation are in line with the results of Model I, implying the presence of highly persistent and asymmetric volatility. This of course is an empirical regularity observed in almost all financial volatility series. Likewise, the base feedback trading parameter γ_1 remains significant for coal and electricity at the 5% level confirming that there exists significant feedback trading in these markets. Interestingly, the arbitrage-related feedback trading parameter γ_2 are also significant (at the 10 % level at least) suggesting that some feedback traders condition their trades upon the observed level of arbitrage opportunities. This finding is consistent with the view that arbitrage opportunities (as measured by the basis) can provide a useful signal for trading. Specifically, when the basis increases beyond a threshold level, speculators or feedback traders can exploit the opportunities by simultaneously trading in the spot and futures markets. Moreover, in line with the results of baseline Model I, it is interesting to note that without accounting for the arbitrage opportunities no feedback trading is present in natural gas market. However, the

[17] Although we use basis as a proxy for arbitrage opportunities in the main analysis, we have also examined the robustness of our results to an alternative proxy using the convenience yield. The results (reported in Section 5) confirm that our main conclusions hold irrespective of the proxy used.

arbitrage-related feedback trading parameter γ_2 is negative and statistically significant (at the 5% level) indicating that some arbitrageurs (negative feedback traders) buy futures when the futures price falls below the underlying spot price in order to profit from price discrepancy. Miller et al. (1994), for example, argues that when spot price is too high relative to futures price and the basis is wider than its theoretical level, arbitrageurs can simultaneously short-sell the spot asset and buy futures to exploit the arbitrage opportunities. Our results confirm the above argument and also support our conjecture that there exists a significant linkage between arbitrage opportunities and feedback trading.

[TABLE 6 about here]

Consider next the results for Model III (Equation 15) given in Table 6. Recall that this model allows the reaction of feedback traders to previous price changes to depend on the observed level of arbitrage opportunities (the lagged basis enters the model multiplicatively). In this model, a positive (negative) γ_2 suggests that feedback traders are more likely short (long) futures when the past futures return and the lagged basis are both positive (negative). Consistent with the results of our previous models, the feedback parameters γ_1 and γ_2 are both insignificant for carbon and crude oil markets, confirming that there is no significant feedback trading in these two markets. On the other hand, for the remaining three markets, both parameters are significant at the 5% level. In coal market, γ_1=-0.0132 and γ_2=0.0913. The results indicate that there is positive feedback trading and the intensity of such trading is conditional on the observed level of basis. When basis is greater than 0.1446, it switches to be negative feedback trading. Similarly, γ_1=-0.0001 and γ_2=0.0005 in natural gas market. When the basis is immaterial in natural gas market, feedback investors have more futures long position after futures price rises, but the degree of positive feedback trading is diminishing and turns to be insignificant when basis approaches 0.2. With regard to the electricity market, negative feedback trading is more prevalent when basis is negligible

(γ_1=0.0009) and the degree of negative feedback trading increases as basis becomes widen (γ_2=0.0595). However, when basis decreases to -0.0151 (i.e. spot price falls below its futures price by 1.52%), it turns to be positive feedback trading. It is also interesting to see that γ_2 parameter for all five markets are positive, albeit some insignificance.

Overall, the results of the above analysis show that the degree of positive (negative) feedback trading decreases (increases) as the lagged basis becomes widen. The lagged spot-futures basis provides useful indicator for feedback trading, who can use this as a signal of 'channel breakouts' in technical analysis. When the basis is within certain thresholds, feedback traders expect that the current trend of futures prices will persist and adopt a trend-following positive feedback trading strategy. However, if the basis is wide enough, the current channel will be broken out by arbitrageurs; as a result, negative feedback trading becomes more profitable. This is consistent with the findings of Marshall et al. (2008) who concludes that channel breakouts trading rules are consistently profitable in the U.S. commodity markets; supporting the argument that many rational arbitrageurs tend to jump on the bandwagon themselves before eventually selling out near the top and take their profit.

5. Robustness checks

5.1 Alternative measure of arbitrage opportunities

While the difference between spot and futures prices (the basis) has been extensively used as a signal and measure of arbitrage opportunities, spot-futures basis is a relatively simple proxy and does not take into account the costs of arbitrage such as borrowing costs and opportunity costs. Convenience yield, on the other hand, reflects these costs because it is estimated from using information on basis, the dynamic risk-free rates, and time-to-maturity.

Economically, convenience yield measures the benefit of holding spot inventory rather than buying futures contracts. It demonstrates the economic relationship between spot and futures prices. Therefore, similar to the basis, convenience yield can also be seen as a useful indicator of the futures price movement. Bertus et al. (2009) and Mellios and Six (2011) show that convenience yield can affect hedging demand and optimal hedge ratio. In this section, we examine the sensitivity of our results to an alternative measure for arbitrage opportunities i.e. convenience yield.

The convenience yield is estimated from the cost-of-carry model. As shown by Brennan (1958), the future price is jointly determined by the spot price, risk-free rate, convenience yield, and the time to maturity in the following fashion:

$$F_{t,T} = S_t e^{(Rft - CYt)(T-t)} \tag{20}$$

where Rf_t is the continuously compounded risk-free rate at time t, T is the maturity time of the futures contract, S_t is spot price at time t, $F_{t,T}$ is the futures price at time t matures at time T, and CY_t is the convenience yield at time t. Rearranging Equation (20) gives CY_t as:

$$CY_t = Rf_t - \frac{1}{T-t}\ln\left(\frac{F_{t,T}}{S_t}\right) = Rf_t + \frac{1}{T-t} Basis_t \tag{21}$$

It can be seen from Equation (21) that convenience yield moves with basis, risk-free rate, and time-to-maturity. This estimation method is widely used in literature, see e.g., Milonas and Henker (2001). To check the sensitivity of our earlier results to this alternative measure, we replace the basis with convenience yield and then repeat the estimations for models II and III:

Model II': $$R_t = \alpha + \rho\sigma_t^2 + (\gamma_0 + \gamma_1\sigma_t^2)R_{t-1} + \gamma_2 CY_{t-1}\sigma_t^2 + \varepsilon_t \tag{22}$$

Model III': $$R_t = \alpha + \rho\sigma_t^2 + (\gamma_0 + \gamma_1\sigma_t^2 + \gamma_2 CY_{t-1}\sigma_t^2)R_{t-1} + \varepsilon_t \tag{23}$$

[TABLE 7 about here]

The estimation results of Model II’ are given in Table 7. To keep the discussion compact, we concentrate on the interpretations of the values for feedback parameters γ_1 and γ_2 which indicate the level of feedback trading and the influence of arbitrage opportunities (as proxied by convenience yield). With an exception of natural gas, the results of γ_1 are largely consistent with models using basis. Although the parameters become smaller than those reported in Table 5, estimates for the arbitrage-related feedback trading parameter γ_2 in electricity and natural gas markets remain negative and statistically significant. This confirms that feedback traders respond positively to last period’s futures return and convenience yield, i.e. they hold long positions in futures when returns and convenience yield are both positive. Feedback traders tend to long futures when convenience yield is positive because they expect the benefits of holding spot asset will diminish and futures prices will increase accordingly.

[TABLE 8 about here]

Table 8 presents the estimation results of Model III’. Consistent with the results in Table 6, γ_1 and γ_2 are both insignificant for carbon and crude oil markets. Again, this implies that there is no significant feedback trading in these markets. For the other energy markets, both feedback parameters retain their sign and significance. It is also worth noting that parameter γ_2 for all five markets are still positive (although it is insignificant for carbon and crude oil). Taken together, the results presented in this section for Models II’ & III’ support our conjecture that the earlier results of Models II & III are not driven by the choice of measure for arbitrage opportunities and the empirical findings are consistent.

5.2 The effect of arbitrage opportunities on feedback trading across market regimes

The results thus far provide a clear evidence of feedback trading in some energy markets, and the spot-futures dynamics has significant influence on the intensity of feedback trading. These are consistent with the argument that basis and convenience yield are linked to arbitrage, hedging and the behaviourally-biased feedback trading activities. However, our sample covers the time periods spanning from bull to bear markets in energy markets. Therefore, in the vein of Chau et al. (2011), it is interesting and informative to further investigate whether the reaction of feedback traders to the observed level of arbitrage opportunities (as measured by the lagged basis and CY) depends on the market regimes. According to the International Monetary Fund (IMF) and World Bank energy index, energy prices reached its historical peak in July 2008 but started to decline subsequently.[18] Thus, we use this as the cut-off point to identify bull market as the period before July 2008 and bear market as the period thereafter. Given the unique design and operation of the European Emission Trading Scheme (EU ETS), we divide the carbon market data into Phase I (06/2005 - 12/2006) and Phase II (03/2008 - 09/2012) and compare the estimation results between Phases in order to examine the sensitivity of our results to the adoption of compliance rule in carbon market.[19]

[TABLES 9 & 10 about here]

Then, following the same estimation procedure, Model III (with basis) and Model III' (with convenience yield) are estimated separately for each market regimes. The results (given in Tables 9 & 10) show that the sign and significance of key parameters are similar regardless of the measures for arbitrage opportunities (either basis or convenience yield). Nonetheless,

---

[18] It is not surprising that commodity prices continued to rise after the onset of financial crisis and stock markets collapse in the summer 2007. Generally speaking, commodities tend to perform well in late expansion and early recessions. This is because interest rates are usually cut to boost economic activities when the economy is slowing down, which in turn may enhance the commodity prices (see Bodie and Rosansky, 1980).

[19] As a result of the banking restrictions imposed during the inter-phase period, the prices were very low at the end of Phase I i.e., 2007. We, therefore, follow Alberola and Chevallier (2009) and exclude 2007 data from our estimation.

the results for carbon market show that in Phase I, 2007 excluded, there is a higher autocorrelation or predictability (γ_0) due to more significant arbitrage-induced feedback trading activity (γ_2). The results of crude oil are however consistent with the full sample results, with insignificant γ_1 and γ_2. For coal market, the results of bear market are consistent with our main results, where γ_1 is negative and significant while γ_2 is positive and significant. The γ_1 in bull market analysis is still negative and significant but γ_2 turns to be insignificant. For electricity market, the results of bear market are also in line with the main tests, with positive and statistically significant γ_1 and $\gamma_{2.}$ With regard to the natural gas, results of bull market are consistent with whole period analysis, with negative and significant γ_1 and positive and significant γ_2.

In addition, two likelihood ratio tests are employed to examine the equality of parameters across market regimes. Specifically, LR1 tests the equality of γ_1 across regimes while LR2 is used to test whether γ_2 in bear market is same as that of bull market. The test results show that feedback trading parameters γ_1, γ_2 vary across market regime in most of the cases, perhaps due to the time-varying feedback trading behaviour over different regimes. One possible explanation is that a substantial amount of feedback trading is due to portfolio insurance strategies and the extensive use of stop-loss orders during market downturns. Margin trading could also be a contributing factor because during the sharp market declines there is a greater feedback activity that arises from the liquidations of margin accounts. Overall, this is consistent with our conjecture that intensity of feedback trading is related to the arbitrage opportunities, and that the significance of such relationship depends on the market regimes.

6. Conclusion

This paper has extended the heterogeneous trader model proposed by Sentana and Wadhwani (1992) in order to examine the presence of feedback trading in carbon emission and energy futures markets and the extent to which such behaviour is linked to arbitrage opportunities. Specifically, we developed and estimated several feedback trading models in which the behaviour of feedback traders is conditional on the level of arbitrage opportunities. We investigated the statistical support for these new models using a daily dataset on emission and energy markets. Results show that there exists significant feedback trading in coal and electricity markets, but not in carbon, natural gas and crude oil markets. As the vast majority of investors in carbon markets are institutions, this result is consistent with the notion that institutional investors are not particularly susceptible to feedback-style investment strategies. In further analysis, we show that the intensity of feedback trading is significantly related to the level of arbitrage opportunities, and that the significance of such relationship varies across market regimes.

Taken together, these findings add to the body of literature that studies the role of behaviourally biased feedback trading in commodity markets and the effect of arbitrage on such investment behaviour. The results in this paper are important in understanding investors' trading behaviour and investment strategies in commodity markets, particularly on the newly opened carbon emission market where we find no evidence of feedback trading and that arbitrage opportunities do not affect the demand for shares by feedback traders. These findings should help policy makers and marker participants to grasp a deeper understanding of the trading behaviour of commodity investors. In particular, as most of the participants in the carbon markets are institutions, our results also add to the debate of whether institutional investors engage in feedback-style investment strategies. There is however some important issues remain in the extant literature that requires further investigation. For instance, future research in this area may seek to identify the reasons why feedback trading is found in coal and electricity, but not in oil and gas, and why feedback trading is linked to arbitrage opportunities.

References

Alberola, E., Chevallier, J., 2009. European carbon prices and banking restrictions: evidence from Phase I (2005–2007). The Energy Journal 30(3), 51–80.

Alexander, C., 2001. Market models: a guide to financial data analysis. John Wiley & Sons, Chichester, UK.

Antoniou, A., Koutmos, G., Pericli, A., 2005. Index futures and postive feedback trading: Evidence from major stock exchanges. Journal of Empirical Finance 12, 219-238.

Baker, H.K., Filbeck, G., 2013. Alternative investments: Instruments, performance, benchmarks, and strategies. John Wiley & Sons, Hoboken, New Jersey.

Bertus, M., Godbey, J.M., Hilliard, J.E., 2009. Minimum variance cross hedging under mean-reverting spread, stochastic convenience yields, and jumps: Application to the airline industry. Journal of Futures Markets 29, 736-756.

Black, F., 1986. Noise. Journal of Finance 41, 529-543.

Bodie, Z., Rosansky, V.I., 1980. Risk and return in commodity futures. Financial Analyst Journal 36, 27-31+33-39.

Bohl, M. T., Siklos, P.L., 2008. Empirical evidence on feedback trading in mature and emerging stock market. Applied Financial Economics, 18, 1379-1389.

Bollerslev, T., Wooldridge, J.M., 1992. Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances. Econometrics Reviews 11, 143-172.

Borger, R., Cartea, A., Kiesel, R., Schindlmayr, G., 2009. Cross-commodity analysis and applications to risk managment. Journal of Futures Markets 29, 197-217.

Brennan, M.J., 1958. The supply of storage. American Economic Review 48, 50-72.

Bunn, D.W., Gianfreda, A., 2010. Integration and shock transmissions across European electricity forward markets. Energy Economics 32, 278-291.

Campbell, J.Y., Chan, Y.L., Viceira, L.M., 2003. A multivariate model of strategic asset allocation. Journal of Financial Economics 67, 41-80.

Cappiello, L., Engle, R.F., Sheppard, K., 2006 Asymmetric dynamics in the correlations of global equity and bond returns. Journal of Financial Econometrics 4, 537-572.

Charles, A., Darné, O., Fouilloux, J., 2011. Testing the martingale difference hypothesis in the CO2 emission allowances. Economic Modelling 28, 27-35.

Chau, F., Deesomsak, R., M.C.K., L., 2011. Investor sentiment and feedback trading: Evidence from exchange-traded fund markets. International Review of Financial Analysis 20, 292-305.

Chau, F., Deesomsak, R., 2014. Business cycle variation in postive feedback trading: Evidence from the G-7 economies. Journal of International Financial Markets, Institutions and Money, in press.

Chung, Y.P., 1991. A transaction data test of stock index futures market efficiency and index arbitrage profitability. Journal of Finance 46, 1791-1809.

Cifarelli, G., Paladino, G., 2010. Oil price dynamics and speculation: A multivariate financial approach. Energy Economics 32, 363-372.

Cutler, D.M., Poterba, J.M., Summers, L.H., 1990. Speculative dynamics and the role of feedback traders. American Economic Review 80, 63-68.

Daskalakis, G., Psychoyios, D., Markellos, R.N., 2009. Modelling CO2 emission allowance prices and derivatives. Journal of Banking and Finance 33, 1230-1241.

De Long, J.B., Shleifer, A., Summers, L.H., Waldmann, R.J., 1990. Positive feedback investment strategies and destabilizing rational expectations. Journal of Finance 45, 379-395.

Ellen, S., Zwikels, R.C.J., 2010. Oil price dynamics: A behavioral finance approach with heterogeneous agents. Energy Economics 32, 1427-1343.

Engle, R.F., Ng., V.K., 1993. Measuring and testing the impacts of news on volatility. Journal of Finance 48, 1749-1778.

Faff, R.W., Hillier, D., McKenzie, M.D., 2005. An investigation of conditional autocorrelation and cross-autocorrelation in emerging markets. Review of Pacific Basin Financial Markets and Policies 8, 467-499.

Garbade, K.D., Silber, W.L., 1983. Price movements and price discovery in futures and cash markets. Review of Economics and Statistics 65, 289-297.

Gerlow, M.E., Irwin, S.H., Liu, T.R., 1993. Economic evaluation of commodity price forecasting models. International Journal of Forecasting 9, 387-397.

Glosten, L.R., Jagannathan, R., Runkle, D.E., 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. Journal of Finance 48, 1779-1801.

Gorton, G.B., Hayashi, F., Rouwenhorst, K.G., 2013. The fundamentals of commodity futures returns. Review of Finance, 17, 35-105.

Heaney, R., 2002. Approximation for convenience yield in commodity futures pricing. Journal of Futures Markets 22, 1005-1017.

Hochradl, M., Rammerstorfer, M., 2012. The convenience yield implied in European natural gas hub trading. Journal of Futures Markets 32, 459-479.

Khoury, N.T., Martel, J.M., 1989. A supply of storage theory with asymmetric information. Journal of Futures Markets 9, 573-581.

Khoury, N.T., Yourougou, P., 1991. The informational content of the basis: Evidence from Canadian barley, oats, and canola futures markets. Journal of Futures Markets 11, 69-80.

Knetsch, T.A., 2007. Forecasting the price of crude oil via convenience yield predictions. Journal of Forecasting, 26, 527-549.

Koutmos, D., 2012. An intertemporal capital asset pricing model with heterogeneous expectations. Journal of International Financial Markets, Institutions and Money 22, 1176-1187.

Kumar, P., Seppi, D.J., 1994. Information and index arbitrage. Journal of Business 67, 481-509.

Laopodis, N., 2005. Feedback trading and autocorrelation interactions in the foreign exchange market: Further evidence. Economics Modelling 22, 811-827.

Lien, D., Yang, L., 2008. Asymmetric effect of basis on dynamic futures hedging: Empirical evidence from commodity markets. Journal of Banking and Finance 32, 187-198.

MacKinlay, A.C., Ramaswamy, K., 1988. Index-futures arbitrage and the behavior of stock index futures prices. Review of Financial Studies 1, 137-158.

Marshall, B.R., Cahan, R.H., Cahan, J.M., 2008. Can commodity futures be profitably traded with quantitative market timing strategies? . Journal of Banking and Finance 32, 1810-1819.

McMillian, D.G., Philip, D., 2012. Short-sale constraints and efficiency of the spot-futures dynamics. International Review of Financial Analysis 24, 129-136.

Miffre, J., Rallis, G., 2007. Momentum strategies in commodity futures markets. Journal of Banking and Finance 31, 1863-1886.

Miller, M.H., Muthuswamy, J., Whale, R.E., 1994. Mean reversion of S&P 500 index basis change: Arbitrage-induced or statistical illusion. Journal of Finance 49, 479-513.

Mellios, C., Six, P., 2011. The traditional hedging model revisited with a nonobservable convenience yield. Financial Review 46, 569-593.

Milonas, N.T., Henker, T., 2001. Price spread and convenience yield behaviour in the international oil market. Applied Financial Economics 11, 23-36.

Nofsinger, J.R., Sias, R.W., 1999. Herding and feedback trading by institutional and individual investors. Journal of Finance 54, 2263-2295.

Salm, C.A., Schuppli, M., 2010. Positve feedback trading in stock index futures: International evidence. International Review of Financial Analysis 19, 313-322.

Sentana, E., Wadhwani, S., 1992. Feedback traders and stock return autocorrelations: Evidence from a century of daily data. Economic Journal 102, 415-425.

Shiller, R.J., 1984. Stock prices and social dynamics. Brookings Papers on Economics Activities 2, 457-498.

Shiller, R.J., 1989. Market volatility. Cambridge: MIT Press.

Shleifer, A., 2000. Inefficient markets: An introduction to behavioural finance. Oxford University Press, New York, NY.

Sofianos, G., 1993. Index arbitrage profitability. Journal of Derivatives 1, 6-20.

The World Bank. 2012. Prospects for commodity markets. Global Economic Prospects 4, 1-165.

Wang, C., Yu, M., 2004. Trading activities and price reversals in futures markets. Journal of Banking and Finance 28, 1337-1361.

Table 1: Descriptive statistics of emission and energy futures returns

	Carbon	Coal	Electricity	Natural gas	Crude oil
Panel A: summary statistics					
Mean	-0.081	0.020	0.016	0.051	0.060
Std. Dev.	2.661	1.719	2.297	4.146	2.176
Skewness	0.075	-0.737	1.370	2.955	-0.114
Kurtosis	7.097	9.331	16.641	27.952	6.067
Jarque-Bera	836.370**	2850.619**	12114.920**	68303.070**	931.706**
LB(12)	15.939	74.068**	57.885**	30.621**	35.812**
$LB^2(12)$	292.580**	1241.600**	56.654**	4.598	1446.9**
ARCH(12)	122.439**	381.844**	35.883**	4.344	514.070**
JOINT	47.291**	108.047**	32.303**	8.432*	61.930**
Panel B : correlation coefficients					
Carbon	1				
Coal	0.295	1			
Electricity	0.256	0.381	1		
Natural gas	0.167	0.267	0.520	1	
Crude oil	0.264	0.360	0.137	0.105	1
Panel C: autocorrelation					
b_0	-0.084	0.015	0.018	0.050	0.064
b_1	0.033	0.193**	0.083**	0.036	-0.064**
b_2	-0.062*	0.005	0.002	-0.062**	-0.007
b_3	0.036	0.019	-0.054*	-0.038	0.017
b_4	0.003	0.034	0.028	-0.050*	0.046*
b_5	-0.004	-0.015	0.064*	-0.001	-0.048*
F-test	1.412	13.375**	4.431**	4.579**	4.436**

Notes: This table provides descriptive statistics of emission and energy futures return series. LB(12) and $LB^2(12)$ are the Ljung-Box Q test of autocorrelation for the level and squared returns; the test statistics are following Chi-squared distribution with n (number of lags) degree of freedom. ARCH (12) is the Lagrange Multiplier (LM) test for ARCH effect. The JOINT test is Engle and Ng's (1993) test for the potential asymmetries in conditional variance. The test is an F-test with the null hypothesis of $b_1=b_2=b_3$ for the regression below:

$$Z_t^2 = a + b_1 S_t^- + b_2 S_t^- \varepsilon_{t-1} + b_2 S_t^+ \varepsilon_{t-1} + v_t$$

where Z_t^2 is the square of standardised residuals; S_t^- is a dummy variable which equals 1 when $\varepsilon_{t-1} < 0$ and 0 otherwise; S_t^+ is a dummy variable which equals 1 when $\varepsilon_{t-1} > 0$ and 0 otherwise. In Panel C, the autocorrelation parameters (b_0 to b_5) are estimated from the following regression:

$$R_t = b_0 + \sum_{i=1}^{5} b_i R_{t-i} + u_t$$

** and * denote statistically significance at 1% and 5% respectively.

Table 2: Summary statistics of spot-futures basis and convenience yield

	Carbon	Coal	Electricity	Natural gas	Crude oil
Panel A: basis statistics					
Mean	-0.008	0.003	-0.001	-0.047	-0.000
Std. Dev.	0.014	0.031	0.060	0.174	0.025
Skewness	-5.798	2.176	-4.027	-1.784	0.033
Kurtosis	58.151	18.252	45.775	18.195	6.589
Panel B: convenience yield statistics					
Mean	-0.001	0.044	0.017	-0.376	0.181
Std. Dev.	0.045	0.327	0.639	0.156	0.223
Skewness	-8.029	2.577	-7.357	-1.540	-0.047
Kurtosis	90.678	23.952	112.541	15.833	7.127

Notes: This table provides descriptive statistics of emission and energy spot-futures basis and convenience yield. The basis is estimated as $Basis_t = \ln(S_t / F_{t,T})$

The convenience yield is approximated as: $CY_t = Rf_t - \frac{1}{T-t}\ln(\frac{F_{t,T}}{S_t})$

Table 3: Results of specification tests for various GARCH models

	GARCH			EGARCH			GJR-GARCH			Model Selected
	Log L	HMSE	AIC	Log L	HMSE	AIC	Log L	HMSE	AIC	
Carbon	-2697	3.570	4.530	**-2686**	3.417	**4.513**	-2690	**3.389**	4.520	EGARCH
Coal	-2732	4.472	3.383	-2741	4.669	3.396	**-2727**	**4.112**	**3.378**	GJR-GARCH
Electricity	-3193	12.904	4.262	**-3174**	**12.529**	**4.238**	-3193	12.855	4.263	EGARCH
Natural gas	-6931	36.709	5.567	**-6860**	**28.460**	**5.511**	-6892	30.504	5.536	EGARCH
Crude oil	-4945	2.874	4.193	-	-	-	**-4939**	**2.770**	**4.186**	GJR-GARCH

Notes: This table shows the results of specification tests for a selection of GARCH models, including standard GARCH, EGARCH and GJR-GARCH:

GARCH: $\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$

GJR-GARCH: $\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \delta I_{t-1} \varepsilon_{t-1}^2$

EGARCH: $\ln \sigma_t^2 = \alpha_0 + \alpha_1 G_{t-1} + \beta \sigma_{t-1}^2 ; \quad G_{t-1} = \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{2}{\pi}} + \delta \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$

The most appropriate model is selected based on several criteria, including the value of log-likelihood function (Log L), heteroscedasticity-adjusted mean squared error (HMSE) and Akaike Information Criterion (AIC). In each criterion, the best model is highlighted in bold. The 'best-performing' GARCH specification for each market is presented in the last column. "-" indicates that convergence cannot be reached.

Table 4: Evidence of feedback trading in the emission and energy markets (Model I)

	Carbon (EGARCH)	Coal (GJR-GARCH)	Electricity (EGARCH)	Natural gas (EGARCH)	Crude oil (GJR-GARCH)
Panel A: conditional mean equation					
α	-0.0006	0.0370	0.0498**	0.0337	0.1295
	(-0.092)	(1.703)	(51.765)	(1.576)	(1.610)
ρ	-0.0001	-0.0003	-0.0200**	-0.0082**	-0.0090
	(-0.019)	(-0.019)	(-44.540)	(-4.839)	(-0.451)
γ_0	0.0063	0.2387**	0.0035**	0.0107	-0.0233
	(0.998)	(8.372)	(18.768)	(1.954)	(-0.819)
γ_1	-0.0033	-0.0093*	0.0009**	-0.0002	-0.0054
	(-0.971)	(-2.020)	(28.966)	(-1.336)	(-1.713)
Panel B: conditional variance equation					
α_0	0.0555*	0.0285**	0.0627**	0.0892**	0.0602**
	(2.551)	(5.231)	(17.217)	(24.228)	(2.846)
α_1	0.2415**	0.1372**	0.2255**	0.2023**	0.0205*
	(3.385)	(8.990)	(33.042)	(15.072)	(2.439)
β	0.9726**	0.8699**	0.9723**	0.9761**	0.9414**
	(92.511)	(196.031)	(529.183)	(629.888)	(73.544)
δ	-0.2820*	-0.0252	-0.0375**	-0.2806**	0.0452**
	(-2.565)	(-1.097)	(-7.391)	(-4.899)	(3.575)
ν	1.3183**	1.2342**	0.8667**	0.7401**	1.5482**
	(16.714)	(23.880)	(31.443)	(44.265)	(22.885)
Panel C: diagnostic tests					
$E(Z_t)$	-0.031	0.005	0.059	0.054	-0.012
$E(Z^2_t)$	0.997	1.002	1.097	1.370	0.999
LB(12)	11.599	15.594	21.477*	22.229**	6.546
$LB^2(12)$	5.097	11.283	3.526	3.130	8.200
ARCH(12)	4.933	11.507	3.617	3.377	8.049
JOINT	2.403	2.889	6.151	1.150	25.626**

Notes: This table presents maximum likelihood estimates of the original SW feedback trading (i.e. baseline Model I) for emission and energy futures markets. The conditional mean equation is

$$R_t = \alpha + \rho\sigma_t^2 + (\gamma_0 + \gamma_1\sigma_t^2)R_{t-1} + \varepsilon_t \qquad \text{(Equation 9)}$$

The conditional variance equation is given by

GJR-GARCH: $\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2$ OR

EGARCH: $\ln\sigma_t^2 = \alpha_0 + \alpha_1 G_{t-1} + \beta\sigma_{t-1}^2$; $G_{t-1} = \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - \sqrt{\frac{2}{\pi}} + \delta\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$

The error terms are assumed to follow the Generalised Error Distribution (GED) with a scale parameter of ν. The estimated t-statistics (shown in the parentheses) are robust to autocorrelation and heteroscedasticity using Bollerslev and Woodridge (1992) standard errors. ** and * denote statistical significance at 1 % and 5 % levels.

Table 5: The effect of arbitrage opportunities on feedback trading (Model II)

	Carbon (EGARCH)	Coal (GJR-GARCH)	Electricity (EGARCH)	Natural gas (EGARCH)	Crude oil (GJR-GARCH)
Panel A: conditional mean equation					
α	0.0048*	0.0475*	0.0248	0.0476**	0.1295**
	(2.107)	(2.022)	(0.737)	(64.410)	(2.901)
ρ	0.0004	-0.0091	-0.0095**	-0.0098**	-0.0090
	(0.106)	(-0.745)	(-4.299)	(-17.143)	(-0.822)
γ_0	0.0048	0.2415**	0.0008	0.0010	-0.0234
	(0.754)	(10.598)	(0.150)	(1.260)	(-0.903)
γ_1	-0.0032	-0.0078*	0.0005**	-0.0000	-0.0050
	(-1.174)	(-2.078)	(9.889)	(-0.874)	(-0.977)
γ_2	0.2175	0.3558	-0.1558**	-0.0023**	0.0365
	(0.246)	(1.854)	(-5.110)	(-149.491)	(0.075)
Panel B: conditional variance equation					
α_0	0.0554*	0.0284**	0.0550	0.0869**	0.0605*
	(2.251)	(5.054)	(1.740)	(7.193)	(2.359)
α_1	0.2430**	0.1364**	0.2047**	0.2008**	0.0204*
	(3.183)	(20.656)	(10.331)	(67.117)	(2.203)
β	0.9727**	0.8708**	0.9761**	0.9770**	0.9414**
	(81.106)	(181.365)	(39.372)	(483.135)	(64.231)
δ	-0.2818*	-0.0257*	0.0248	-0.2660**	0.0452**
	(-2.550)	(-2.222)	(0.121)	(-25.459)	(3.111)
ν	1.3195**	1.2306**	0.8590**	0.7385**	1.548**
	(14.855)	(24.599)	(14.357)	(24.633)	(19.639)
Panel C: diagnostic tests					
$E(Z_t)$	-0.030	0.004	0.052	0.055	-0.012
$E(Z^2_t)$	0.997	1.002	1.096	1.368	0.999
LB(12)	11.931	17.645*	19.429*	22.506*	6.548
$LB^2(12)$	5.197	11.057	3.470	3.128	8.816
ARCH(12)	5.043	0.501	3.549	3.374	8.035
JOINT	3.458	2.493	7.244	1.334	25.611**

Notes: This table presents maximum likelihood estimates of our augmented SW feedback trading (i.e. Model II) for emission and energy futures markets. The level of arbitrage opportunities are measured by the lagged basis. The conditional mean equation is

$$R_t = \alpha + \rho\sigma_t^2 + (\gamma_0 + \gamma_1\sigma_t^2)R_{t-1} + \gamma_2 B_{t-1}\sigma_t^2 + \varepsilon_t \qquad \text{(Equation 12)}$$

The conditional variance equation is given by

GJR-GARCH: $\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2$ OR

EGARCH: $\ln\sigma_t^2 = \alpha_0 + \alpha_1 G_{t-1} + \beta\sigma_{t-1}^2$; $G_{t-1} = \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - \sqrt{\frac{2}{\pi}} + \delta\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$

The error terms are assumed to follow the Generalised Error Distribution (GED) with a scale parameter of ν. The estimated t-statistics (shown in the parentheses) are robust to autocorrelation and heteroscedasticity using Bollerslev and Woodridge (1992) standard errors. ** and * denote statistical significance at 1 % and 5 % levels.

Table 6: The effect of arbitrage opportunities on feedback trading (Model III)

	Carbon (EGARCH)	Coal (GJR-GARCH)	Electricity (EGARCH)	Natural gas (EGARCH)	Crude oil (GJR-GARCH)
Panel A: conditional mean equation					
α	-0.0007	0.0327	0.0447**	0.0461**	0.1078
	(-0.101)	(1.393)	(22.044)	(70.101)	(1.212)
ρ	-0.0001	0.0052	-0.0170**	-0.0087**	-0.0016
	(-0.017)	(0.422)	(-28.631)	(-46.919)	(-0.067)
γ_0	0.0063	0.2452**	0.0019**	0.0075**	-0.0245
	(0.892)	(10.689)	(6.879)	(2029.944)	(-0.782)
γ_1	-0.0033	-0.0132**	0.0009**	-0.0001**	-0.0050
	(-0.751)	(-3.274)	(19.289)	(-25.101)	(-1.279)
γ_2	0.0034	0.0913*	0.0595**	0.0005**	0.0262
	(0.010)	(2.515)	(26.703)	(72.152)	(0.569)
Panel B: conditional variance equation					
α_0	0.0555*	0.0296**	0.0619**	0.0850**	0.0601*
	(2.547)	(8.105)	(13.729)	(35.112)	(2.488)
α_1	0.2415**	0.1381**	0.2242**	0.1969**	0.0202*
	(3.309)	(40.428)	(37.780)	(109.364)	(2.433)
β	0.9726**	0.8678**	0.9731**	0.9775**	0.9417**
	(92.340)	(468.580)	(476.477)	(5730.473)	(71.040)
δ	-0.2820**	-0.0236**	-0.0403	-0.2806**	0.0449**
	(-2.617)	(-3.957)	(-1.344)	(-217.348)	(3.106)
ν	1.3182**	1.2274**	0.8641**	0.7389**	1.5501**
	(16.490)	(23.609)	(33.688)	(50.511)	(25.364)
Panel C: diagnostic tests					
$E(Z_t)$	-0.031	0.005	0.064	0.052	-0.013
$E(Z^2_t)$	0.997	1.002	1.095	1.366	0.999
LB(12)	11.611	14.611	21.110*	22.865**	6.512
$LB^2(12)$	5.098	11.986	3.591	3.072	8.286
ARCH(12)	4.934	12.131	3.669	3.308	8.134
JOINT	2.464	2.783	6.394	1.267	23.048**

Notes: This table presents maximum likelihood estimates of our augmented SW feedback trading (i.e. Model III) for emission and energy futures markets. The level of arbitrage opportunities are measured by the lagged basis. The conditional mean equation is

$$R_t = \alpha + \rho\sigma_t^2 + (\gamma_0 + \gamma_1\sigma_t^2 + \gamma_2 B_{t-1}\sigma_t^2)R_{t-1} + \varepsilon_t \qquad \text{(Equation 15)}$$

The conditional variance equation is given by

GJR-GARCH: $\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2$ OR

EGARCH: $\ln\sigma_t^2 = \alpha_0 + \alpha_1 G_{t-1} + \beta\sigma_{t-1}^2$; $G_{t-1} = \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - \sqrt{\frac{2}{\pi}} + \delta\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$

The error terms are assumed to follow the Generalised Error Distribution (GED) with a scale parameter of ν. The estimated t-statistics (shown in the parentheses) are robust to autocorrelation and heteroscedasticity using Bollerslev and Woodridge (1992) standard errors. ** and * denote statistical significance at 1 % and 5 % levels.

Table 7: The effect of arbitrage opportunities on feedback trading (Model II')

	Carbon (EGARCH)	Coal (GJR-GARCH)	Electricity (EGARCH)	Natural gas (EGARCH)	Crude oil (GJR-GARCH)
Panel A: conditional mean equation					
α	-0.0002 (-0.017)	0.0470* (2.001)	0.0577** (14.789)	0.0316** (29.115)	0.1269 (1.574)
ρ	-0.0003 (-0.057)	-0.0094 (-0.765)	-0.0226** (-9.730)	-0.0081** (-20.204)	-0.0092 (-0.451)
γ_0	0.0060 (0.264)	0.2413** (10.597)	0.0023 (1.061)	0.0062** (22.884)	-0.0235 (-0.899)
γ_1	-0.0033 (-0.900)	-0.0081* (-2.179)	0.0012** (6.869)	-0.0004** (-20.640)	-0.0022 (-0.3145)
γ_2	0.0452 (0.306)	0.0349 (1.952)	-0.0099** (-237.698)	-0.0010** (-34.507)	0.0361 (0.711)
Panel B: conditional variance equation					
α_0	0.0558* (2.390)	0.0283** (5.039)	0.0599** (4.229)	0.0938** (17.675)	0.0601* (2.275)
α_1	0.2424** (3.146)	0.1363** (20.687)	0.2203** (7.116)	0.2083** (48.231)	0.0203 (1.708)
β	0.9725** (83.699)	0.8712** (181.706)	0.9738** (179.547)	0.9746** (3084.200)	0.9415** (61.787)
δ	-0.2814** (-2.761)	-0.260* (-2.265)	-0.0303 (-0.907)	-0.2695** (-15.948)	0.0454* (2.509)
ν	1.3189** (14.428)	1.2294** (24.583)	0.8686** (23.006)	0.7367** (30.144)	1.5492** (21.305)
Panel C: diagnostic tests					
$E(Z_t)$	-0.030	0.004	0.062	0.052	-0.012
$E(Z^2_t)$	0.997	1.002	1.100	1.361	0.999
LB(12)	11.658	18.023*	19.632*	22.770**	6.658
$LB^2(12)$	5.117	10.917	3.483	3.201	8.179
ARCH(12)	4.956	11.193	3.568	3.461	8.019
JOINT	3.072	2.421	6.437	1.196	24.578**

Notes: This table presents maximum likelihood estimates of our augmented SW feedback trading (i.e. Model II') for emission and energy futures markets. The level of arbitrage opportunities are measured by convenience yield. The conditional mean equation is

$$R_t = \alpha + \rho\sigma_t^2 + (\gamma_0 + \gamma_1\sigma_t^2)R_{t-1} + \gamma_2 CY_{t-1}\sigma_t^2 + \varepsilon_t \qquad \text{(Equation 22)}$$

The conditional variance equation is given by

GJR-GARCH: $\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2$ OR

EGARCH: $\ln\sigma_t^2 = \alpha_0 + \alpha_1 G_{t-1} + \beta\sigma_{t-1}^2$; $G_{t-1} = \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - \sqrt{\frac{2}{\pi}} + \delta\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$

The error terms are assumed to follow the Generalised Error Distribution (GED) with a scale parameter of ν. The estimated t-statistics (shown in the parentheses) are robust to autocorrelation and heteroscedasticity using Bollerslev and Woodridge (1992) standard errors. ** and * denote statistical significance at 1 % and 5 % levels.

Table 8: The effect of arbitrage opportunities on feedback trading (Model III')

	Carbon (EGARCH)	Coal (GJR-GARCH)	Electricity (EGARCH)	Natural gas (EGARCH)	Crude oil (GJR-GARCH)
Panel A: conditional mean equation					
α	-0.0007 (-0.075)	0.0343 (1.458)	0.0448** (7.663)	0.0216** (13.548)	0.1294 (1.395)
ρ	-0.0000 (-0.001)	0.0036 (0.292)	-0.0171** (-7.055)	-0.0040** (-56.161)	-0.0090 (-0.364)
γ_0	0.0057 (0.484)	0.2451** (10.742)	0.0018 (0.564)	0.0100** (70.465)	-0.0233 (-0.780)
γ_1	-0.0032 (-0.856)	-0.0127** (-3.371)	0.0008** (5.846)	-0.0003** (-82.057)	-0.0054 (-1.390)
γ_2	0.0188 (0.480)	0.0083** (2.925)	0.0052** (50.597)	0.0004** (188.229)	0.0000 (0.004)
Panel B: conditional variance equation					
α_0	0.0553* (2.229)	0.0293** (5.105)	0.0600** (15.415)	0.0875** (6.588)	0.0602* (2.439)
α_1	0.2411** (3.198)	0.1377** (20.384)	0.2223** (13.489)	0.1988** (341.708)	0.0204 (1.871)
β	0.9728** (78.799)	0.8684** (177.265)	0.9740** (331.295)	0.9765** (273.398)	0.9414** (64.553)
δ	-0.2830** (-2.913)	-0.0239* (-1.991)	-0.0376 (-0.560)	-0.2707** (-85.447)	0.0452** (2.968)
ν	1.3177** (13.421)	1.228** (24.692)	0.8653** (31.474)	0.7321** (28.612)	1.5482** (20.480)
Panel C: diagnostic tests					
$E(Z_t)$	-0.030	0.005	0.062	0.043	-0.012
$E(Z^2_t)$	0.997	1.002	1.098	1.359	0.999
LB(12)	11.520	14.593	20.968*	22.799**	6.546
$LB^2(12)$	5.125	12.214	3.577	3.076	8.200
ARCH(12)	4.959	12.357	3.656	3.316	8.049
JOINT	2.571	2.739	6.456	1.310	25.625**

Notes: This table presents maximum likelihood estimates of our augmented SW feedback trading (i.e. Model III') for emission and energy futures markets. The level of arbitrage opportunities are measured by convenience yield. The conditional mean equation is

$$R_t = \alpha + \rho\sigma_t^2 + (\gamma_0 + \gamma_1\sigma_t^2 + \gamma_2 CY_{t-1}\sigma_t^2)R_{t-1} + \varepsilon_t \qquad \text{(Equation 23)}$$

The conditional variance equation is given by

GJR-GARCH: $\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2$ OR

EGARCH: $\ln\sigma_t^2 = \alpha_0 + \alpha_1 G_{t-1} + \beta\sigma_{t-1}^2$; $G_{t-1} = \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - \sqrt{\frac{2}{\pi}} + \delta\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$

The error terms are assumed to follow the Generalised Error Distribution (GED) with a scale parameter of ν. The estimated t-statistics (shown in the parentheses) are robust to autocorrelation and heteroscedasticity using Bollerslev and Woodridge (1992) standard errors. ** and * denote statistical significance at 1 % and 5 % levels.

Table 9: The effect of arbitrage opportunities on feedback trading across market regimes (Model III)

	Phase I	Bull Market				Phase II	Bear Market			
	Carbon (EGARCH)	Coal (GJR-GARCH)	Electricity (EGARCH)	Natural gas (EGARCH)	Crude oil (GJR-GARCH)	Carbon (EGARCH)	Coal (GJR-GARCH)	Electricity (EGARCH)	Natural gas (EGARCH)	Crude oil (GJR-GARCH)
Panel A: conditional mean equation										
α	0.0880 (1.564)	0.0751 (1.690)	0.0867** (18.251)	0.0467** (83.348)	0.1669 (0.235)	-0.0007 (-0.101)	0.0069 (0.196)	0.0874** (8.310)	-0.0346** (-7.517)	0.0789 (0.862)
ρ	-0.0054 (-0.939)	0.0287** (6.720)	-0.0130** (-36.058)	-0.0110** (-446.346)	0.0017 (0.008)	-0.0001 (-0.017)	-0.0043 (-0.230)	-0.0469** (-11.793)	-0.0067** (-8.637)	-0.0084 (-0.349)
γ_0	0.2369** (20.397)	0.2570** (12.356)	0.0321** (95.805)	0.0985** (196.299)	0.0332 (0.292)	0.0063 (0.892)	0.2403** (6.769)	-0.0409 (-1.934)	-0.0482** (-78.476)	0.0265 (0.684)
γ_1	-0.0002 (-0.295)	-0.0203** (-4.224)	-0.0002** (-12.319)	-0.0009** (-187.517)	-0.0287 (-0.925)	-0.0033 (-0.751)	-0.0115** (-2.784)	0.0162** (35.415)	0.0031** (9.336)	-0.0063 (-1.620)
γ_2	-0.0003** (-3.320)	-0.0316 (-1.534)	0.0264** (220.960)	0.0002** (363.464)	0.2788 (1.259)	0.0034 (0.010)	0.0852* (2.496)	0.1363** (2.615)	0.0064** (7.130)	0.0019 (0.047)
Panel B: conditional variance equation										
α_0	0.1989** (3.225)	0.0676* (2.136)	0.1344** (190.588)	0.2779** (912.242)	0.1462 (0.715)	0.0555* (2.547)	0.0249* (2.545)	0.0338 (1.556)	0.0369* (2.150)	0.0466 (0.114)
α_1	0.5794** (36.400)	0.2204** (5.347)	0.3097** (31.075)	0.3670** (222.132)	0.0201 (1.895)	0.2415** (3.309)	0.1161** (11.377)	0.1485** (5.153)	0.1706** (7.545)	0.0103 (0.655)
β	0.9114** (31.686)	0.8047** (18.742)	0.9566** (819.173)	0.9222** (1302.311)	0.9252** (12.581)	0.9726** (92.340)	0.8771** (112.780)	0.9813** (50.177)	0.9896** (203.004)	0.9411** (32.815)
δ	-0.2265** (-5.413)	-0.0706** (-3.408)	-0.2263** (-52.147)	-0.3881** (-143.684)	0.0286 (0.863)	-0.2820** (-2.617)	-0.0004 (-0.014)	0.1718 (0.369)	-0.2689* (-2.541)	0.0732** (2.661)
ν	1.1593** (11.397)	1.1537** (12.448)	0.7838** (31.110)	0.6576** (46.885)	1.7200** (14.503)	1.3182** (16.490)	1.250** (18.014)	0.9073** (22.795)	0.9741** (16.197)	1.3754** (14.457)
Panel C: likelihood ratio tests										
LR1	-	-	-	-	-	0.506	8.349**	1285.321**	144.494**	33.133**
LR2	-	-	-	-	-	0.0001	10.820**	4.447*	47.727**	48.807**

Table 9 (Continued)

	Phase I	Bull Market				Phase II	Bear Market			
	Carbon (EGARCH)	Coal (GJR-GARCH)	Electricity (EGARCH)	Natural gas (EGARCH)	Crude oil (GJR-GARCH)	Carbon (EGARCH)	Coal (GJR-GARCH)	Electricity (EGARCH)	Natural gas (EGARCH)	Crude oil (GJR-GARCH)
Panel D: diagnostic tests										
$E(Z_t)$	-0.082	0.031	0.099	0.067	-0.006	-0.031	-0.006	0.057	0.049	-0.020
$E(Z^2_t)$	1.040	1.000	1.013	1.453	0.998	0.997	1.007	1.107	1.115	1.001
LB(12)	25.827**	6.636	17.970*	9.812	4.864	11.611	11.824	13.064	27.274**	8.233
$LB^2(12)$	9.633	3.204	2.112	3.665	16.864	5.098	12.968	2.890	3.198	14.930
ARCH(12)	9.281	2.872	2.156	4.208	17.500	4.934	13.638	2.929	3.159	14.361
JOINT	2.003	3.019	2.106	0.314	17.819**	2.464	2.428	8.945*	4.113	15.990**

Notes: This table presents maximum likelihood estimates of our augmented SW feedback trading (i.e. Model III) for emission and energy futures markets across different market regimes. The level of arbitrage opportunities are measured by the lagged basis. The bull market is defined as the period before 31 July 2008 and bear market is the period thereafter. For carbon market, we compare the results between Phase I (June 2005 to December 2006) and Phase II (March 2008 to September 2012, i.e., the initial full sample period). The conditional mean equation is

$$R_t = \alpha + \rho\sigma_t^2 + (\gamma_0 + \gamma_1\sigma_t^2 + \gamma_2 B_{t-1}\sigma_t^2)R_{t-1} + \varepsilon_t \qquad \text{(Equation 15)}$$

The conditional variance equation is given by

GJR-GARCH: $\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2$ OR

EGARCH: $\ln\sigma_t^2 = \alpha_0 + \alpha_1 G_{t-1} + \beta\sigma_{t-1}^2$; $G_{t-1} = \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - \sqrt{\frac{2}{\pi}} + \delta\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$

The error terms are assumed to follow the Generalised Error Distribution (GED) with a scale parameter of ν. The estimated t-statistics (shown in the parentheses) are robust to autocorrelation and heteroscedasticity using Bollerslev and Woodridge (1992) standard errors. ** and * denote statistical significance at 1 % and 5 % levels. LR1 is the likelihood ratio tests for the equality of γ_1 across market regimes and LR2 is the test for equality of γ_2 in bull and bear markets (or Phases I & II).

Table 10: The effect of arbitrage opportunities on feedback trading across market regimes (Model III')

	Phase I	Bull Market				Phase II	Bear Market			
	Carbon (EGARCH)	Coal (GJR-GARCH)	Electricity (EGARCH)	Natural gas (EGARCH)	Crude oil (GJR-GARCH)	Carbon (EGARCH)	Coal (GJR-GARCH)	Electricity (EGARCH)	Natural gas (EGARCH)	Crude oil (GJR-GARCH)
Panel A: conditional mean equation										
α	0.0822	0.0753	0.0722**	0.0299**	0.2884	-0.0007	0.0079	0.1080**	-0.0333**	0.0918
	(0.627)	(1.860)	(16.594)	(706.041)	(0.461)	(-0.075)	(0.242)	(14.324)	(-15.896)	(0.995)
ρ	-0.0047	0.0287**	-0.0098**	-0.0074**	-0.0361	-0.0000	-0.0051	-0.0573**	-0.0069**	-0.0131
	(-0.452)	(3.446)	(-47.423)	(-58.493)	(-0.200)	(-0.001)	(-0.364)	(-38.552)	(-44.818)	(-0.555)
γ_0	0.2322**	0.2583**	0.0303**	0.0790**	0.0276	0.0057	0.2419**	-0.0370**	-0.0477**	0.0284
	(3.189)	(139.026)	(64.712)	(101.711)	(0.238)	(0.484)	(9.960)	(-262.204)	(-116.127)	(0.816)
γ_1	-0.0001	-0.0203**	-0.0004**	-0.0005**	-0.0286	-0.0032	-0.0115**	0.0164**	0.0032**	-0.0067
	(-0.168)	(-40.681)	(-4.466)	(-53.254)	(-0.957)	(-0.856)	(-4.288)	(93.560)	(40.091)	(-1.645)
γ_2	-0.0002**	-0.0032	0.0020**	0.0000	0.0196	0.0188	0.0079**	0.0021*	0.0005**	-0.0016
	(-6.738)	(-1.483)	(144.546)	(0.069)	(0.847)	(0.480)	(2.7875)	(2.145)	(186.894)	(-0.327)
Panel B: conditional variance equation										
α_0	0.2017**	0.0676	0.14112**	0.300**	0.1659	0.0553*	0.0249**	0.0387**	0.371**	0.0460*
	(3.528)	(1.816)	(62.868)	(81.749)	(0.4126)	(2.229)	(3.159)	(34.744)	(34.378)	(2.001)
α_1	0.5848**	0.2202**	0.3083**	0.3886**	0.0219	0.2411**	0.1159**	0.1651**	0.1714**	0.0104
	(26.490)	(8.772)	(11.994)	(33.088)	(0.651)	(3.198)	(4.525)	(12.969)	(27.437)	(0.753)
β	0.9104**	0.8048**	0.9535**	0.9152**	0.9175**	0.9728**	0.8772**	0.9789**	0.9895**	0.9412**
	(31.008)	(19.085)	(867.714)	(1968.260)	(12.786)	(78.799)	(47.166)	(5983.324)	(548.652)	(48.778)
δ	-0.2306*	-0.0705**	-0.2345**	-0.3564**	0.0294	-0.2830**	-0.0001	0.0777**	-0.2656**	0.0731**
	(-2.336)	(-2.959)	(-15.648)	(-25.951)	(0.651)	(-2.913)	(-0.005)	(4.999)	(-3.658)	(3.386)
ν	1.1573**	1.1538**	0.7810**	0.6547**	1.7074**	1.3177**	1.2507**	0.9131**	0.9740**	1.3744**
	(11.868)	(12.484)	(21.784)	(48.946)	(14.578)	(13.421)	(18.094)	(21.407)	(29.563)	(17.381)
Panel C: likelihood ratio tests										
LR1	-	-	-	-	-	2.113	9.737**	9184.956**	2144.525**	28.403**
LR2	-	-	-	-	-	0.149	14.145**	0.004	34929.384**	18.436**

Table 10 (Continued)

	Phase I	Bull Market				Phase II	Bear Market			
	Carbon (EGARCH)	Coal (GJR-GARCH)	Electricity (EGARCH)	Natural gas (EGARCH)	Crude oil (GJR-GARCH)	Carbon (EGARCH)	Coal (GJR-GARCH)	Electricity (EGARCH)	Natural gas (EGARCH)	Crude oil (GJR-GARCH)
Panel D: diagnostic tests										
$E(Z_t)$	-0.080	0.031	0.109	0.064	-0.006	-0.030	-0.007	0.056	0.048	-0.020
$E(Z^2_t)$	1.038	1.000	1.047	1.455	0.999	0.997	1.007	1.107	1.115	1.001
LB(12)	25.426**	6.613	18.011*	10.606	5.052	11.520	11.914	12.990	27.062**	8.261
$LB^2(12)$	9.593	3.200	2.177	3.497	17.286	5.125	13.225	3.024	3.180	14.901
ARCH(12)	9.300	2.868	2.246	3.990	17.859	4.959	13.883	3.056	3.140	14.318
JOINT	1.832	3.021	2.649	0.691	16.945**	2.571	2.481	9.131*	4.100	16.009**

Notes: This table presents maximum likelihood estimates of our augmented SW feedback trading (i.e. Model III') for emission and energy futures markets across different market regimes. The level of arbitrage opportunities are measured by convenience yield. The bull market is defined as the period before 31 July 2008 and bear market is the period thereafter. For carbon market, we compare the results between Phase I (June 2005 to December 2006) and Phase II (March 2008 to September 2012, i.e., the initial full sample period). The conditional mean equation is

$$R_t = \alpha + \rho\sigma_t^2 + (\gamma_0 + \gamma_1\sigma_t^2 + \gamma_2 CY_{t-1}\sigma_t^2)R_{t-1} + \varepsilon_t \qquad \text{(Equation 23)}$$

The conditional variance equation is given by

GJR-GARCH: $\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2$ OR

EGARCH: $\ln\sigma_t^2 = \alpha_0 + \alpha_1 G_{t-1} + \beta\sigma_{t-1}^2$; $G_{t-1} = \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - \sqrt{\frac{2}{\pi}} + \delta\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$

The error terms are assumed to follow the Generalised Error Distribution (GED) with a scale parameter of ν. The estimated t-statistics (shown in the parentheses) are robust to autocorrelation and heteroscedasticity using Bollerslev and Woodridge (1992) standard errors. ** and * denote statistical significance at 1 % and 5 % levels. LR1 is the likelihood ratio tests for the equality of γ_1 across market regimes and LR2 is the test for equality of γ_2 in bull and bear markets (or Phases I & II).