Modelling the Time Series Dynamics of Carbon Emission Markets

SHI, YUKUN

Modelling the Time Series Dynamics of Carbon Emission Markets

By

YUKUN SHI

A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy in Finance

Durham University Business School

University of Durham

December 2013

Abstract

Carbon emission markets, which are designed to reduce emissions of global greenhouse gases (GHGs), have experienced rapid ongoing development even during the recent recession and have attracted considerable attention from policy makers and investors. Therefore, it is important to understand the time series dynamics of carbon asset prices and the behaviour of trading activities in carbon emission markets. This thesis, using the second commitment period data of the European Union emission trading scheme (EU ETS), examines the underlying dynamics driving carbon emission markets, including the performance of state dependent hedge ratios, the impact of arbitrage opportunities on feedback trading activities, as well as the influence of carbon allowance submission deadlines on the relationship between carbon spot and futures markets.

The research models the relationship between carbon spot and futures markets by incorporating state dependent characteristics into the return and volatility processes, and finds that the class of regime switching hedging strategies, particularly the proposed new framework which combines regime switching behaviour and disequilibrium adjustment in the mean with state dependent dynamic volatility process, significantly outperform competing methods for all the measures considered, and for both in-sample and out-of-sample analysis. The results indicate that risk managers using Markov regime switching models to hedge the risk in carbon markets achieve greater variance reduction and better hedging performance. Secondly, this study extends Sentana and Wadhwani's (1992) feedback trading model by allowing arbitrage opportunities to affect the demand of feedback traders in carbon markets. The results suggest that there is no evidence of feedback trading in the carbon market, where institutional investors dominate, although the effect persists in a few other energy markets.

This finding supports the view that institutional investors are not necessarily all feedback traders. Thirdly, when examining the influence of the carbon allowance submission deadline on the time series dynamics of carbon spot and futures markets, it is found that the equilibrium level, mean-reverting speed and no-arbitrage boundaries are affected by the submission deadline. However, the submission of allowances does not change the price discovery process of carbon emission markets, where this thesis finds that both the spot and futures markets Granger-cause each other. Furthermore, there is evidence that the volatility spillover process is different before and after the submission deadline, particularly from the spot market to the futures market. Therefore, in modelling the relationship between carbon spot and futures prices, the difference in the mean-reverting process of futures mispricing before and after the submission deadline should be accounted for. Overall, the thesis finds that the carbon emission markets yield different time series characteristics and trading behaviours from other financial markets. The findings of this thesis are of interest to risk managers, investors and arbitragers operating in the carbon emission market and could aid regulators in improving the mechanisms of the EU ETS in the next commitment period.

Table of Contents

List of Figures

List of Tables

Chapter Three

Chapter Four

Chapter Five

Declaration

The material contained in the thesis has not previously been submitted, either in whole or in part, for a degree in this or any other institution.

Statement of Copyright

Acknowledgements

It has been a long and frustrating undertaking for me to complete this thesis. I have encountered a number of difficulties in the four-year journey. I have dreamed so many times that I can draw a line under it, however endless it seemed. Finally, I am now about to submit the thesis, although I think it is still far from perfect. Firstly, I have to say, without the help, guidance, support and encouragement of my primary supervisor, Dr. Dennis Philip, it would have been impossible for me to fulfil this task. I would like to express my heartfelt thanks to him, who guides me in the academic world. We always have long meetings which inspire me with new research ideas. In addition, I am grateful to Professor Alessandra Guariglia, Dr. Frankie Chau, Dr. Jing-Ming Kuo and Dr. Wenxuan Hou for discussing research ideas and providing comments on my chapters, and for the help and guidance during my time as a PhD student.

Doing a PhD is a lengthy and lonely journey. I would like to thank all my friends at Durham, who have accompanied and supported me during the past four years. My life would be significantly different without the following professors, colleagues and friends I have met in the UK (in an arbitrary order): Dr. Jin Suk Park, Dr. Zhiyun Li, Dr. Guangxiang Li, Dr. Rataporn Deesomsak, Dr. Binghan Zheng, Dr. Qi Fang, Dr. Yongjie Xie, Dr. Zhimin Xiao, Dr. Boya Wang, Dr. Yang Fan, Dr. Xiong Wei, Dr. EY Oh, Ying Chen, Miao Han, Junhong Yang, Jia Luo, Zhenlong Li, Pei Liu, Jiayuan Xin, Nan Hu, Ziwei Zheng, Zhuang Zhang, Qingjing Zhang, Xiehua Ji, Yang Zhao, Yujie Hu, Yunhan Hu, Xuying Du, Yingying Huang, Jiankang Shi, Sheng Yang, and many significant others. In addition, I would like to thank all the staff of the Durham University Business School for their help and support.

Last but not least, I owe my deepest gratitude to my beloved parents, Baohong Shi and Shexiang Wang. Their love and encouragement have provided the strong support that has enabled me to finish this thesis.

To my beloved parents

Chapter 1

Introduction

1.1. Focus of the thesis

The international community has now reached a consensus that our world is experiencing serious environmental problems caused by the emission of carbon dioxide (CO_2) and other greenhouse gases (GHGs). The level of greenhouse gases is expected to reach twice the level of pre-industrial times between 2030 and 2060 (Stern, 2007). This will increase the world average temperature by 2°C to 5°C by the end of the twenty-first century. Ice in Greenland and the Antarctic will melt dramatically, raising sea levels and disturbing the distribution of world ocean currents. More droughts and floods are likely, and more land will be under the threat of desertification, all of which will lead to significant detrimental economic and social consequences for humanity.

In addressing these international environmental issues, the United Nations (UN) instigated the Kyoto Protocol in 1997, which aims to reduce GHG emissions through international cooperation. Under this treaty, the Kyoto Protocol requires industrialised countries and countries in transition to reduce their collective greenhouse gas emissions by 5.2% of the level reached in 1990 before 2012 (UNFCCC, 1997). In order to improve the efficiency and reduce the costs of emissions abatement, the global GHG emission trading markets, or the carbon emission markets, were launched under the framework of the Kyoto Protocol.

Global carbon emission markets have experienced rapid ongoing development and have attracted increasing investment since their inception. The total value of the markets stood at more than $175 billion in 2011, which is over 20 times higher than in 2005 (World Bank, 2012), and business activities in all sectors of the economy are influenced by carbon emission trading (Calel, 2013). Given the novel features and increasing importance of the carbon emission markets, there has been a growing body of literature studying the characteristics of carbon emission allowance prices and the financial markets for carbon assets.[1] The most important carbon emission market is the European Union emission trading scheme (EU ETS), which is a "cap-and-trade" system requiring firms to surrender a certain amount of tradable permits corresponding to the firms' GHG emissions by a specific deadline, otherwise they will incur a penalty. The EU ETS has three commitment periods (Phase I: 2005-2007; Phase II: 2008-2012; Phase III: 2012-2020), each with different characteristics. This thesis will focus on the issues associated with the second phase of the EU ETS.

It has been shown that carbon allowance prices experience price jumps, spikes and high volatility, and are very sensitive to government policies (e.g. Daskalakis, Psychoyios and Markellos, 2009; Benz and Trück, 2009). These irregularities demonstrate the importance of understanding the time series properties of carbon allowance prices. In addition, the unique regulatory framework of carbon emission markets may lead to different behaviours within trading activities in carbon emission markets. Therefore, the focus of this thesis is to

[1] For example the determinants of carbon allowance prices (e.g. Alberola, Chevallier, and Chèze 2008; Creti, Jouvet and Mignon, 2012); the efficiency of carbon emission markets (e.g. Daskalakis and Markellos, 2008; Joyeux and Milunovich, 2010; Charles, Darné and Fouilloux, 2011); the comovement of carbon allowance prices and the prices of other financial assets (e.g. Chevallier, 2011a, b; Koch, 2011), etc.

investigate the time series dynamics of carbon allowance prices and trading behaviour in the carbon emission markets.

1.2. Objectives of the thesis

As it is important to understand the underlying dynamics driving the carbon emission markets, attention has been increasingly drawn to the econometric analysis of carbon allowance prices. For example, Paolella and Taschini (2008) analyse the time series properties of carbon allowance prices and examine the fitness of a series of GARCH models. It has been found that the GARCH model with generalised asymmetric *t* distribution performs best in the in-sample fitness; however, none of the models considered can provide accurate value of risk (VaR) forecasting. Other studies of time series analysis in carbon emission markets mainly focus on modelling the relationship between carbon spot and futures prices (e.g. Uhrig-Homburg and Wagner, 2009; Joyeux and Milunovich, 2010; Chevallier, 2010; Rittler, 2012, among others). Apart from these studies, a very important issue is the impact of the regulations governing carbon emission markets on the time series characteristics of carbon allowance prices and the implications of these special properties for hedging, arbitrage and other trading activities in carbon emission markets. Therefore, it is useful to model the time series dynamics of carbon spot and futures markets by considering the special characteristics of carbon emission markets, and analyse how these models can be applied to trading activities.

Previous research has shown that carbon allowance prices experience frequent jumps and spikes and that the volatility of carbon emission markets is high compared to other financial markets (Daskalakis, et al., 2009; Benz and Trück, 2009). Thus, managing the financial risk in carbon emission markets is important for market participants. However, few studies have been conducted to estimate the hedge ratios and to evaluate the hedging performance in carbon emission markets. Only Pinho and Madaleno (2010) and Fan, Roca and Akimov (2013) examine the effectiveness of conventional hedging strategies in European carbon emission markets, including the naive hedge, constant OLS, VECM and GARCH approaches. These hedging strategies fail to consider the special characteristics of carbon emission markets and therefore cannot achieve a significant improvement on the simple naive hedge approach.

Benz and Trück (2009) compare the usefulness of GARCH and regime switching approaches in modelling the dynamics of carbon allowance prices. The results show that the Markov regime switching model outperforms the GARCH model in both in-sample fit and out-of-sample forecasting. This is because the regime switching model can capture the economic and econometric characteristics of carbon allowance prices. From an economic perspective, the regime switching model can reflect the fluctuations in the demand and supply of carbon allowances based on different regulatory frameworks, production levels and weather conditions, by allowing a systematic switching between high variance (unstable) state and low variance (stable) state. In addition, the Markov regime switching models, in which the regimes are determined by an unobservable state variable, are more appropriate for carbon emission markets as several determinants of carbon allowance prices (e.g. the regulatory and sociological variables) are unquantifiable and unobservable. From an econometric perspective, the regime switching models which allow consecutive jumps and extreme values in asset prices can better capture the statistical characteristics of carbon allowance prices.

The findings above imply that the regime switching models may produce better hedging performance than the GARCH approaches as they can capture the dynamics of carbon emission markets more effectively. Therefore, in Chapter 3, this thesis models the relationship between carbon spot and futures markets by considering state dependent properties in the return and volatility processes, and evaluates the performance of Markov regime switching and alternative hedging strategies. In particular, this chapter introduces a new framework with which to model the carbon spot and futures relationship, which incorporates regime switching behaviour and the long run disequilibrium adjustment in the mean with the state dependent dynamic volatility process. In assessing the effectiveness of competing approaches, this chapter uses a variety of hedging performance measures, including the variance of hedged portfolio, hedger's utility and value at risk exposure. In addition, this chapter also considers the downside risk measures, different hedging positions and tests the statistical significance of improvements by using state dependent hedge ratios.

After evaluating the hedging performance of Markov regime switching models, the thesis turns its attention to attempting to understand the trading behaviour of investors in carbon emission markets, as they are governed by a different regulatory framework than other financial markets. The design and mechanisms of the EU ETS mean that the vast majority of investors in European carbon emission markets are institutional investors, which provides us with a unique and natural opportunity to investigate the institutional investors' trading behaviour. In particular, feedback trading is an important trend chasing strategy which has attracted an increasing amount of attention in recent studies (e.g. Sentana and Wadhwani, 1992; Antoniou, Koutmos and Pericli, 2005; Laopodis, 2005; Salm and Schuppli, 2010; Chau, Deesomsak and Lau, 2011, among others). However, no previous study has examined feedback trading in carbon emission markets, where institutional investors dominate. This provides a motivation for examining whether there is significant feedback trading in carbon emission markets, and comparing the results with other energy markets, which is the second aim of the thesis.

Conventional feedback trading models assume that the feedback traders' demand for shares is only determined by the return in the last period. However, it has been argued that arbitrage opportunities can also affect the trading behaviour of feedback traders. Arbitrage, which is a form of rational speculation, is among the most important factors contributing to feedback trading (De Long, Shleifer, Summers and Waldmann, 1990). In addition, it has been shown that arbitrage opportunities contain some predictive value for future price movements (e.g. Khoury and Yourougou, 1991; Knetsch, 2007; Gorton, Hayashi and Rouwenhorst, 2013). For the reasons outlined above, the thesis argues that, in addition to the last period's return, potential arbitrage opportunities can also determine the demand function of feedback traders. Therefore, Chapter 4 extends Sentana and Wadhwani's (1992) feedback trading model by allowing arbitrage opportunities to affect the feedback traders' demand function, and examines whether there is significant feedback trading in carbon emission and energy markets. In the augmented feedback trading model, the demand from feedback traders is influenced by arbitrage opportunities, which is measured by using the spot-futures basis and the convenience yield, in both an additive and a multiplicative way. The chapter also tests whether the effects of arbitrage opportunities on feedback trading are different across bull and bear market conditions.

Beside the fact that carbon emission markets are dominated by institutional investors, there is another important characteristic of European carbon emission markets that needs to be addressed. Firms are required to submit a certain amount of their carbon allowances to the EU by a fixed deadline each year to comply with the EU ETS regulations; otherwise they will incur a heavy penalty. In order to avoid the fine, firms with insufficient carbon allowances need to purchase the rest of their allowances in the markets before the submission deadline. This causes trading to be more active before the submission deadline than after. After the submission, the total amount of carbon allowances in the markets is significantly lower than before the submission deadline, which also means that investors' trading activities differ before and after the submission deadline. Therefore, the time series dynamics driven by trading activities should have changed after the submission deadline. In order to observe the change intuitively, the author plots the time series of the difference between observed futures prices and theoretical futures prices derived from the cost of carry model. Persistent mispricing of carbon futures is observed before the submission deadline, which supports the previous argument. The reasons outlined above provide a strong motivation to examine the impact of the allowance submission deadline on the time series dynamics of carbon emission markets, which is the last objective of this thesis. In particular, in Chapter 5, this thesis examines the impact of the allowance submission deadline (30 April each year), set by the European Union emission trading scheme (EU ETS), on the relationship between carbon spot and futures markets. In particular, this chapter studies whether there is a shift in the mean-reverting process of the carbon spot and futures relationship, the price discovery process and volatility spillovers of carbon spot and futures markets before and after the submission deadline. The effects described above are examined by using intraday data with different time frequencies.

1.3. Contributions of the thesis

By investigating the research objectives outlined above, the thesis makes unique contributions to the existing literature in the following respects.

Firstly, in order to model the joint distribution of carbon spot and futures prices, this thesis formulates a new framework in Chapter 3 which incorporates the concepts of regime switching, disequilibrium adjustment and volatility clustering. In particular, this approach allows Markov regime switching (MRS) behaviour and adjustment to the long run equilibrium (LR) in modelling the relationship between spot and futures returns, and state dependent characteristics in the dynamics volatility process, which is modelled by Engle's (2002) dynamic conditional correlation (DCC) GARCH (referred as MRS-LR-DCC). This is important because, if there is a long run relationship between spot and futures prices, overlooking the cointegration relationship will cause misspecification of the models and consequently the performance of the hedging strategy could be unsatisfactory (e.g. Kroner and Sultan, 1993; Lien, 1996). In addition, by allowing the conditional variance parameters to be state dependent, this thesis is the first to introduce the regime switching dynamic volatility process into the carbon emission markets. Previous studies only consider the state dependent characteristics in the return process of carbon allowances (e.g. Benz and Trück, 2009; Chevellier, 2011a, b). However, Chevellier (2011c) shows that the conditional variances of carbon asset returns exhibit strong shifts and instability. Therefore, it is important to allow regime switching in carbon asset volatilities.

The second contribution of the thesis is to demonstrate that the class of Markov regime switching approaches perform the best in hedging the financial risk in carbon emission markets. As Markov regime switching models can capture the economic and econometric properties of carbon allowance prices, the state dependent hedging strategies are expected to produce a superior performance. The class of Markov regime switching approaches outperform OLS and GARCH strategies in all the hedging performance measures considered, including variance reduction, hedgers' utility and value at risk. White's (2000) reality check is used to test the statistical significance of the improvement offered by the MRS-LR-DCC model over other approaches. The results show that the MRS-LR-DCC model significantly outstrips all the other strategies at conventional levels. Furthermore, the findings above are still significant after considering the downside risk measures and the difference in long and short hedging positions.

Thirdly, this thesis finds that there is no significant feedback trading in carbon emission markets. This is important because most of the investors in carbon markets are institutional investors. The unique features of carbon emission markets make the results obtained in this thesis significant in understanding the trading behaviour of institutional investors.

Also, by examining the impact of arbitrage opportunities on feedback trading, this thesis contributes to a rising number of studies investigating how arbitrage opportunities affect investors' trading behaviour. Arbitrage, which is regarded as a type of rational speculation, is suggested as one of the causes of feedback trading (De Long et al., 1990). In addition, arbitrage opportunities can be used to predict future price movements (e.g. Khoury and Martel, 1989; Khoury and Yourougou, 1991). Therefore, it is possible that feedback traders also consider the positional arbitrage opportunities as an indicator to trade. For this reason, this thesis extends Sentana and Wadhwani's (1992) feedback trading model by allowing arbitrage opportunities to affect feedback traders' demand for shares, in both an additive and a multiplicative way. The results show that the impact of arbitrage opportunities on feedback trading is significant in some energy markets. Furthermore, this thesis shows that the impact of arbitrage opportunities on the level of feedback trading is different across bull and bear market regimes. Finally, this thesis also differs from previous studies which only assume a particular specification of the conditional variance process, by conducting a comprehensive examination of specifications in order to select the most appropriate volatility model for each market.

Last but not least, by examining the impact of the allowance submission deadline on the European carbon emission markets, this thesis finds in Chapter 5 that the time series dynamics of the carbon emission markets change after the submission deadline. Due to the EU ETS regulations, investors' trading activities in carbon emission markets may be different before and after the submission deadline, which can induce a change in the time series characteristics of carbon allowance prices. Therefore, the results obtained are significant in understanding the trading activities, especially arbitrage activities, in carbon emission markets. In particular, this thesis finds that the equilibrium level, mean-reverting speed and no-arbitrage boundaries of the carbon futures mispricing are affected by the submission deadline. However, the cointegration relationship between spot and futures prices is not affected. As previous studies show mixed results for the cost-of-carry relationship between carbon spot and futures prices, the results obtained show that submission of allowances is not the underlying reason for the mixed results. In addition, this study incorporates the impact of allowance submission into the examination of the causal relationship between spot and futures returns in the carbon emission markets. These results show that the price discovery process does not change after the allowance submission deadline. Furthermore, by using realised measures, this thesis finds that the submission of allowances has a significant impact on the volatility spillovers between carbon spot and futures markets, particularly from the spot market to the futures market.

Overall, this thesis proposes a time series model (MRS-LR-DCC) for carbon emission markets that can explain the data generation process (DGP) accurately and also provide a superior hedging performance. Moreover, this thesis introduces a new feedback trading model in which arbitrage opportunities affect the demand from feedback traders. Finally, the thesis finds that carbon emission markets yield different time series characteristics from other financial markets, which is dependent on the submission deadline.

Chapter 2

Overview of the Global Carbon Emissions Markets

2.1. Global warming and the Kyoto protocol

The observed average temperature of the Earth's surface has shown a tendency to increase since the start of the twentieth century. The average surface temperature of the Earth rose by around 0.8°C over the past century, and about 0.6°C of this increase has occurred since 1980 (National Research Council, 2011). In addition, the projected world average temperature will increase by 2°C to 5°C by the end of the twenty-first century (Stern, 2007). Continuous global warming will have significant adverse economic and social consequences, such as more droughts, floods, and severe weather conditions, desertification of land and reductions in agricultural production.

It has been shown that global warming is strongly associated with the emission of greenhouse gases (GHGs), and there is an increasing awareness that it is important to reduce GHG emissions. In order to address the climate change issue, the United Nations launched the United Nations Framework Convention on Climate Change (UNFCCC) in 1992 to reduce the worldwide emission of GHGs. 194 countries have acknowledged that the international community needs to control the accumulation of GHGs in the atmosphere, by keeping them under a certain level in order to avoid the hazardous impact of global warming on the climatic system (Newell, Pizer and Raimi, 2012).

The UNFCCC further proposed an agreement on how to achieve global emission reduction, known as the Kyoto Protocol, which was initially adopted in December 1997 in Kyoto, Japan. The treaty requires 37 industrialised countries or countries in transition (known as Annex I countries of the Kyoto Protocol) to reduce their collective GHG emissions by 5.2% of the level reached in 1990 before 2012 (UNFCCC, 1997). The Kyoto Protocol also designed a “cap-and-trade” system to reduce the emissions more efficiently and economically. Under this system, central authorities set up a standard or “cap” on the total amount of greenhouse gases that each country or region can emit within a year or other fixed period. The authorities then allocate the allowance of emission units, which is the right to emit a certain amount of GHGs. Firms’ emissions should not exceed the allocated allowance represented by their in-hand credits; otherwise they must deliver the missing carbon credits in the next year and will also incur a heavy penalty. For example, the penalty in the EU is €40 per ton of CO_2 equivalent before 2008 and €100 per ton after 2008. The total amount of credits should not exceed the cap. As a consequence, the total amount of emissions can be controlled and kept under a target level. If a company needs to emit more than its allocated allowance, it can buy the carbon credits from another company with a remaining emission allowance. This is how the “cap-and-trade” system works. According to the Coase theorem (Coase, 1937, 1960), under the assumption of no transaction costs, and if the authorities allocate the credits and protect the rights of credit holders very effectively, the “cap-and-trade” system can completely solve the externality problem of market failure. By adopting the “cap-and-trade” mechanism, many countries and regions implemented emission reduction programmes, and gradually created the global GHG emission markets, which are also known as the carbon emission markets as CO_2 is the predominant gas in GHGs. The global carbon emission markets had reached a market value of $144 billion by the end of 2009, and had an annual growth rate of 6% even at the height of the economic recession (World Bank, 2010).

The value further increased to more than $175 billion in 2011, which is over 20 times higher than in 2005 (World Bank, 2012), while business activities in all sectors of the economy are influenced by carbon emission trading (Calel, 2013).[2]

The Kyoto Protocol designed three “flexibility mechanisms” to be used by Annex I countries in order to meet their emission reduction obligations, which are: the International Emissions Trading (IET); the Clean Development Mechanism (CDM); and Joint Implementation (JI). The IET allows participating countries to trade their emission rights assigned by the UN, which are known as Assigned Amount Units (AAUs, or carbon emission allowances). The most important emission trading programme in the world is the European Union Emission trading scheme (EU ETS) organised by the European Union Commission. The CDM is designed to promote international environmental cooperation between industrialised counties and developing countries, by allowing Annex I parties to develop emission reduction projects in developing countries and generate Certified Emission Reduction units (CERs), which can be used to fulfil the emission reduction requirements or traded in the global carbon emission markets. Similarly, the JI is a mechanism which allows an Annex I country to invest in emission reduction projects in another Annex I country, in exchange for Emission Reduction Units (ERUs), which are also a form of carbon credits accepted by the UN. These flexibility mechanisms reduce the overall costs of emission reductions and boost the spillovers of clean energy technologies.

2.2. The EU ETS

[2] The financial instruments traded in the carbon emission markets are called carbon credits. Because the carbon emission market is a futures-dominated market and always a sub-market of energy exchanges, carbon credits are commonly viewed as a special type of commodities (Button, 2008). Hence, some research methods intensively employed in commodity markets are adopted in this thesis.

The European Union Emission Trading Scheme (EU ETS) is a “cap-and-trade” system, operating under the Kyoto Protocol. Launched in 2005, the total value of European Union Allowance (EUA)[3] transactions is 118.5 billion US dollars with an 18% growth rate, which is considerably faster than the growth of the global carbon emission market (World Bank, 2010). Accounting for 83% of the market value of global carbon emission markets, the EU ETS is the most influential and successful emission trading programme in the world. The firms covered by the EU ETS comprise approximately 12,000 installations which have a net generating capacity of more than 20 megawatts (MW), located in 28 countries in the EU and 3 European countries outside of the EU (Iceland, Liechtenstein and Norway). The sections included are: power stations; mineral or oil refineries; ferrous metal; glass production; coke ovens; ceramic production; cement manufacture; and finally the aviation industry which joined in 2012 (Ibikunle, 2012).

After the “cap” or total amount of GHG emissions was decided, the EUAs were distributed to the participating nations and then the installations within them through National Allocation Plans (NAPs). The distribution approaches include free allocation, which is based on historic patterns of emissions in a specific sector (also known as grandfathering), auctioning, or a combination of both methods. As firms may receive windfall profits through free allocation, the EU gradually increases the proportion of auctioning in the EUA allocations. In any year, the government authorities have to issue the auctioned or freely allocated carbon emission allowances to the participating firms by 28 February. On 30 April of the following year, all firms covered by the EU ETS are required to surrender the specified quantity of EUAs or other accepted carbon financial instruments (including CERs and ERUs under some conditions) corresponding to the GHG emissions in the previous year. Those GHG emissions not covered by the surrendered carbon allowances are penalised at €40 per

[3] EUA is the carbon emission allowance traded under EU ETS.

ton of CO_2 before 2008 and €100 per ton of CO_2 after 2008. In addition, the uncovered carbon allowance should also be surrendered in the next compliance year. Therefore, in order to avoid the penalty, firms that do not have sufficient carbon allowances to surrender have to purchase the uncovered allowances in the spot market before the submission deadline, boosting trading activities in carbon emission allowances before 30 April each year. All the operators' allowance holdings and carbon allowance trading are registered in the EU ETS Transaction Log. The data show that less than 6% of the total accounts are personal holding accounts (2,050 out of a total of 34,492 accounts) in November 2012, indicating that the vast majority of the participants in the European carbon emission markets are institutional investors. This is because individuals cannot claim carbon allowance from their personal emissions reduction, resulting in individuals being disadvantaged in terms of carbon emission trading compared to participating firms. The participants in the EU ETS include the 12,000 installations covered by the scheme, firms investing in the CDM and JI projects, government carbon funds, international organisations, arbitragers, speculators and other environmental investors.

The EU ETS has three commitment periods, each with different mechanisms. Phase I spans the period from January 2005 to the end of 2007, which is the trial period. All the carbon emission allowances were freely allocated through grandfathering. In addition, it did not permit banking and borrowing of carbon allowances between different phases. The penalty in this commitment period was €40 per CO_2 ton not surrendered plus the submission of uncovered carbon allowances in the next year. The period from January 2008 to December 2012 constitutes the second phase of the EU ETS; interphase banking restrictions were relaxed to some extent and more countries such as Norway, Iceland, and Liechtenstein joined the scheme. The aviation industry has also been included in the scheme since 2012. The financial penalty for default increased to €100 per CO_2 ton of uncovered emissions. A small fraction of carbon emission allowances (less than 10%) was distributed through auctioning. In the third commitment period of the EU ETS (2013–2020), a series of changes will be made by the European Union. For example, the proportion of carbon emission allowances allocated through auctioning will gradually increase from 20% in 2013 to 70% in 2020, and this allocation will not be done through NAPs but through EU-wide distributions. Interphase banking restrictions will be completely abolished. In addition, the European commission will restrict the use of carbon offsets outside of the EU as a substitute for the EUA. This makes the characteristics of carbon emission trading in EU ETS Phase III different from the first two commitment periods. Therefore, with increasing data availability, it will be of interest to investigate the new features of carbon emission markets in EU ETS Phase III.

2.3. The European carbon emission trading markets

The previous section has described the mechanisms and the primary markets (auction or free allocation) of the EU ETS. In this section, the thesis will focus on the secondary markets of the EU ETS, i.e. European carbon emission trading markets, which are the markets used for the empirical investigation carried out in this thesis.

Spot and derivative carbon allowances are traded in a number of exchanges, including the European Climate Exchange (ECX) under the Intercontinental Exchange (ICE), BlueNext exchange,[4] European Energy Exchange (EEX), Nordpool Exchange, Green Exchange, and the Climex. Futures contracts for the EUAs are the dominant financial instrument in European carbon emission markets (World Bank, 2008). More than 90% of carbon futures contracts are traded on the ICE ECX. The ICE ECX futures market opens from 07:00 to

[4] The BlueNext exchange was shut down in December 2012 as it failed to win a bid to run the EUA auctions from the start of the third commitment period of the EU ETS (2013-2020). European Energy Exchange won the bid so that will now be the leading spot market for the carbon allowances.

17:00 GMT Monday to Friday, and the futures contracts are listed on a quarterly expiry cycle, i.e. contracts expire in March, June, September and December each year. The expiry date is the last Monday of the contract month. The most liquid futures contract is the one which expires in December each year. The leading spot market for the EUA is the Bluenext exchange for the first and second commitment periods, and it will be the EEX for EU ETS Phase III. Trading on the BlueNext spot market occurs from 08:00 to 17:30 UTC+1, Monday to Friday. Therefore, this thesis uses the EUAs futures contracts data from the ICE ECX and spot contracts data from the BlueNext.

[Insert Figure 2.1 here]

The time series of the EUA futures prices in EU ETS Phase I and Phase II are presented in Figure 2.1. It can be observed that the carbon allowance prices are volatile and are characterised by frequent jumps and spikes, especially in the first commitment period of the EU ETS (2005-2007). The significant drop in the EUA prices during the last week of April 2006 is because the installations' emission data was disclosed and market participants realised that the EUAs were oversupplied. The over-allocation of the EUAs and windfall profits from the free allocation made the EUAs worthless and they gradually declined to zero (or almost zero) during the second half of 2007. Alberola et al. (2008) show that, in Phase I of the EU ETS, there are two structural changes in the carbon allowance prices and the price drivers are energy prices, weather conditions and unexpected policies. Given the high volatility of carbon allowance prices, there is a consensus that the European carbon emission markets are not efficient during EU ETS Phase I (e.g. Daskalakis and Markellos, 2008; Miclaus, Dumitrescu and Bobirca, 2008; Frunza and Guegan, 2009; Montagnoli and De Vries, 2010; Joyeux and Milunovich, 2010; Charles, et al., 2011).

During Phase II of the EU ETS, the European Commission revised the National Allocation Plans (NAPs) to stabilise the carbon allowance prices. The significant decline in prices from August 2008 to April 2009 was because of the global financial crisis. After that, the carbon allowance prices became less volatile. During this commitment period, the interaction between carbon allowance prices and macroeconomic variables becomes stronger (e.g. Chevallier, 2011a, b), while the efficiency of the market has also been improved (e.g. Charles, et al., 2011; Charles, Darné, and Fouilloux, 2013).

[Insert Figure 2.2 here]

Figure 2.2 presents the annual market value of the European carbon emission market. Charles, et al. (2011) identify that the European carbon emission market was a thin trading market during EU ETS Phase I, although it is growing rapidly. It can be observed from the figure that the market value stood at only around $50 billion by the end of 2007 but jumped to $100 billion in 2008. The European carbon emission market was worth approximately $150 billion by 2011, which is 20 times higher than in 2005. It is now a sizable market and consequently is attracting an increasing amount of investment.

Finally, it can be inferred from the design and regulations of the EU ETS, and the price-volume analysis above, that the characteristics of European carbon markets have phase-dependent issues. This thesis only considers the data in the second commitment period of the EU ETS, for the following reasons. Firstly, the second phase of the EU ETS is the most recent commitment period and has not been fully investigated. Secondly, the mechanisms of EU ETS Phase I and Phase II had been significantly changed; therefore, it would not be viable to examine the Phase I and Phase II data together. Thirdly, due to inter-phase banking restrictions, the spot prices were close to zero at the end of Phase I, i.e. the second half of

2007 (Chevellier, 2011a). Therefore, it is not appropriate to use the spot prices at that stage to study the time series dynamics of carbon emission markets.

From Figure 2.1 and Figure 2.2 it can be observed that the European carbon market becomes less volatile and more liquid, although it is open to some criticisms, for example over-allocated allowances, the VAT fraud and the low prices at the end of the first phase. The European commission has made many changes in the mechanisms of Phase III designed to resolve these issues. The most important ones include auctioning the carbon allowances and reforming the National Allocation Plans (NAP). These actions will strongly support carbon prices and help the market to become mature.

2.4. Other emission trading markets

Prior to the EU ETS, the US SO_2 market, which is also a “cap-and-trade” system, was created in 1995. Similar to the EU ETS, it consists of two phases with different targets. The price for SO_2 was high in the first phase, and subsequently dropped to a very low level because technological advances reduced the cost of SO_2 emission reduction. The market has been very successful as the SO_2 emissions and acid rain levels dropped significantly after the programme was introduced. We can therefore expect the EU ETS, which has similar mechanisms to the US SO_2 market, to be very successful in the future.

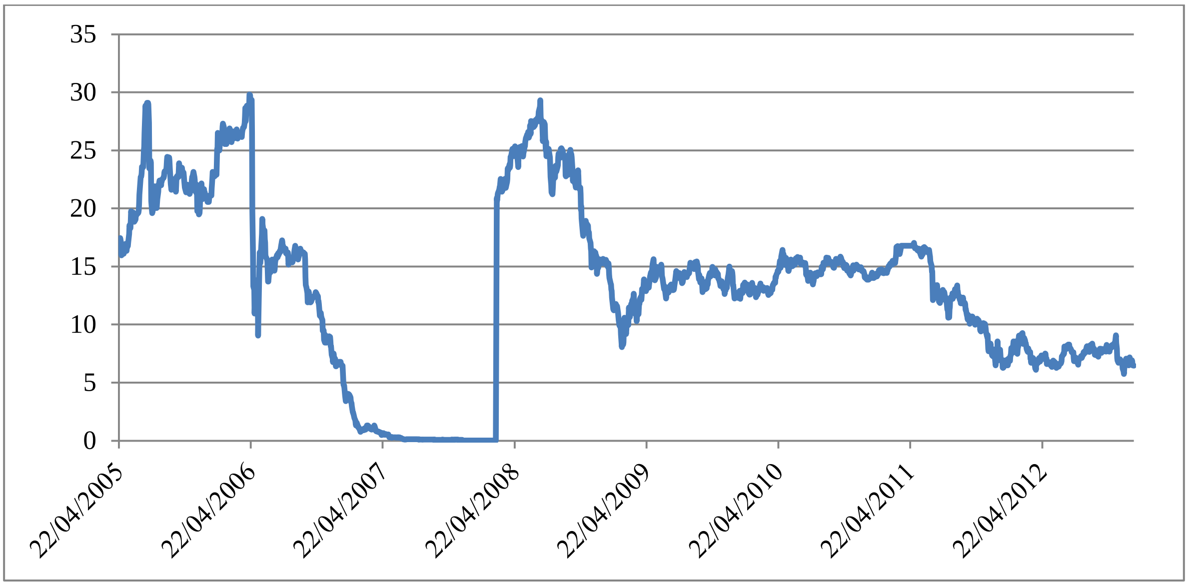
Among the world’s carbon markets, the US voluntary carbon market is one of the most important. Currently there are no federal carbon regulations but only regional initiatives for carbon emission reductions in the United States, for example the Regional Greenhouse Gas Initiative (RGGI) for the north-eastern states and emission trading in California. The US carbon emission market is a voluntary and pre-compliance carbon offset market, which can be viewed as an experimental market for mandatory greenhouse gas “cap-and-trade” at federal level. The House of Representatives passed the Waxman-Markey Bill[5] in June 2009 and it is now waiting for Senate to vote on it. According to Point Carbon’s survey, 81% of participants expect the US to introduce an emission trading scheme in 2014 (Point Carbon, 2010). Viswanathan (2010) proposes a hybrid approach to regulate the future U.S. carbon emission market, which involves a combination of exchange-traded centralised trading for large financial intermediates and over-the-counter (OTC) transactions for small contracts. If a U.S. emission trading programme was to be introduced, the trading volume of the global carbon market as a whole would be boosted, and it would probably surpass the EU ETS to become the largest carbon market within a few years.

Other carbon emission markets include: New Zealand’s emission trading scheme (NZ ETS), launched in 2008; the emission trading programme in Quebec, Canada (launched in 2013); and a number of provincial carbon emission markets in China (initiated from 2013 onwards). Australia will implement an emission trading programme in 2015 and will link it to the EU ETS. Furthermore, Kazakhstan, Japan, South Korea, Brazil and Mexico have all passed legal procedures for introducing their own emission trading programmes.

More than 15 years have passed since the signing of the Kyoto Protocol. Since then, global carbon emission markets have experienced ongoing development. Currently, carbon emission markets are sizeable and are continuing to expand rapidly. The regulatory framework for carbon emissions is not static; it incorporates the lessons learned from previous experience (Newell et al., 2012). Overall, carbon emission markets aid the efficient reduction of GHG emission and will attract an increasing amount of investment in the future (Newell, Pizer and Raimi, 2013).

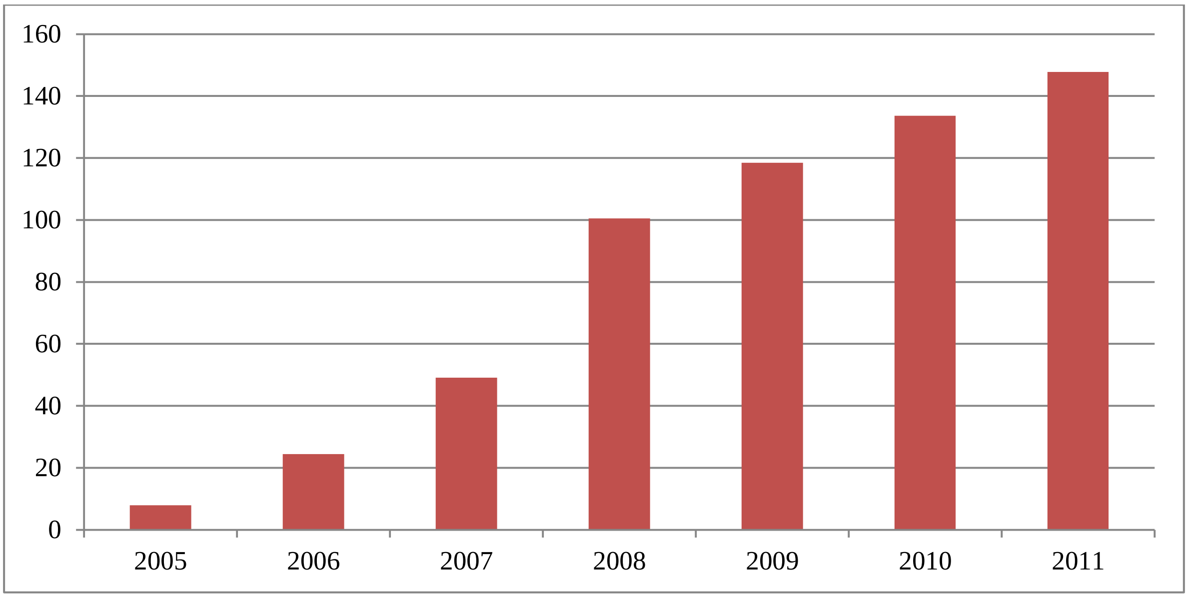
[5] This is a mandatory emission reduction Act, which requires U.S. to reduce GHG emission by 20% below 2005 emission levels before 2020, and introduced a series of long-term targets.

Figure 2.1: Time series of the EUA prices (€ per CO_2 ton, continuous futures contracts)



Note: This figure displays the time series of the EUA futures prices in the first and second commitment periods of the EU ETS (from 22 April, 2005 to 31 December, 2012). To construct a continuous series of futures prices, the futures contracts switch over on the first day of a new month's trading, for all available trading months.

Figure 2.2: Market value of European carbon emission market ($ billion)



Note: This figure presents the annual market value of the European carbon emission market. The data is obtained from the World Bank (currently there is no data available for 2012).

Chapter 3

Hedging carbon emission allowances using Markov regime switching approaches

Abstract

Using the second commitment period data for the European Union emission trading scheme (EU ETS), this chapter models the relationship between carbon spot and futures markets by incorporating state dependent characteristics in the return and volatility processes, and assesses the effectiveness of constant and dynamic hedge ratios. In particular, this chapter proposes a new framework for the carbon emission markets which combines regime switching behaviour and disequilibrium adjustment in the mean with a state dependent dynamic volatility process. It is found that the class of regime switching hedging strategies, especially the new approach proposed in this chapter, significantly outperform competing methods for all the measures considered, and for both in-sample and out-of-sample analysis. The results indicate that risk managers using state dependent hedge ratios to manage the financial risk in carbon emission markets can achieve greater variance reduction and better hedging performance.

3.1. Introduction

Launched in 2005, the European Union emission trading scheme (EU ETS) is a "cap-and-trade" system[6] aimed at reducing emissions of carbon dioxide and other greenhouse gases (GHGs) efficiently and economically. Since its inception, European carbon emission markets under the EU ETS have experienced rapid ongoing development and have attracted considerable attention from policy makers and investors. The total value of European Union allowances (EUAs)[7] transactions had risen to 118.5 billion U.S. dollars with an 18% growth rate even during the recent global financial crisis (2008-2009), which is considerably faster than the growth rate in other financial markets (World Bank, 2010).

Given the novel features and rapid growth of the carbon emission markets, an increasing number of studies have been conducted within this market. The existing literature mainly focuses on pricing carbon spot and derivatives assets (e.g. Benz and Trück, 2009; Daskalakis et al., 2009), or modelling the relationship between spot and futures prices (e.g. Uhrig-Homburg and Wagner, 2009; Joyeux and Milunovich, 2010; Chevallier, 2010; Rittler, 2012; among others). However, little attention has been paid to risk management, especially hedging, in carbon emission markets. The risk associated with carbon markets involves the possibility of being fined for uncommitted allowances and the uncertainty of carbon

---

[6] Under this system, central authorities set up a standard or "cap" on the total amount of greenhouse gases that a country or region is allowed to emit within a year. The authorities then allocate the allowance of emission units, which is the right to emit a certain amount of greenhouse gases. Companies' GHG emissions should not exceed the allocated allowance represented by their in-hand allowances; otherwise they must deliver the missing carbon allowances in the next year and also incur a heavy penalty. The GHG emissions not covered by the surrendered carbon allowances incur a fine of €40 per CO_2 ton in Phase I and €100 per CO_2 ton in Phase II. In addition, the uncovered carbon allowance should also be surrendered in the next compliance year. The total amount of allowances should not exceed the cap. As a consequence, the total amount of emissions can be controlled and kept under a target level. If a company needs to emit more than its allocated allowance, it can buy carbon allowances from another company which has some emission allowances remaining. According to the Coase theorem (Coase, 1937, 1960), under the assumption of zero transaction costs, and if the authorities allocate and protect the rights of allowance holders very effectively, the "cap-and-trade" system can completely solve the externalities problem of market failure.

[7] The financial instruments traded in the carbon emission markets are known as carbon allowances. EUA is the carbon allowance traded under the EU ETS.

emission prices. Exceptions include Fan et al.’s (2013) study of hedging performance in the European carbon markets. The authors estimate the optimal hedge ratios in the first and second commitment periods of the EU ETS, which are obtained from the ordinary least squares (OLS) model, the two-stage error correction model (ECM), and the vector ECM (VECM) model, as well as the VECM model with bivariate generalised autoregressive conditional heteroskedasticity (GARCH) errors. The results indicate that the static hedge ratio from the simple OLS model can provide the greatest variance reduction in most cases.

However, Kroner and Sultan (1993) argue that if the asset prices follow time-varying distributions, time variation should also be taken into account for the optimal hedge ratio. Lien (2008) suggests that the OLS model tends to underperform dynamic hedging approaches in a number of empirical studies. The inferior performance of dynamic hedge ratios in Fan et al.’s (2013) study may be attributed to the fact that the VECM-GARCH model does not fit the data very well. Benz and Trück (2009) estimate the dynamics of carbon spot prices using various time series models. It is found that the Markov regime switching model outperforms the AR (1)-GARCH (1, 1) model in terms of in-sample fit and out-of-sample forecasting. Benz and Trück (2009) argue that the regime switching model is a promising approach for modelling the price dynamics of carbon emission allowances because it can capture the economic and econometric characteristics of carbon allowance prices. Firstly, the demand and supply of carbon allowances, which determine the carbon allowance prices, fluctuate according to the regulatory framework, production level, weather conditions and other factors. The regime switching model can reflect such fluctuations by allowing a systematic switching between a high variance (unstable) state and a low variance (stable) state. In particular, the Markov regime switching models, where the regimes are determined by an unobservable state variable, are more appropriate for carbon emission markets because the regulatory and sociological variables which could affect carbon allowance prices are unquantifiable and unobservable. Secondly, the carbon allowance prices and returns exhibit price jumps, spikes and high volatility (Benz and Trück, 2009; Daskalakis et al., 2009). The regime switching model can capture these econometric properties by allowing for several successive price jumps and very high or low returns, which is important in risk management. In addition, Chevellier (2011a, b) also showed the advantages of using the Markov regime switching (MRS) vector autoregressive (VAR) model over the single regime VAR model in examining the relationship between carbon allowance prices and macroeconomic variables. The evidence discussed above implies that the hedge ratios generated from regime switching models could outperform single regime hedging models in carbon emission markets.

Motivated by the above results and arguments, this chapter aims to investigate the performance of state dependent hedge ratios in the European carbon emission markets. This thesis adopts the Markov regime switching model rather than another non-linear model (e.g. threshold models) because the hedging performance of threshold models is poor in the literature and the Markov regime switching model is shown to have good in-sample fit and out-of-sample forecasting for carbon markets. The Markov regime switching hedging strategies have been found to outperform the OLS and GARCH model in various financial markets (e.g. Alizadeh and Nomikos, 2004; Lee and Yoder, 2007a, b; Alizadeh, Nomikos and Pouliasis, 2008; Salvador and Arago, 2013). However, the Markov regime switching approaches to hedging have not been applied in the carbon emission markets.

By examining the research question above, this chapter contributes to the literature in the following respects. Firstly, this chapter proposes a new framework with which to model the relationship between carbon spot and futures markets, which incorporates the concepts of regime switching, disequilibrium adjustment and volatility clustering. This method considers

Markov regime switching (MRS) behaviour and the long run relationship between spot and futures prices (LR) in the mean, and the state dependent dynamic volatility process which is modelled by Engle's (2002) dynamic conditional correlation (DCC) GARCH (MRS-LR-DCC). This approach differs from Lee and Yoder's (2007b) MRS-TVC-GARCH model by allowing the disequilibrium adjustment coefficients to be state dependent.[8] It has been shown that if spot and futures prices are cointegrated, overlooking the adjustment of the long run relationship between spot and futures prices will result in model misspecification and therefore inferior hedging performance (e.g. Kroner and Sultan, 1993; Lien, 1996). In addition, the author's model differs from the MRS-BEKK method used by Alizadeh et al. (2008) because it allows the conditional correlations to be time-varying and state dependent. Secondly, this chapter first adopts the Markov regime switching approaches in order to hedge the financial risk in carbon emission markets. Given the economic and econometric properties of carbon prices, the state dependent hedge ratios are expected to provide higher variance reductions. Thirdly, although the first moment of carbon emission returns have been modelled using Markov regime switching approaches in both univariate (Benz and Trück, 2009) and bivariate frameworks (Chevellier, 2011a, b), no previous research has allowed the conditional variance of carbon asset returns to be state dependent. Chevellier (2011c) demonstrates that there are strong shifts and significant instability in the conditional variance of carbon asset returns. For this reason, this chapter is the first to introduce the state dependent dynamic volatility process into the study of carbon emission markets.

[8] Another difference in the author's model and the MRS-TVC-GARCH model is that this chapter uses Engle's (2002) method to model the condition correlations while Lee and Yoder (2007b) employed Tse and Tsui's (2002) approach. The only difference between the two methods is the way in which they standardise the residuals in the conditional correlation equation.

In this chapter, the optimal hedge ratios of different strategies are estimated using daily spot and futures prices in the second phase of the EU ETS.[9] For completeness and comparison, in addition to the MRS-LR-DCC model, this chapter also considers the optimal hedge ratios obtained from the naïve hedge, the constant OLS method, the VECM model, the DCC-GARCH, MRS and MRS with a long run relationship (MRS-LR) approaches. In order to compare the in-sample and out-of-sample performance of these strategies, both symmetric and downside risk measures are employed. Symmetric measures include variance, utility and VaR, while asymmetric measures comprise semi-variance, semi-utility and asymmetric VaR. In addition, the difference between short and long hedgers' positions is also examined in the downside risk analysis.

The main findings of this chapter are summarised as follows. Firstly, it is found that the class of Markov regime switching approaches substantially outperform alternative strategies for all the measures considered, including portfolio variance reduction, utility maximisation and VaR exposure minimisation, for both in-sample and out-of-sample analysis. In particular, within the class of regime switching models, the MRS-LR-DCC model achieves the greatest and most significant variance improvement compared to competing strategies, indicated by the results of White's (2000) reality check (RC). In addition, it is found that the MRS-LR model constantly outperforms the MRS model in both in-sample and out-of-sample analysis, which supports the argument that the hedging performance can be improved by incorporating the long run relationship between spot and futures prices. Secondly, the results of in-sample and out-of-sample hedging effectiveness of different hedge positions

[9] The EU ETS has three phases, each with different mechanisms. Phase I spans the period from January 2005 to the end of 2007, and did not permit banking and borrowing of carbon allowances between different phases. The period from January 2008 to December 2012 constitutes the second phase of the EU ETS; interphase banking and borrowing restrictions were relaxed to some extent and more countries, such as Norway, Iceland, and Liechtenstein, were covered by the scheme. The aviation industry has also been included in the scheme since 2012. In Phase III of the EU ETS (2013–2020), a series of changes will be made by the European Union. For example, a fraction of carbon allowances will be moved from free allocation to auctioning; more restrictions will be imposed on using carbon offsets outside of the EU as a substitute for EUAs, etc.

using downside risk measures are mostly in line with those using symmetric metrics, i.e. the class of Markov regime switching approaches underperforms alternative strategies. This implies that no matter what position market participants hold, they can benefit from using state dependent hedge ratios.

The remainder of the chapter is organised as follows. Section 3.2 summarises the previous literature about regime switching hedging strategies, presents the specifications of the Markov regime switching models and demonstrates the minimum-variance hedge ratio methodology. Section 3.3 presents the summary statistics and preliminary diagnostic tests for the data. In Section 3.4, the estimation results of the key models are provided and discussed. The hedging effectiveness of proposed strategies is evaluated and the data snooping basis is checked in Section 3.5. Section 3.6 further analyses the hedging performance by considering downside risk measures and short/long hedging positions. The findings are summarised and conclusions drawn in Section 3.7.

3.2. Markov regime switching hedging strategies

3.2.1. Previous studies on regime switching hedging

Since introduced by Hamilton (1989, 1990), regime switching models have been widely applied within economic and finance studies, including dynamic hedging using futures. Sephton (1998) suggests that dynamic hedging using GARCH models is too unstable to provide hedging effectiveness and that the regime switching hedging strategy could be used as an alternative as it allows time-varying but not volatile hedge ratios.

The regime switching hedging strategies have been found to outperform the OLS and GARCH model in numerous financial markets.[10] For example, Alizadeh and Nomikos (2004) find that the univariate MRS model improves the hedging effectiveness of the constant OLS and GARCH strategies in the U.K and U.S. stock index markets. Lee, Yoder, Mittelhammer and McCluskey (2006) allow the random coefficient autoregressive (RCAR) model to be state dependent and find that the hedge ratios generated from the model outperform competing strategies in Lead and Aluminium markets. This paper is the first to adopt White's (2000) reality check in hedging performance analysis. In addition, Lee and Yoder (2007a) extend Gray's (1996) univariate MRS-GARCH model to a bivariate framework and examine the hedging effectiveness of the MRS-GARCH model with Engle and Kroner's (1995) BEKK form covariance matrix, in Corn and Nickel markets. The results indicate that the MRS-BEKK GARCH model has a greater but insignificant variance reduction than the OLS and single regime GARCH approaches. Lee and Yoder (2007b) further allow the conditional correlations of spot and futures returns to be time-varying and state dependent, and develop a MRS-GARCH model with time-varying conditional correlations (MRS-TVC-GARCH). The model is applied to Japanese and Hong Kong stock markets and yields better hedging performance than competing models. Furthermore, Alizadeh et al. (2008) incorporate the long run error correction into Lee and Yoder's (2007b) MRS-BEKK GARCH model and find that the new model provides significant reductions in both symmetric and downside risk measures in oil markets.

In addition, Lee (2009a) proposes a regime switching Gumbel-Clayton (RSGC) copula GARCH model for hedging agriculture commodities, which uses a copula function in the switching process instead of the normality assumption and also solves the path-dependency problem. The results show that the RSGC model can provide a superior out-of-sample

[10] For a comprehensive review of the hedging performance of regime switching models, please see Lien (2012).

hedging performance. Lee (2009b) allows jumps in Markov regime switching GARCH models and finds the model can achieve greater variance reduction and utility in the U.K. stock market. Moreover, Lee (2010) introduces an independent switching dynamic conditional correlation (IS-DCC) GARCH to hedging and allows the number of regimes considers being greater than two. The empirical results support the advantage of using the IS-DCC hedging model in commodity markets. Most recently, Salvador and Arago (2013) compare the hedging performance of different linear and nonlinear GARCH hedging models in the main European stock markets and find the GARCH model with state dependent characteristics performs the best. However, the previous literature shows that the regime switching approaches to hedging have not been applied in the carbon emission markets.

3.2.2. The Markov regime switching model (MRS-LR-DCC)

The idea of a regime switching model is to divide the time series into several periods, which are known as regimes or states. For each state, the prices or returns are modelled in a separate and independent process. If the switches between regimes are driven by unobservable variables and are modelled by Markov chains, they become Markov regime switching models. The Markov regime switching approach to hedging is used to generate state dependent hedge ratios which can account for differences in the spot-futures relationship across various market states. This chapter first introduces the MRS-LR-DCC hedging model, in which both the conditional mean and conditional variance processes are dependent on the volatility of the regime (i.e. high/low variance state). In addition, similarly to Alizadeh et al. (2008), the long run relationship between spot and futures prices is incorporated into the return process and the coefficient of the long run relationship is allowed to be state dependent. Lien and Yang (2008) argue that the lagged basis can help to determine the movement of spot and futures prices and facilitate the mean-reverting process, and therefore can serve as the proxy for the long run relationship. Kroner and Sultan (1993), and Lai and Sheu (2010), among others, also use the lagged basis for the long run relationship. Therefore, the lagged basis serves as the long run relationship in this chapter. The conditional means of spot and futures returns of the MRS-LR-DCC model are specified as:

$$\Delta S_t = \mu_{s,st} z_{t-1} + \varepsilon_{s,st,t} \tag{3.1}$$

$$\Delta F_t = \mu_{f,st} z_{t-1} + \varepsilon_{f,st,t} \tag{3.2}$$

$$\boldsymbol{\varepsilon}_{st,t} = \begin{pmatrix} \varepsilon_{s,st,t} \\ \varepsilon_{f,st,t} \end{pmatrix} \Big| \Omega_{t-1} \sim IN(0, \mathbf{H}_{st,t}) \tag{3.3}$$

where ΔS_t and ΔF_t are spot and futures returns at time t, respectively; and z_t is the spot-futures basis at time t, which serves as the long run relationship. The basis is calculated as the logarithmic difference between spot and futures prices multiplied by 100. $\boldsymbol{\varepsilon}_{st,t}$ is a vector of the state dependent Gaussian white noise processes with a time-varying covariance matrix of $\mathbf{H}_{st,t}$ at time t. The parameters of the long run relationship and residuals in the MRS-LR-DCC model depend on the market regime at time t. The unobservable state variables st= {1, 2} are assumed to follow a first order, two-state Markov process with the following transition probability matrix:

$$\hat{\mathbf{P}} = \begin{pmatrix} \Pr(s_t = 1 \mid s_{t-1} = 1) = P_{11} & \Pr(s_t = 1 \mid s_{t-1} = 2) = P_{21} \\ \Pr(s_t = 2 \mid s_{t-1} = 1) = P_{12} & \Pr(s_t = 2 \mid s_{t-1} = 2) = P_{22} \end{pmatrix} = \begin{pmatrix} 1 - P_{12} & P_{21} \\ P_{12} & 1 - P_{21} \end{pmatrix} \tag{3.4}$$

where P_{11} provides the probability that state 1 will be followed by state 1; and P_{12} gives the probability that state 1 will be followed by state 2; and by analogy for the other notations.

The transition probabilities above are presumed to be constant between consecutive periods, and are assumed to follow a logistic distribution:

$$P_{12,t} = \frac{1}{1+\exp(\phi_1)}; P_{21,t} = \frac{1}{1+\exp(\phi_2)} \tag{3.5}$$

where ϕ_1 and ϕ_2 are unstrained constant terms which are estimated along with other unknown parameters through Maximum likelihood estimation.

The conditional variances of spot and futures returns are modelled as GARCH (1, 1) processes developed by Bollerslev (1986).[11] The time-varying, state dependent and positively defined conditional covariance matrix, $\mathbf{H}_{st,t}$, is specified as:

$$\mathbf{H}_{st,t} = \begin{pmatrix} h^2_{s,st,t} & h_{sf,st,t} \\ h_{sf,st,t} & h^2_{f,st,t} \end{pmatrix} = \begin{pmatrix} h_{s,st,t} & 0 \\ 0 & h_{f,st,t} \end{pmatrix} \begin{pmatrix} 1 & \rho_{st,t} \\ \rho_{st,t} & 1 \end{pmatrix} \begin{pmatrix} h_{s,st,t} & 0 \\ 0 & h_{f,st,t} \end{pmatrix} \tag{3.6}$$

where $\rho_{st,t}$ is the state dependent conditional correlation between spot and futures returns at time t in state st= {1, 2}; $h^2_{s,st,t}$ and $h^2_{f,st,t}$ are the state dependent conditional variances at time t in state st for spot and futures returns, respectively. Specifically, the conditional variances and conditional correlation in Engle's (2002) dynamic conditional correlation (DCC) GARCH framework are shown as:

$$h^2_{s,st,t} = \gamma_{s,st} + \alpha_{s,st}\varepsilon^2_{s,t-1} + \beta_{s,st}h^2_{s,t-1} \tag{3.7}$$

$$h^2_{f,st,t} = \gamma_{f,st} + \alpha_{f,st}\varepsilon^2_{f,t-1} + \beta_{f,st}h^2_{f,t-1} \tag{3.8}$$

$$\rho_{st,t} = (1-\theta_{1,st} - \theta_{2,st})\rho + \theta_{1,st}\boldsymbol{\eta}_{t-1}\boldsymbol{\eta}'_{t-1} + \theta_{2,st}\rho_{st,t-1} \tag{3.9}$$

[11] In some cases in the out-of-sample analysis, convergence results cannot be generated by using standard GARCH (1, 1) specification. In order to get convergence results, Ding, Granger and Engle's (1993) asymmetric power ARCH (APARCH) model is adopted in these cases.

where $\theta_{1,st}$ and $\theta_{2,st}$ are the DCC parameters, ρ is the initial value of the conditional correlation, and $\boldsymbol{\eta}_t$ is a matrix for the standardised residuals. At this stage, all the parameters in the system are state dependent.

However, because both conditional variances and conditional correlations are based on all the past information recursively, the basic form of GARCH models with state dependent coefficients is intractable (e.g. Hamilton and Susmel, 1994; Cai, 1994). Gray (1996) solves the path-dependency problem in the univariate GARCH framework by formulating the conditional variance process as the conditional expectation of the variance. Following Gray (1996), Lee and Yoder (2007a) extend the collapsing method for conditional residuals, conditional variances and conditional covariance to the bivariate framework. For example, the conditional variance and conditional residuals of the spot returns are recombined as

$$h_{s,t}^2 = \pi_{1,t}(r_{s,1,t}^2 + h_{s,1,t}^2) + (1-\pi_{1,t})(r_{s,2,t}^2 + h_{s,2,t}^2) - [\pi_{1,t} r_{s,1,t} + (1-\pi_{1,t}) r_{s,2,t}]^2 \tag{3.10}$$

$$\varepsilon_{s,t} = \Delta S_t - [\pi_{1,t} r_{s,1,t} + (1-\pi_{1,t}) r_{s,2,t}] \tag{3.11}$$

where $\pi_{1,t}$ is the probability of being in state 1 at time t and then $1- \pi_{1,t}$ is the probability of being in state 2 at time t; while $r_{s,st,t}$ is the state dependent conditional mean equation of the spot returns. Lee and Yoder (2007b) further recombine the conditional correlation as[12]

$$\begin{aligned}\rho_t = \frac{1}{h_{s,t} h_{f,t}} \{ &[\pi_{1,t}(r_{s,1,t} r_{f,1,t} + \rho_{1,t} h_{s,1,t} h_{f,1,t}) + (1-\pi_{1,t})(r_{s,2,t} r_{f,2,t} + \rho_{2,t} h_{s,2,t} h_{f,2,t})] \\ &- [\pi_{1,t} r_{s,1,t} + (1-\pi_{1,t}) r_{s,2,t}][\pi_{1,t} r_{f,1,t} + (1-\pi_{1,t}) r_{f,2,t}] \}\end{aligned} \tag{3.12}$$

After the recombination procedures shown in Equation (3.10) to (3.12), the MRS-LR-DCC model becomes path-independent, as the variance-covariance matrix is not dependent on all the past information but only on the current regime. The model can then be estimated through

[12] For details of the collapsing methods for conditional residuals, conditional variances, conditional covariance and conditional correlations, please see Gray (1996) and Lee and Yoder (2007a, b).

Maximum likelihood estimation. The density function mixed with the probability distribution of the state variable is shown as:

$$f(\mathbf{X}_t;\boldsymbol{\theta}) = \frac{\pi_{1,t}}{2\pi} |\mathbf{H}_{1,t}|^{-1/2} \exp(-\frac{1}{2}\boldsymbol{\varepsilon}_{1,t}^{'}\mathbf{H}_{1,t}^{-1}\boldsymbol{\varepsilon}_{1,t}) + \frac{(1-\pi_{1,t})}{2\pi} |\mathbf{H}_{2,t}|^{-1/2} \exp(-\frac{1}{2}\boldsymbol{\varepsilon}_{2,t}^{'}\mathbf{H}_{2,t}^{-1}\boldsymbol{\varepsilon}_{2,t}) \tag{3.13}$$

where $\boldsymbol{\theta}$ is the vector of unknown parameters and $\pi_{1,t}$, $\mathbf{H}_{st,t}$ and $\boldsymbol{\varepsilon}_{st,t}$ are defined as previously described. The unknown parameter vector $\boldsymbol{\theta}$ can be estimated by maximising the following log-likelihood function [13]:

$$L(\boldsymbol{\theta}) = \sum_{t=1}^{T} \log f(\mathbf{X}_t;\boldsymbol{\theta}) \tag{3.14}$$

L($\boldsymbol{\theta}$) is subject to the constraint that $0 \leq \pi_{1,t} \leq 1$ and is maximised using the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm. The optimal hedge ratios are given by:

$$\gamma_t = \frac{Cov(\Delta S_t, \Delta F_t)}{Var(\Delta F_t)} = \frac{h_{sf,t}}{h_{f,t}^2} = \rho_t \frac{h_{s,t}}{h_{f,t}} \tag{3.15}$$

When $\pi_{1,t} = 1$, the MRS-LR-DCC model collapses into Engle's (2002) DCC-GARCH model. The optimal hedge ratios of DCC-GARCH models are also given by Equation (3.15).[14] When all the conditional variance parameters are set to zero, the MRS-LR-DCC model collapses into the Markov regime switching models in the mean equation. The minimum variance hedge ratios of the Markov regime switching model (MRS) can be calculated by estimating the following equation:

$$\Delta S_t = \gamma_{0,st} + \gamma_{1,st}\Delta F_t + \varepsilon_{st,t};\ \varepsilon_{st,t} \sim iid(0, \sigma_{st,t}^2) \tag{3.16}$$

where ΔS_t and ΔF_t are defined as described above. The coefficients of futures returns in each state, $\gamma_{1,1}$ and $\gamma_{1,2}$, are the minimum variance hedge ratios, given the state of the market. The

[13] The MRS-LR-DCC model is estimated by using the Time Series Modelling (TSM) package version 4.39, developed by Professor James Davidson from the University of Exeter. I would like to thank Professor James Davidson for providing this package.

[14] For simplicity, the DCC-GARCH model to hedge is not shown in this chapter.

transition probabilities of the MRS model are also presumed to follow a logistic distribution described in Equation (3.5). The optimal hedge ratio at any time t is then determined as the weighted average of the minimum variance hedge ratios in each state, according to the probability of being in each state, which is shown as:

$$\gamma_t^* = \pi_{1,t}\gamma_{1,1} + (1-\pi_{1,t})\gamma_{1,2} \tag{3.17}$$

In order to account for the information contained in the basis, the MRS model for hedging is extended by incorporating the lagged basis as an independent variable, which serves as the long run relationship. The MRS model with a long run relationship (MRS-LR) is specified as:

$$\Delta S_t = \gamma_{0,st} + \gamma_{1,st}\Delta F_t + \gamma_{2,st} z_{t-1} + \varepsilon_{st,t} ; \varepsilon_{st,t} \sim iid(0, \sigma_{st,t}^2) \tag{3.18}$$

where ΔS_t, ΔF_t, z_t and the transition probabilities are defined as described above. The optimal hedge ratios of the MRS-LR model are also given by Equation (3.17).

3.3. Data and preliminary diagnostics

The dataset comprises daily closing (settlement) spot and futures prices of EUAs in the second phase of the EU ETS, i.e. from 3 March, 2008 to 30 November 2012. This chapter only considers the data from EU ETS Phase II for the following reasons. Firstly, the second phase of the EU ETS is the most recent commitment period, and has not been fully investigated. Secondly, the mechanisms of the EU ETS were significantly changed between Phases I and II; therefore, it is not reasonable to examine the Phase I and Phase II data together. Thirdly, due to inter-phase banking restrictions, the spot prices are close to zero at the end of Phase I, i.e. the second half of 2007 (Chevellier, 2011a). Therefore, it is not appropriate to use the spot prices at that stage for developing hedge models. In this chapter, the author uses the spot carbon allowances traded on the BlueNext Exchange and carbon futures contracts listed on the Intercontinental Exchange (ICE).[15] Data for the period from 3 March, 2008 to 31 May, 2012 are used for in-sample analysis (1,109 observations), while the out-of-sample period runs from 1 June, 2012 to 30 November, 2012 (six months, 131 observations). All the data are collected from DataStream. In order to construct a continuous series of futures prices, it is assumed that hedgers will switch over futures contracts from the nearest to maturity contract to the second nearest to maturity contract on the first business day after the expiry date of the nearest to maturity contract, for all available trading months.[16]

[Insert Table 3.1 here]

The spot prices and continuous futures prices are then converted into natural logarithms and daily spot and futures returns are calculated as the first differences of logarithmic spot and futures prices multiplied by 100. The summary statistics, unit root and cointegration tests of spot and futures price levels and returns series for both in-sample and out of-sample periods are shown in Table 3.1. It is found that the mean prices of spot and futures for the out-of-sample period are significantly lower than those for the in-sample period, while the mean returns of spot and futures for the out-of-sample period are higher and closer to zero than those for the in-sample period. The standard deviation, skewness and kurtosis for price levels and returns, and for spot and futures also show significant differences between the in-sample and out-of-sample periods. This indicates that the distributions of prices and returns are different in the two periods, which may mean that the effectiveness of the out-of-sample

[15] Carbon futures were initially listed on the European Climate Exchange (ECX) from 2005. In 2010, the ICE acquired ECX as its emission markets. Therefore, the carbon futures are currently traded on the ICE.

[16] The EUA futures contracts are listed in the ICE on a quarterly expiry cycle, i.e. contracts expire in March, June, September and December each year. The expiry day is the last Monday of the contact month. For instance, the June 2011 contract expires on 27 June, 2011, and then the contract is switched over to the September 2011 contract on 28 June, 2011.

hedging based forecasting is not as effective as the in-sample forecasting.[17] The Jarque and Bera (1980) statistics show that all the series considered significantly depart from a normal distribution. The results of Ljung and Box (LB)'s (1978) Q tests for the 12th lags of autocorrelation indicate that spot and futures prices are serially correlated, while there is no evidence of serial correlation in the spot and futures return series, for both in-sample and out-of-sample periods. Furthermore, the LB tests on the squared series for Engle's (1982) ARCH effect suggest the presence of volatility clustering in all series except for the out-of-sample spot returns. The results of Phillips and Perron's (1988) unit root tests indicate that all the price series are non-stationary while all the return series are stationary. Finally, Johansen's (1988) cointegration test shows that the spot and futures prices are cointegrated with one cointegration vector. The normalised cointegration vector is very close to (1 -1 0), indicating that the spot-futures basis can serve as the long run relationship.

[Insert Figure 3.1 here]

The time series of the spot-futures basis in percentage form is plotted in Figure 3.1. It is shown that the basis of carbon emission allowances is below zero in most of the cases, indicating that the carbon markets are normally in backwardation. Moreover, the basis generally lies in the range between -3% and 1%, which is less volatile than that for the WTI crude oil markets studied by Alizadeh et al. (2008).

3.4. Estimation Results

This section presents in-sample estimates of key hedging strategies, starting with the Markov regime switching models in the mean equation. All the Markov regime switching

[17] This may be because the out-of-sample period is approaching the end of the second phase of the EU ETS and some carbon emission allowances cannot be used in the next phase due to the interphase banking restrictions.

models in this chapter are assumed to have two regimes, i.e. the high variance state and the low variance state. Table 3.2 displays the estimation results of the MRS and MRS-LR models.

[Insert Table 3.2 here]

Several interesting points are revealed by Table 3.2. Firstly, it can be observed that the adjusted R^2 in the MRS-LR model is higher than the MRS model for more than 2%, indicating that the MRS-LR model explains the dynamics of the spot-futures relationship more effectively than the MRS model, after considering the number of parameters. This supports the view that using the lagged basis as the long run relationship can provide additional information for modelling the relationship between spot and futures returns. Secondly, the minimum variance hedge ratio ($\gamma_{1,st}$) of the MRS-LR model is higher than that of the MRS model in state 1, but lower in state 2. Alizadeh and Nomikos (2004) suggest that $\gamma_{1,1}$ and $\gamma_{1,2}$ can be considered as the upper and lower boundaries of the optimal hedge ratios. Therefore, the MRS-LR model provides a broader window of optimal hedge ratios than the MRS model, which has the potential to manage more sophisticated market conditions. Thirdly, the volatilities (σ_{st}) and inter-state transitional probabilities (P_{12} and P_{21}) are lower in the MRS-LR model than the MRS model, suggesting that the MRS-LR is more stable. For the above reasons, it is expected that the hedging performance of the MRS-LR model will be better than the MRS model.

[Insert Table Figure 3.2 and Figure 3.3 here]

From the volatilities in each state it can be observed that state 1 is the low variance state while state 2 is the high variance state. It can be observed from Table 3.2 that the minimum variance hedge ratio in the low variance state is higher and closer to the naïve hedge (γ=1) than in the high variance state. This may be because when variance is low, the spot-futures relationship is more stable and closer to the long-run equilibrium of (1 -1 0), and therefore the hedge ratio is close to 1. The high variance state captures the price jumps so that the optimal hedge ratio deviates from 1. In addition, the transitional probability from the low variance state to the high variance state (P_{12}) is lower than the probability in the opposite direction (P_{21}), indicating that the low variance state is more stable and has a longer duration. For instance, the inter-state transition probabilities of the MRS model are P_{12}=0.0517 and P_{21}=0.1377, suggesting that the average expected durations (AED) of being in state 1 and state 2 are approximately 19 (=1/0.0517) days and 7 (=1/0.1377) days, respectively.[18] These findings are in line with the study by Alizadeh and Nomikos (2004) of the oil markets. To observe the probabilities of being in each state intuitively, the smooth regime probabilities of the MRS and MRS-LR models are presented in Figure 3.2 and Figure 3.3, respectively.[19] Panel A and Panel B in Figure 3.2 and Figure 3.3 show the probabilities in the high variance state and low variance state, respectively. It can be observed that the high variance state is short-lived for both models, confirming the results of the average expected durations. For the residual diagnostics of the models, it is shown that the residuals are not normally distributed and have significant autocorrelation and heteroskedasticity problems. Therefore, it may be more promising to use the Markov regime switching models with GARCH errors for hedging as they can solve these residual problems.

[Insert Table 3.3 here]

---

[18] Hamilton (1989) shows that the average expected duration in the first state is calculated as:
$$AED_1 = \sum_{i=1}^{\infty} iP_{11}^{i-1}(1-P_{11}) = (1-P_{11})^{-1} = P_{12}^{-1} .$$

[19] After estimating the unknown parameter vector $\boldsymbol{\theta}$ from the data spanning the period from t to T, three regime probabilities: filtered probabilities; smooth probabilities; and predicted probabilities, can be obtained with respect to the unobservable state variable. The filtered regime probabilities for state i are the estimated probabilities for the unobservable state variable at time t=1 given the observations from 1 to $t<T$. The smooth regime probabilities for state i are the estimated probabilities for the unobservable state variable at time t=1 given the whole sample of observations from 1 to T. The predicted regime probabilities for state i are the estimated probabilities for the unobservable state variable at time T+1=1 given the observations from 1 to T. For details of estimated regime probabilities, please see Hamilton (1994)

The results of single state and Markov regime switching two state DCC-GARCH models are shown in Table 3.3.[20] For the conditional mean equation, the parameters of the lagged basis, $\mu_{s,st}$ and $\mu_{f,st}$, govern the adjustment speed of spot and futures prices to their long-run equilibrium. In the low variance state of the MRS-LR-DCC model, the speed of adjustment is negative and significant for the spot equation, while it is positive and insignificant for the futures equation. This implies that spot prices will converge towards a long-run equilibrium relationship. More specifically, if there is a positive deviation from the equilibrium at time t-1 (i.e. $S_{t-1} > F_{t-1}$), the spot price at time t will decrease as a response to the deviation while the response of the futures price at time t will be insignificant. As a consequence, the long-run relationship between spot and futures price is restored. In the high variance state, the speed of adjustment is still negative and significant for the spot equation, and insignificant for the futures equation. However, the magnitude of the adjustment speed increases dramatically compared to the low variance state. This suggests that when there is a large deviation from the equilibrium (i.e. in the high variance state), the response of the spot price in the next period would be more significant in order to re-establish the long-run relationship. Compared with the results of the single regime DCC-GARCH model, the coefficients of the lagged basis for both spot and futures equations are negative and significant, which are qualitatively different from both the low and high state results of the MRS-LR-DCC model. The results imply that the dynamics of the relationship between spot and futures prices are different across various market states. More specifically, there are regime shifts in the mean-reverting process, while the responses to shocks deviating from the long-run equilibrium depend on the volatility of the states.

The next focus of investigation is the conditional variance and conditional correlation equations. It can be observed from Table 3.3 that the variance constant, ARCH and GARCH

[20] The estimation results of the other models, such as constant OLS and VECM, are available upon request.

parameters in the low variance state are distinct from those in the high variance state. This suggests that the conditional variance process in the carbon emission markets is also state dependent, which has not been documented in the literature. Following Alizadeh et al. (2008), this chapter calculates the measure of the degree of volatility persistence, i.e. $\alpha^2_{ii,st}+\beta^2_{ii,st}$, for st= {1, 2}. A positive relationship has been found between the degree of volatility persistence and the high/low volatility status of the state. That is, the high variance state is associated with higher volatility persistence compared to the corresponding low variance state. These results are in line with the studies by Alizadeh et al. (2008) and Fong and See (2002) of oil markets. When compared with the single regime DCC-GARCH model, it is found that the degrees of volatility persistence of both high and low variance states are higher than the single regime volatility model. In addition, the dynamic conditional correlation coefficients are significant, supporting the use of DCC-GARCH for the second moment of spot and futures returns.

[Insert Figure 3.4 here]

For the regime transition probabilities of the MRS-LR-DCC model, it is shown that the transitional probability from the low variance state to the high variance state (P_{12}=0.0781) is significantly smaller than the probability in the opposite direction (P_{21}=0.3888), showing that the low variance state is steadier and has a longer average expected duration (AED=1/0.0781≈13 days) than the high variance state (AED=1/0.3888≈3 days). In order to collapse the conditional residuals, conditional variances and conditional correlations to make them state dependent, the probabilities of being each state should be estimated. Smooth regime probabilities are used to recombine the variables in Equation (3.10) into Equation (3.12). Figure 3.4, Panel A, presents the smooth regime probabilities of the MRS-LR-DCC model in the high variance state, which indicates the likelihood of being in that state. It can be observed from Figure 3.4 that the high variance state is generally short-lived while the low variance state prevails for longer. The high variance is mainly distributed in the first year of EU ETS Phase II, as a number of regulatory changes had been made from Phase I to Phase II. Finally, the residual diagnostic tests of the DCC and MRS-LR-DCC models are shown at the bottom of Table 3.3. The results of the LB (12) and LB^2 (12) tests indicate that the residuals from the two models do not have significant autocorrelation and heteroskedasticity problems, which represents a dramatic improvement on the MRS and MRS-LR models.

3.5. Optimal hedge ratios and hedging performance

Following the estimation of the MRS-LR-DCC model, time-varying conditional variances and conditional correlations are generated. The optimal hedge ratios of the MRS-LR-DCC model are then calculated by using Equation (3.15). For completeness and comparison, this chapter also considers the constant optimal hedge ratios obtained from the naïve hedge (i.e. hedge ratio is constantly equal to 1), the single regime OLS estimates of Equation (3.16), Engle and Granger's (1987) vector error correction model (VCEM), as well as time-varying hedge ratios generated from the DCC-GARCH, MRS and MRS-LR models. Figure 3.5 compares the constant OLS, DCC-GARCH and MRS-LR-DCC GARCH hedge ratios for the in-sample period while the comparison of in-sample hedge ratios within the class of Markov regime switching models (the MRS, MRS-LR, MRS-LR-DCC models) are displayed in Figure 3.6. It can be observed that the MRS-LR-DCC hedge ratios are the most volatile of all the competing hedging strategies, implying that a hedged portfolio consisting of spot and futures contracts would have to be rebalanced frequently.

[Insert Figure 3.5 and Figure 3.6 here]

The previous literature has shown a positive relationship between the magnitude of the basis and the volatility of the markets (e.g. Lee, 1994; Choudhry, 1997; Zhong, Darrat and Otero, 2004). That is, the market should be in the low variance state when the basis hovers around zero while the market is expected to be in the high variance state when the basis significantly deviates from zero. The relationship described above is confirmed in the case of carbon emission markets by regressing the smooth regime probability of being in the high variance state on the absolute value of the basis, where the slope coefficient is significantly positive. It can be observed from Equations (3.10) to (3.12) and Equation (3.15) that the optimal hedge ratio is also dependent on the probabilities of being in each state. This provides a motivation to investigate the relationship between the magnitude of the basis and the MRS-LR-DCC hedge ratios. Following Alizadeh et al. (2008), the MRS-LR-DCC hedge ratio is regressed on the absolute value of the basis. The coefficient of the slope is negative and significant, suggesting that the hedge ratios are high and less volatile when the basis is close to zero (in the low variance state). The results are consistent with the findings of Alizadeh et al. (2008).

[Insert Table 3.4 here]

To evaluate the hedging performance of the MRS-LR-DCC and the competing strategies, the hedged portfolios are constructed every trading day and the returns (x_{t+1}) are given by

$$x_{t+1} = \Delta S_{t+1} - \gamma^{*}_{t+1} \Delta F_{t+1} \tag{3.19}$$

where γ^{*}_{t} denotes the optimal hedge ratios from each model. A smaller variance for the hedged portfolio ($Var(x_{t+1})$) indicates a better hedging strategy. The in-sample hedging effectiveness of Markov regime switching approaches compared with alternative hedging strategies is displayed in Table 3.4, Panel A. It is shown that the hedged portfolio generated from the MRS-LR-DCC model has the lowest variance among all the hedging strategies, followed by the MRS-LR and MRS models. This indicates that the class of Markov regime switching models outperforms the other constant and time-varying hedging models in terms of in-sample variance reduction. In particular, the MRS-LR-DCC provides an impressive level of improvement in terms of in-sample variance over other models, rising from approximately 14.7% to 22.9%. The results are significantly greater than the improvements for Markov regime switching hedging models in other markets; for example, the studies by Lee and Yoder (2007a) for the Corn and Nickel markets, Lee and Yoder (2007b) for Japanese and Hong Kong stock index markets, Alizadeh et al. (2008) for the Oil markets, as well as Salvador and Arago (2013) for the UK, European and German stock index markets. The above results strongly support the view expressed in this thesis that regime switching is important in carbon emission markets, particularly for the purpose of hedging.

Hedgers are required to frequently rebalance their hedged portfolios when implementing dynamic hedging strategies. Therefore, transaction costs are not negligible in the hedging performance of different strategies. A study by Kroner and Sultan (1993), among others, employs the hedger's utility as a measure of hedging performance, which takes into account the economic benefits of hedging. The utility function of a hedger is given by:

$$E_t U(x_{t+1}) = E_t(x_{t+1}) - kVar_t(x_{x+1}) \tag{3.20}$$

where x_t is the hedged portfolio return at time t and k is the degree of risk aversion. Following Lee (2010), it is assumed that the expected hedged portfolio return is zero and the degree of risk aversion is 4.[21] Take the MRS-LR-DCC model and the constant OLS as an example. It can be observed from Table 3.4, Panel A, that the average daily variance of a hedged portfolio is 0.5161 when the MRS-LR-DCC model is used and 0.6358 when the constant OLS model is adopted. A hedger using the MRS-LR-DCC approach can gain an average

[21] All the mean returns of the hedged portfolios using different hedging strategies in this study are less than 0.00%; thus it is reasonable to assume the expected return is zero.

daily utility of U=-4*0.5161=-2.0644, while a hedger using the constant OLS approach gains only U=-4*0.6358=-2.5432 units of utility. Therefore, by using the MRS-LR-DCC model, hedgers in the carbon emission markets can benefit from an improvement in the daily average utility of about 0.4788-y units, over the constant OLS hedging strategy, where y stands for the reduced return incurred by the transaction costs of portfolio rebalancing. Mizrach and Otsubo (2013) estimated that the average transaction cost was 0.14% for the EUA contracts in 2009. The costs of rebalancing are even lower as only a fraction of the portfolio is rebalanced. Therefore, using the MRS-LR-DCC model to hedge can provide an increase in utility for hedgers after taking the relevant transaction costs into consideration.

Another measure with which to assess hedging effectiveness is the value at risk (VaR) method used by Cotter and Hanley (2006). A better hedging strategy can provide a reduction in the VaR exposure. Assuming the hedged portfolio return follows a normal distribution, the VaR of the hedged portfolio at confidence level α is shown as:

$$VaR = W_0[E(x_{t+1}) + Z_\alpha \sqrt{Var(x_{t+1})}] \tag{3.21}$$

where W_0 denotes the initial wealth of the portfolio and Z_α represents the quantile of the normal distribution. Assuming initial wealth of €1 million and a 95% confidence level, the daily average VaR for the MRS-LR-DCC model is VaR=€1m[-1.645*(0.5161)1/2]=-€11,817.5, which represents a decrease of €1,299.5, compared to the VaR for the constant OLS model (VaR=€1m[-1.645*(0.6358)1/2]=-€13,117.0). The above results strongly support the use of the Markov regime switching models to hedge carbon emission allowances as they can provide economic benefits such as an increase in utility and a decrease in the amount of VaR exposure, after accounting for the costs of portfolio rebalancing.

Nevertheless, the superior performance of the MRS-LR-DCC model may be because of the data snooping bias. Sullivan, Timmermann and White (1999) and White (2000) suggest that the data snooping bias occurs when a specific dataset is used more than once for the purpose of inference and model selection, which is inevitable if only a single history of the dataset is available for time-series analysis. In other words, the probability of achieving satisfactory results may increase if the same dataset is used repeatedly for testing different models. The satisfactory results may only occur by chance or by using posterior information. White (2000) introduces a reality check (RC) for data snooping and the RC test can also be used to examine the statistical significance of relative hedging performance for different hedging strategies.[22] The statistics of RC tests for hedging performance are defined as:

$$f_{k,t+1} = -(\Delta S_{t+1} - \hat{\gamma}_{MRS-DCC,t+1}\,\Delta F_{t+1})^2 + (\Delta S_{t+1} - \hat{\gamma}_{k,t+1}\,\Delta F_{t+1})^2 \tag{3.22}$$

where k is the kth model which is used as a benchmark; $\hat{\gamma}_{k,t}$ represents the optimal hedge ratio at time t generated from the kth benchmark model; and $\hat{\gamma}_{MRS-DCC,t}$ is the dynamic optimal hedge ratios from the MRS-LR-DCC model. The expression in parentheses is the loss function, which is the squared hedged portfolio returns and can be used as an unbiased estimator of the real conditional variance (e.g. Andersen and Bollerslev, 1998). The statistics should be positive if the MRS-LR-DCC model achieves greater variance reduction than the kth model. In order to test the statistical significance of the variance reduction, the null hypothesis is set, as the MRS-LR-DCC model is not superior to the kth model in terms of variance reduction, which can be expressed as:

[22] Thanks to Mr Arnout Tilgenkamp from Erasmus University in Rotterdam for sharing the MATLAB code for White's (2000) reality check on the MATLAB Central website.

$$H_0 : \max_k \left\{ E(f_k) \le 0 \right\} \tag{3.23}$$

Next, following White (2000), the null hypothesis is tested by computing the observed test statistics for the RC, which is shown as $T_n^{RC} = \max_k (n^{1/2} \bar{f_k})$, where $\bar{f_k} = \frac{1}{n} \sum_{t=1}^{n} f_{k,t}$ and n is the number of one step ahead forecasting periods. In order to construct the distribution of the test statistics, Politis and Romano's (1994) stationary bootstrap method is adopted to reproduce the random paths of portfolio returns, while retaining the original series' distributional characteristics. This method is used in order to resample the original data with different block lengths, assuming the block length follows a geometric distribution with a given mean (see Politis and Romano (1994) for details of the stationary bootstrap method). After obtaining the simulated portfolio returns, the loss function of Equation (3.22) is used to generate a distribution of test statistics for each hedging strategy. The p value of the RC test is computed by comparing the observed test statistics $T^{RC}{}_n$ with the quantiles of the simulated distribution of test statistics $T^{RC*}{}_n$, which is given by:

$$T_n^{RC*} = \max_k \left\{ n^{1/2} [\bar{f}_k^*(b) - \bar{f_k})] \right\} \tag{3.24}$$

where $\bar{f}_k^*(b)$ denotes the sample mean of relative hedging performance measures shown in Equation (22) computed from the bth simulated sample, for b=1, 2, …, L. This chapter employs White's (2000) RC test with bootstrapping 1,000 times (i.e. L=1,000) to examine the null hypothesis that the variance improvement of the MRS-LR-DCC model is not significantly better than alternative models. The results of the RC tests in Table 4, Panel A, show that the MRS-LR-DCC model significantly outperforms other hedging strategies in the in-sample analysis, at conventional levels.

The in-sample results have already shown the advantages of using Markov regime switching models to hedge carbon emission allowances. However, risk managers are more concerned about how the models will perform in the future, i.e. the out-of-sample performance. In the out-of-sample analysis, all the models are estimated recursively with the data only up to a particular date. Specifically, the estimates of the MRS-LR-DCC model at time t are employed to perform the one step ahead forecast for the conditional variances and conditional correlation at time $t+1$.[23] The optimal hedge ratio at time $t+1$ can then be calculated by Equation (3.15). On the next day ($t+1$) the MRS-LR-DCC model is re-estimated with the new observation at $t+1$ included in the estimation dataset, to compute the optimal hedge ratio at time $t+2$. The exercise is repeated for every observation in the out-of-sample period. For the VECM hedging strategy, the out-of-sample hedge ratios are generated by re-estimating the model every day. In the case of the DCC-GARCH model, the model is re-estimated for every new observation and the out-of-sample hedge ratios are obtained through the one step ahead forecast of the conditional variances and conditional correlation. With respect to the univariate Markov regime switching MRS and MRS-LR models, the chapter first forecasts the regime probability at time $t+1$ using the regime transition probability and smooth regime probabilities at time t. Subsequently, the optimal hedge ratio at time $t+1$ is computed as the average of optimal hedge ratios in each state at time t weighted by the forecasted regime probabilities.[24]

The hedging performance of the Markov regime switching approaches compared to alternative hedging strategies in the out-of-sample period is presented in Table 3.4, Panel B. The results demonstrate a consistent picture, as for the in-sample analysis. That is, the MRS-LR-DCC model provides the greatest variance reduction, followed by the MRS-LR and MRS

[23] See Alizadeh et al. (2008) for details of the forecasting procedure.

[24] See Alizadeh and Nomikos (2004) for details of how to generate out-of-sample hedge ratios for the univariate Markov regime switching models.

models which rank second and third in terms of variance reduction, respectively, and lastly the non-Markov regime switching hedging strategies. The improvement in the MRS-LR-DCC model for the out-of-sample period is not as great as that for the in-sample period, but is still encouraging. In addition, hedgers can gain an incremental average daily utility of 0.958 if they use the MRS-LR-DCC hedge ratios compared to the constant OLS hedge ratios. They can also reduce the average daily VaR exposure by €1,193.3 by implementing the MRS-LR-DCC hedging approach. Finally, the results of the RC tests indicate that the MRS-LR-DCC model can provide significant out-of-sample variance reduction compared to alternative models at the 5% level.

To summarise, the above results show that the class of Markov regime switching models considerably outperform competing models in terms of portfolio variance reduction, utility maximization and reduction in VaR exposure, both for in-sample and out-of-sample periods. In particular, the MRS-LR-DCC model achieves the greatest variance reduction, and the RC test results demonstrate that the improvements in variance gained by using the MRS-LR-DCC model over competing models are significant. The above findings illustrate the importance of using Markov regime switching models in hedging carbon emission allowances.

3.6. Additional analysis

The findings above suggest that Markov regime switching can reduce the overall risk in carbon emission markets; however, it has been shown that risk managers are generally more concerned about the downside risk (e.g. Adams and Montesi, 1995). Traditional measures of risk, such as variance, allocate equal weight to positive profits and negative losses, which is a double-sided measure. Demirer and Lien (2003) suggest that it is more appropriate to use downside risk measures, such as lower partial moments (LPM), in the hedging effectiveness analysis. In addition, different hedging positions, i.e. short hedge or long hedge, should be considered separately. If spot and futures returns are both systemically distributed, the hedging effectiveness of short hedge and long hedge in terms of LPM are the same. Otherwise, using the same hedge ratios for short/long hedging positions should result in dissimilar performances (Demirer and Lien, 2003). Cotter and Hanley (2006) adopt the LPM measure to evaluate the effectiveness of various hedging strategies in short/long hedging positions, and find that the best strategies based on LPM are different from the traditional measure of variance.

The nature and statistical properties of Markov regime switching models also provide a motivation for examining the difference in hedging performance between short and long hedging positions. The asymmetries of typical financial data, i.e. non-zero skewness and excess kurtosis, may affect short hedge and long hedge positions differently. Alizadeh et al. (2008) suggest that time-varying skewness and excess kurtosis are inherent in the Markov regime switching models, indicated by the dynamics of conditional means and conditional variances.[25] Therefore, it is interesting to examine whether the Markov regime switching models can capture the possible asymmetries and then provide superior hedging performance.

In this chapter, the author adopts the semi-variance metric used by Cotter and Hanley (2006) and Alizadeh et al. (2008) to assess the hedging performance of competing hedge models in long and short hedging positions. The (negative) semi-variance metric is a special case of the LPM, which can be shown as:

[25] Haas, Mittnik and Paolella (2004) show details of the higher moments (skewness and kurtosis) of a mixed normal distribution GARCH model and the related Markov regime switching GARCH model.

$$SVar_{(-)} = \frac{1}{T}\sum_{i=1}^{T}[\min(0, x_{t-1} - \tau)]^2 \tag{3.25}$$

where τ is the target return which is normally set to be zero, enabling positive and negative hedged portfolio returns x_{t+1} to be distinguished. The hedged portfolio return is different for long and short hedge positions. A short hedging strategy involves selling a number of futures contracts to hedge the purchase of the underlying spot assets; therefore the hedged portfolio return is calculated as $\Delta S_{t+1} - \gamma^*_{t+1}\Delta F_{t+1}$. Similarly, a long hedge is equivalent to buying futures contracts against the sale of the spot assets, and the hedged portfolio return is given by $-\Delta S_{t+1} + \gamma^*_{t+1}\Delta F_{t+1}$, which is the opposite of short hedged portfolio returns. If a unified definition of a portfolio return, shown in Equation (19), is employed, a short hedger is mainly concerned with the negative returns of the portfolio while long hedgers focus on the positive returns.

[Insert Table 3.5 here]

Table 3.5 presents the in-sample and out-of-sample hedging effectiveness of Markov regime switching models compared with alternative hedging models in carbon emission markets, for long and short hedging positions. The short hedge results are shown in Panel A while the results of long hedge positions are displayed in Panel B. In addition to the semi-variance metric, this study also considers other asymmetric measures of hedging performance, i.e. the semi-utility and the asymmetric VaR exposure. The semi-utility and asymmetric VaR are calculated from Equations (3.20) and (3.21), respectively, by substituting variance with semi-variance. The same quantiles of normal distribution are used to estimate the asymmetric VaR exposure, assuming positive and negative returns of the hedged portfolio follow half normal distribution. In the in-sample analysis, the hedging performance of short hedgers and long hedgers' positions produces a consistent picture. The results show that the MRS-LR-

DCC model provides the greatest semi-variance reduction, followed by the MRS-LR and MRS models, and then the non-Markov regime switching hedging strategies. In addition, according to White's (2000) RC tests, the semi-variance improvements in the MRS-LR-DCC model are statistically significant compared to competing models for both short and long hedging positions. The MRS-LR-DCC model performs considerably better for a short hedge (with a semi-variance improvement of 23.7%-29.5%) than a long hedge (6.0%-14.5% improvement), implying that the MRS-LR-DCC model captures the asymmetries of negative returns better than positive returns. Furthermore, the MRS-LR-DCC model outperforms alternative models in terms of maximising semi-utility and minimising asymmetric VaR exposure.

For the out-of-sample analysis, it is shown that the MRS-LR-DCC model still performs best for the short hedgers' position in terms of semi-variance reduction, semi-utility maximization and asymmetric VaR minimization. The MRS-LR and MRS models are the second and third best. The semi-variance improvements offered by the MRS-LR-DCC model compared to other models are quite remarkable (64.1%-72.0% improvement) and strongly significant (all the *p*-values of RC=0.00). However, for the long hedgers' position, the MRS-LR-DCC model is the sixth best model, only outperforming the unhedged strategy and the DCC-GARCH model, in all asymmetric hedging performance measures. The MRS-LR and MRS model rank fourth and fifth best, respectively, also performing poorly. It is notable that the MRS-LR model outstrips the MRS model for both in-sample and out-of-sample analysis, and for both short and long hedging positions. This indicates that the basis serving as the long run relationship can provide additional information for hedging. The best hedging strategy is provided by the VECM model, which offers an improvement of more than 6% in semi-variance compared to the MRS-LR-DCC model. The significant difference in hedging performance using the MRS-LR-DCC model and other Markov regime switching models show that the Markov regime switching models can capture the asymmetries of negative returns well, but not of positive returns. The findings are in line with the in-sample analysis and imply that it is more appropriate to use Markov regime switching approaches for short hedging positions in carbon emission markets, i.e. when investors have some spot carbon emission allowances in-hand, and want to sell a number of carbon futures contracts to offset the potential losses incurred by the drop in spot carbon prices.

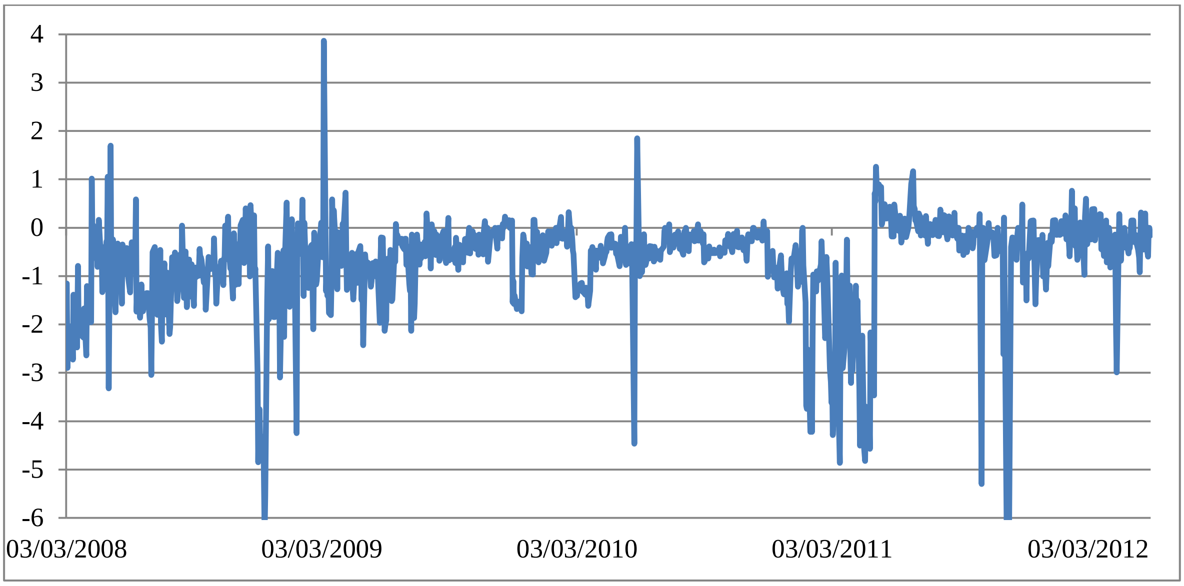
3.7. Conclusion

This chapter estimates the relationship between carbon spot and futures markets using Markov regime switching models and investigates the hedging effectiveness of state dependent hedge ratios in the European carbon emission markets. This is motivated by Benz and Trück (2009) who find that the carbon asset prices can be better characterised by regime switching models. Therefore, the relationship between carbon spot and futures prices may also be state dependent. This implies that the hedge ratios generated from regime switching models could provide a superior hedging performance to single regime hedging models. For this reason, this chapter proposes a new framework, i.e. Markov regime switching approaches, to hedge the financial risk in carbon emission markets. In particular, this chapter proposes a Markov regime switching model with a long run relationship and DCC-GARCH errors, to connect the idea of disequilibrium measured by a lagged basis with that of uncertainty modelled by DCC-GARCH, across different market regimes. This model differs from the MRS-BEKK model used by Alizadeh et al. (2008) in allowing the conditional correlation to be time-varying, and is distinct from Lee and Yoder’s (2007b) MRS-TVC-GARCH model because it incorporates the long run relationship into the return process.

Using daily spot and futures price data for EU ETS Phase II, the chapter finds that the class of Markov regime switching approaches considerably outperform competing hedging strategies for all the hedging performance measures considered, i.e. portfolio variance reduction, utility maximisation and VaR exposure minimisation, for both in-sample and out-of-sample analysis. In particular, the MRS-LR-DCC strategy achieves the greatest variance reduction, and the results of White's (2000) RC test demonstrate that the variance improvements offered by the MRS-LR-DCC model over competing approaches are statistically significant. Furthermore, it is found that the MRS-LR model consistently outperforms the MRS model in both in-sample and out-of-sample analysis, which supports the view that the lagged basis serving as the long run relationship can provide additional information for hedging. In addition to these symmetric hedging performance measures, this chapter further analyses the hedging effectiveness of the Markov regime switching approaches by considering downside risk and distinguishing the difference between short and long hedging positions. The in-sample results of downside risk metrics are consistent with those results produced using symmetric measures, for both short hedge and long hedge, where the MRS-LR-DCC, MRS-LR and MRS models are the top three hedging strategies. The only difference between short and long hedgers' positions is that the semi-variance reduction of the MRS-LR-DCC model for a short hedge is considerably greater than for a long hedge. The difference becomes more significant in the out-of-sample analysis. The MRS-LR-DCC model is still the best and achieves a very impressive improvement in semi-variance for short hedge positions; however, the class of Markov regime switching models underperforms some competing strategies for long hedge positions. These results suggest that the Markov regime switching models capture the asymmetries of negative returns better than they capture positive returns. Overall, market participants can benefit from using regime switching hedging strategies, no matter what position they hold.

To summarise, the above findings demonstrate the importance of using Markov regime switching approaches in hedging carbon emission allowances. Financial risk managers who adopt state dependent hedge ratios can achieve greater variance reduction and better hedging performance.

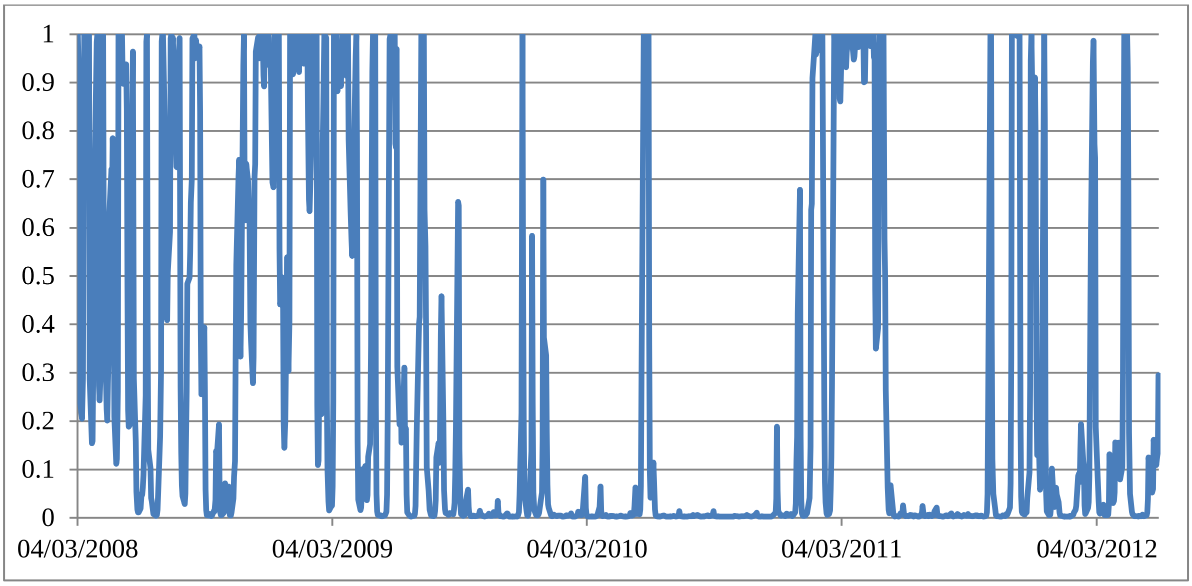
Figure 3.1: Spot-futures basis for carbon emission allowances



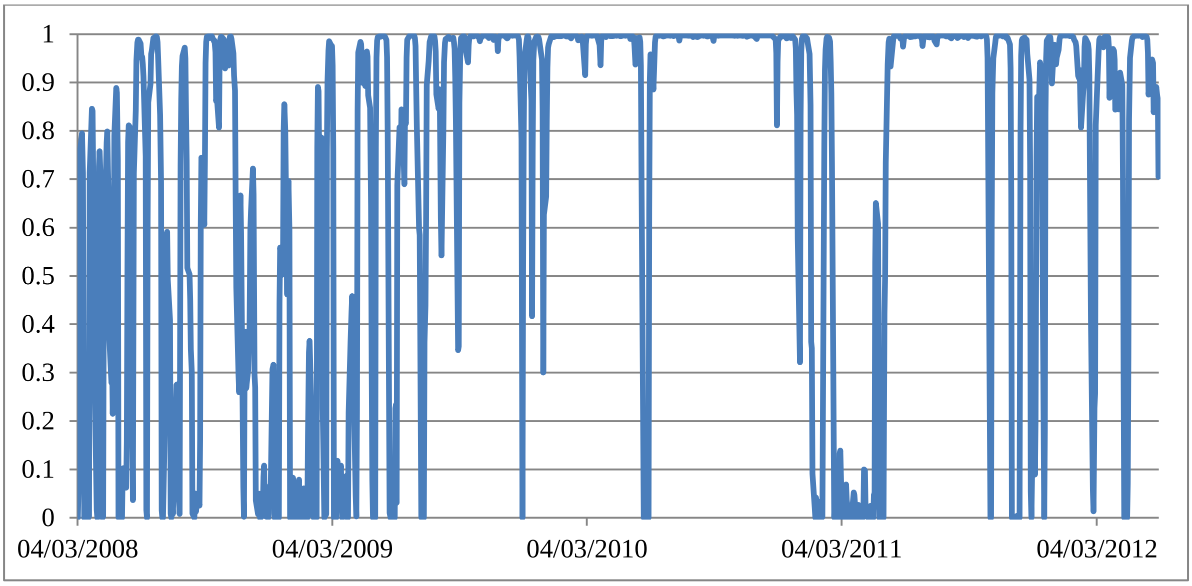
Note: This figure displays the time series of spot-futures basis for carbon emissions from 3 March, 2008 to 31 May, 2012 (in-sample period, 1,109 observations). Basis is defined as the logarithmic difference between spot and futures prices in percentage form.

Figure 3.2: Smooth regime probabilities of MRS model for carbon emissions

Panel A: The high variance state



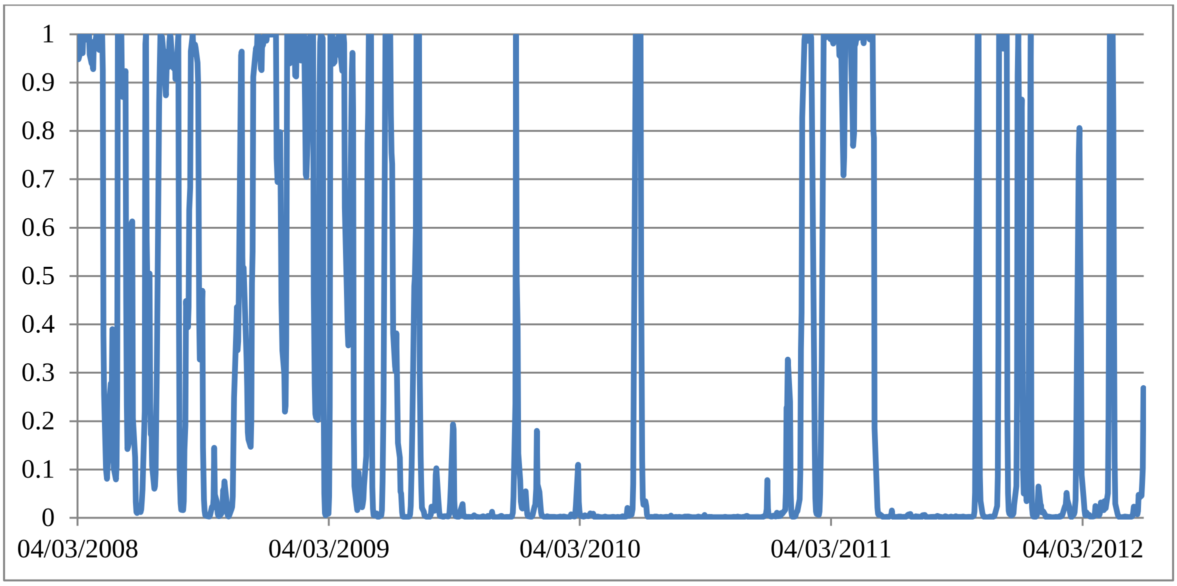
Panel B: The low variance state



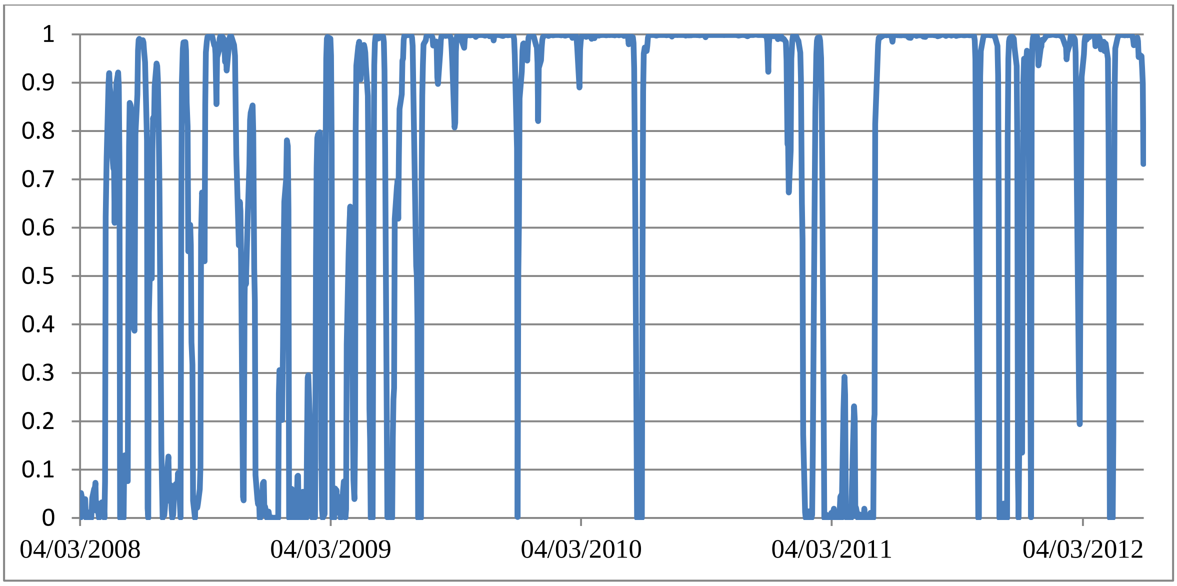
Note: This graph shows the smooth regime probabilities of the MRS model for carbon emissions from 3 March, 2008 to 31 May, 2012 (in-sample period, 1,109 observations). The probabilities in the high variance state are presented in Panel A while those in the low variance state are shown in Panel B.

Figure 3.3: Smooth regime probabilities of MRS-LR model for carbon emissions

Panel A: The high variance state



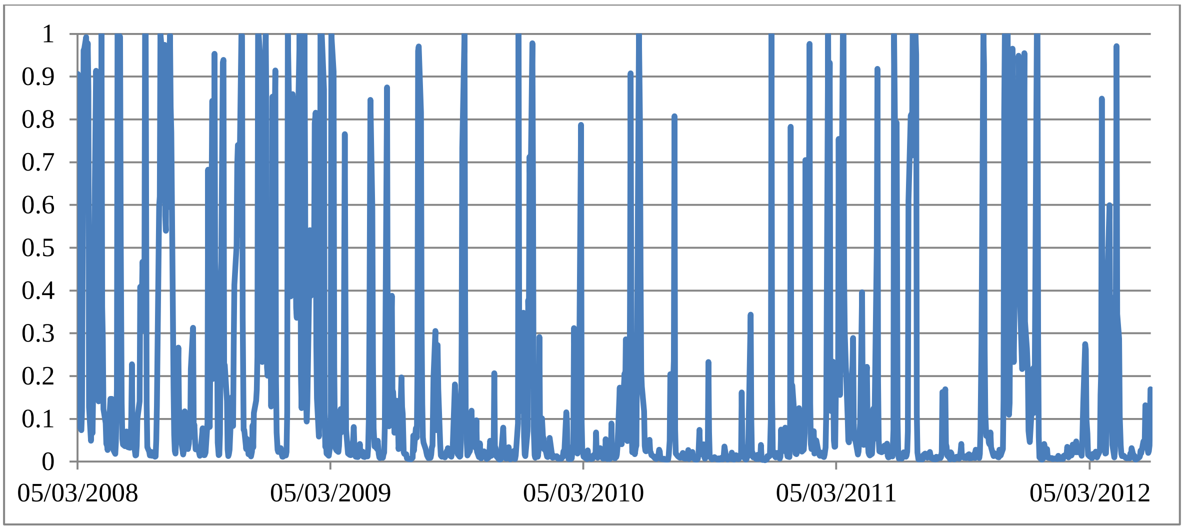
Panel B: The low variance state



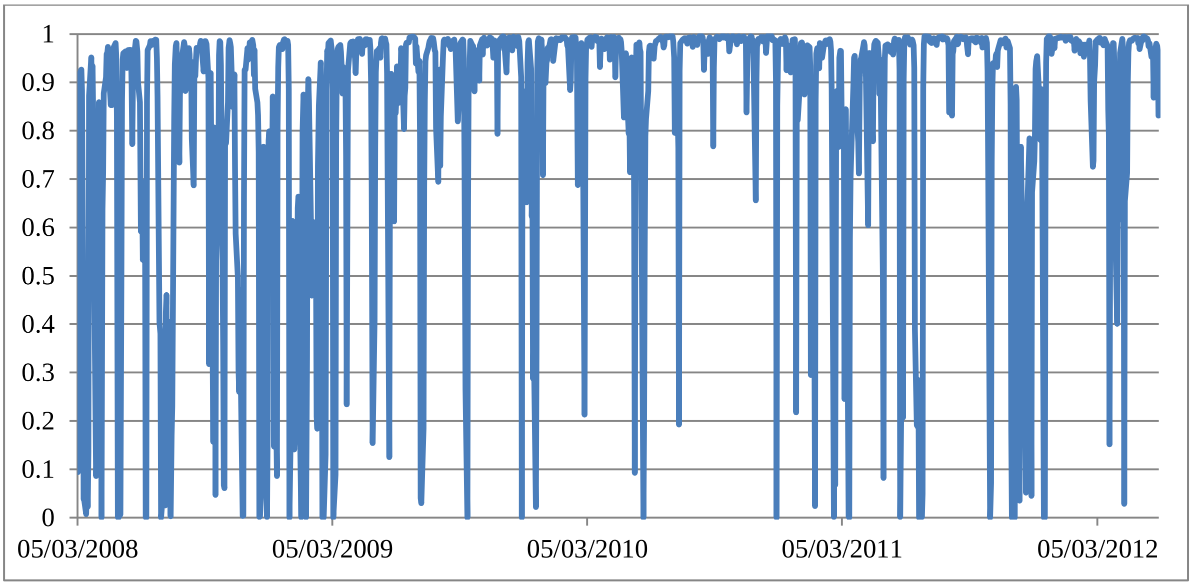
Note: This graph shows the smooth regime probabilities of the MRS model for carbon emissions from 3 March, 2008 to 31 May, 2012 (in-sample period, 1,109 observations). The probabilities in the high variance state are presented in Panel A while those in the low variance state are shown in Panel B.

Figure 3.4: Smooth regime probabilities of MRS-LR-DCC models for carbon emissions

Panel A: The high variance state

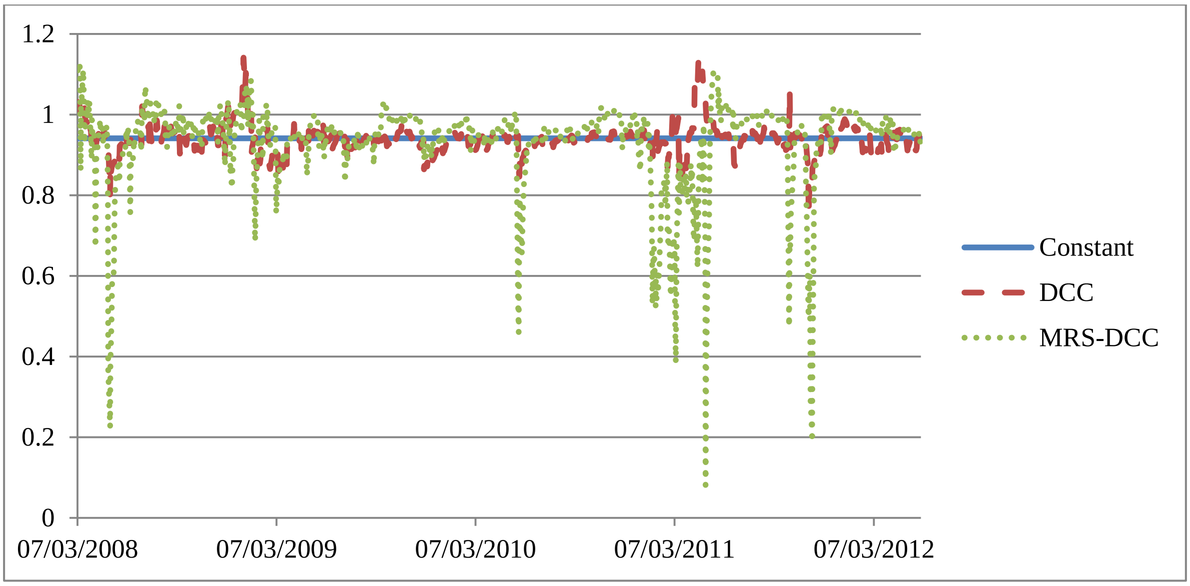


Panel B: The low variance state



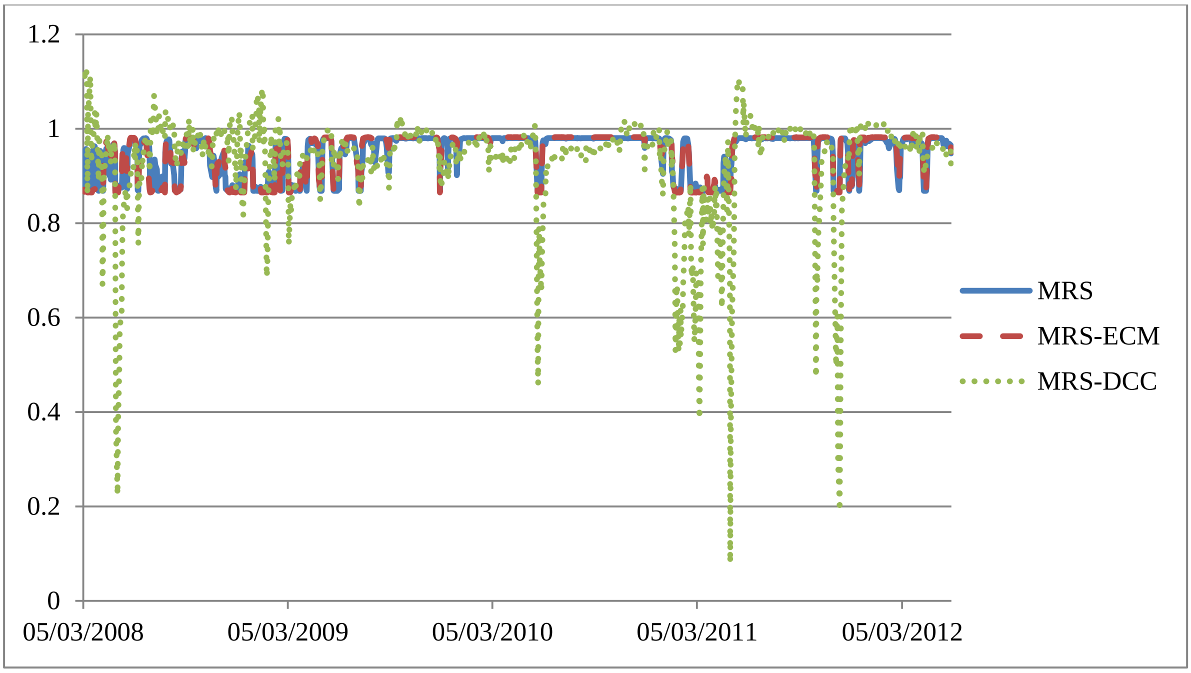
Note: This graph shows the smooth regime probabilities of the MRS-LR-DCC model for carbon emissions from 3 March, 2008 to 31 May, 2012 (in-sample period, 1,109 observations). The probabilities in the high variance state are presented in Panel A while those in the low variance state are shown in Panel B.

Figure 3.5: Constant OLS, DCC-GARCH and MRS-LR-DCC hedge ratios for carbon emissions.



Note: This figure shows the constant and dynamic hedge ratios of the constant OLS, DCC-GARCH model and MRS-LR-DCC models from 3 March, 2008 to 31 May, 2012 (in-sample period, 1,109 observations).

Figure 3.6: MRS, MRS-LR and MRS-LR-DCC hedge ratios for carbon emissions.



Note: This figure shows the dynamic hedge ratios of the MRS, MRS-LR and MRS-LR-DCC models from 3 March, 2008 to 31 May, 2012 (in-sample period, 1,109 observations).

Table 3.1: Summary statistics, unit root and cointegration tests for spot and futures prices of carbon emissions

Panel A: Descriptive statistics

	In-sample				Out-of-sample			
	Log levels		% Returns		Log levels		% Returns	
	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures
Mean	2.6261	2.6333	-0.1077	-0.1086	2.0068	2.0195	-0.0012	-0.0086
S.D.	0.3364	0.3386	2.6375	2.6707	0.0874	0.0766	3.0608	2.7929
Skewness	-0.241	-0.238	0.103	0.104	-0.637	-0.521	1.053	-0.498
Kurtosis	3.163	3.154	7.858	7.306	2.496	2.488	11.230	4.905
J-B	11.960	11.589	1091.3	858.10	10.244	7.359	393.91	25.218
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.03)	(0.00)	(0.00)
LB(12)	12388	12383	13.211	13.401	421.3	383.4	10.542	9.975
	(0.00)	(0.00)	(0.35)	(0.34)	(0.00)	(0.00)	(0.57)	(0.62)
$LB^2(12)$	12488	12484	221.75	290.90	417.10	381.50	8.327	21.388
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.76)	(0.05)
PP test	-0.525	-0.515	-32.308	-32.330	-2.217	-2.243	-8.967	-9.654
	(0.88)	(0.89)	(0.00)	(0.00)	(0.20)	(0.19)	(0.00)	(0.00)

Panel B: Cointegration tests (in-sample only)

Lag	H_0	λ_{max} test	λ_{trace} test	Normalised CV (1 β_2 β_0)
2	k=0	75.595***	75.344***	(1 -0.9941 -0.0082)
	k≤1	0.251	0.251	

Note: The table provides summary statistics, unit root and cointegration tests for spot and futures prices of carbon emission allowances, for both in-sample and out-of-sample periods. The in-sample period runs from 3 March, 2008 to 31 May, 2012 (1,109 observations) whereas the out-of-sample period runs from 1 June, 2012 to 30 November, 2012 (six months, 131 observations). J-B stands for the Jarque and Bera (1980) test for Normality. LB(12) and $LB^2(12)$ are Ljung and Box's (1978) Q tests for 12th order autocorrelation in the level and squared series, respectively. The PP test is Phillips and Perron's (1988) unit root test. Lag is the optimal lag length of the unrestricted VAR model in levels. Optimal lag length is selected based on Schwartz (1978) Information Criterion (SIC). The null hypochapter of λ_{max} tests and λ_{trace} tests is that the number of cointegration vectors is less than or equal to k, where k is 0 or 1. Normalised CV is the normalised cointegration vector of spot and futures prices. Figures in parentheses are P-values. ***, **, * indicate statistically significant at 1%, 5% and 10%, respectively.

Table 3.2: Estimation results of Markov regime switching model and Markov regime switching model with long run relationship for carbon emissions

	MRS		MRS-LR	
$\gamma_{0,st=1}$	0.0014	(0.012)	-0.1057	(0.018)***
$\gamma_{1,st=1}$	0.9803	(0.009)***	0.9820	(0.006)***
$\gamma_{2,st=1}$			-0.2731	(0.037)***
$\sigma_{st=1}$	0.3080	(0.028)***	0.2986	(0.017)***
$\gamma_{0,st=2}$	-0.0149	(0.082)	-0.7478	(0.136)***
$\gamma_{1,st=2}$	0.8680	(0.055)***	0.8646	(0.041)***
$\gamma_{2,st=2}$			-0.4649	(0.071)***
$\sigma_{st=2}$	1.4188	(0.167)***	1.2218	(0.100)***
ϕ_1	2.9097	(0.262)***	3.2463	(0.350)***
ϕ_2	-1.8350	(0.329)***	-2.1818	(0.613)***
P_{12}	0.0517		0.0375	
P_{21}	0.1377		0.1014	
Log-L	-877.762		-779.28	
SIC	-905.803		-814.331	
Adj. R^2	0.912		0.936	
S.D.	0.783		0.667	
Skewness	0.007		0.054	
Kurtosis	3.600		3.327	
J-B	16.644***		5.461*	
LB(12)	157.727***		69.779***	
$LB^2(12)$	57.313***		46.836***	

Note: The table provides the estimation results of the Markov regime switching model (MRS) and Markov regime switching model with long run relationship (MRS-LR) for carbon emissions. The sample period runs from 3 March, 2008 to 31 May, 2012 (in-sample period, 1,109 observations). Figures in parentheses are standard errors. ***, **, * indicate statistically significant at 1%, 5% and 10%, respectively. P_{12} gives the probability that state 1 will be followed by state 2 and P_{21} is the probability that state 2 will be followed by state 1. Log-L stands for log likelihood. SIC is the Schwartz (1978) Information Criterion. The standard deviation, skewness and kurtosis are for the residuals. J-B stands for the Jarque and Bera (1980) test for Normality of residuals. LB(12) and $LB^2(12)$ are Ljung and Box's (1978) Q tests for 12th order autocorrelation in the level and squared residuals, respectively. The models are specified as:

MRS: $\Delta S_t = \gamma_{0,st} + \gamma_{1,st}\Delta F_t + \varepsilon_{st,t}$; $\varepsilon_{st,t} \sim iid(0, \sigma^2_{st,t})$

MRS-LR: $\Delta S_t = \gamma_{0,st} + \gamma_{1,st}\Delta F_t + \gamma_{2,st} z_{t-1} + \varepsilon_{st,t}$; $\varepsilon_{st,t} \sim iid(0, \sigma^2_{st,t})$

Logistic function for transition probabilities: $P_{12,t} = \dfrac{1}{1+\exp(\phi_1)}; P_{21,t} = \dfrac{1}{1+\exp(\phi_2)}$

Table 3.3: Estimation results of DCC-GARCH and Markov regime switching DCC model with long run relationship for carbon emissions

	DCC-GARCH		MRS-LR-DCC	
Conditional mean equation				
$\mu_{s,st=1}$	-0.1355	(0.041)***	-0.0935	(0.042)**
$\mu_{f,st=1}$	-0.0696	(0.034)**	0.0317	(0.035)
$\mu_{s,st=2}$			-0.2861	(0.113)**
$\mu_{f,st=2}$			-0.0472	(0.121)
Conditional variance equation				
$\gamma_{s,st=1}$	1.1234	(0.146)***	0.7054	(0.129)***
$\gamma_{f,st=1}$	1.1171	(0.137)***	0.7066	(0.129)***
$\alpha_{s,st=1}$	0.1885	(0.046)***	0.0390	(0.017)**
$\alpha_{f,st=1}$	0.1828	(0.042)***	0.0379	(0.017)**
$\beta_{s,st=1}$	0.7911	(0.046)***	0.9412	(0.023)***
$\beta_{f,st=1}$	0.7967	(0.042)***	0.9426	(0.024)***
$\theta_{1,st=1}$	0.3304	(0.080)***	0.0000	(0.000)
$\theta_{2,st=1}$	0.4679	(0.152)***	0.0379	(0.017)**
$\rho_{,st=1}$	0.9651	-	0.9080	-
$\gamma_{s,st=2}$			1.9076	(0.734)***
$\gamma_{f,st=2}$			1.8927	(0.633)***
$\alpha_{s,st=2}$			0.1076	(0.076)
$\alpha_{f,st=2}$			0.1126	(0.073)
$\beta_{s,st=2}$			0.9373	(0.036)***
$\beta_{f,st=2}$			0.9351	(0.036)***
$\theta_{1,st=2}$			0.0000	(0.000)
$\theta_{2,st=2}$			0.0379	(0.017)**
$\rho_{,st=2}$			0.9080	-
Transition parameters				
ϕ_1			-2.4680	(0.277)***
ϕ_2			0.4525	(0.475)
P_{12}			0.0781	-
P_{21}			0.3888	-
Residual diagnostics				
Log-L	-2431.66		-2255.51	
SIC	-2498.24		-2335.62	
	Spot	Futures	Spot	Futures
S.D.	2.627	2.676	2.634	2.684
Skewness	-0.542	-0.392	-0.317	-0.216
Kurtosis	4.638	4.349	3.074	2.932
J-B	177.493***	112.007***	18.843***	8.850**
LB(12)	9.440	10.041	5.499	4.338
$LB^2(12)$	9.475	5.423	16.663	19.499*

Note: The table provides the maximum likelihood estimates of the DCC-GARCH model and Markov regime switching DCC model with long run relationship (MRS-LR-DCC) for carbon emission allowances. The sample period runs from 3 March, 2008 to 31 May, 2012 (in-sample period, 1,109 observations). Figures in parentheses are standard errors. ***, **, * indicate statistically significant at 1%, 5% and 10%, respectively. P_{12} gives the probability that state 1 will be followed by state 2 and P_{21} provides the probability that state 2 will be followed by state 1. Log-L stands for log likelihood. SIC is the Schwartz (1978) Information Criterion. J-B stands for the Jarque and Bera (1980) test for Normality. LB (12) and LB^2 (12) are Ljung and Box's (1978) Q tests for 12th order autocorrelation in the level and squared residuals, respectively. The models are specified as:

$$\Delta S_t = \mu_{s,st} z_{t-1} + \varepsilon_{s,st,t}\,;\ \ \Delta F_t = \mu_{f,st} z_{t-1} + \varepsilon_{f,st,t}\,;\ \ \boldsymbol{\varepsilon}_{st,t} = \begin{pmatrix} \varepsilon_{s,st,t} \\ \varepsilon_{f,st,t} \end{pmatrix} \Big| \Omega_{t-1} \sim IN(0, \mathbf{H}_{st,t})$$

$$\mathbf{H}_{st,t} = \begin{pmatrix} h^2_{s,st,t} & h_{sf,st,t} \\ h_{sf,st,t} & h^2_{f,st,t} \end{pmatrix} = \begin{pmatrix} h_{s,st,t} & 0 \\ 0 & h_{f,st,t} \end{pmatrix} \begin{pmatrix} 1 & \rho_{st,t} \\ \rho_{st,t} & 1 \end{pmatrix} \begin{pmatrix} h_{s,st,t} & 0 \\ 0 & h_{f,st,t} \end{pmatrix}$$

$$h^2_{s,st,t} = \gamma_{s,st} + \alpha_{s,st}\varepsilon^2_{s,t-1} + \beta_{s,st} h^2_{s,t-1}\,;\ \ h^2_{f,st,t} = \gamma_{f,st} + \alpha_{f,st}\varepsilon^2_{f,t-1} + \beta_{f,st} h^2_{f,t-1}$$

$$\rho_{st,t} = (1 - \theta_{1,st} - \theta_{2,st})\rho + \theta_{1,st}\boldsymbol{\eta}_{t-1}\boldsymbol{\eta}'_{t-1} + \theta_{2,st}\rho_{st,t-1}\,;\ \ \boldsymbol{\eta}_t = \begin{pmatrix} \varepsilon_{s,st,t} / h_{s,st,t} \\ \varepsilon_{f,st,t} / h_{f,st,t} \end{pmatrix}$$

$$P_{12,t} = \frac{1}{1 + \exp(\phi_1)}\,; P_{21,t} = \frac{1}{1 + \exp(\phi_2)}$$

Table 3.4: Effectiveness of Markov regime switching hedge ratios against alternative hedge ratios in carbon emission markets[a]

	Variance[b]	Variance improvement of MRS-LR-DCC[c]	Utility[d]	VaR $_{(5\%)}$[e] (€)
Panel A: In-sample hedging effectiveness				
Unhedged	6.9562	92.58%***	-27.825	-43,386.2
Naïve	0.6604	21.85%***	-2.641	-13,367.7
Constant	0.6358	18.83%***	-2.543	-13,117.0
VECM	0.6360	18.86%***	-2.544	-13,119.3
DCC-GARCH	0.6464	20.16%***	-2.585	-13,225.3
MRS	0.6100	15.40%***	-2.440	-12,848.3
MRS-LR	0.6053	14.74%**	-2.421	-12,798.2
MRS-LR-DCC	**0.5161**	**-**	**-2.064**	**-11,817.5**
Panel B: Out-of-sample hedging effectiveness				
Unhedged	9.3685	72.12%***	-37.474	-50,350.1
Naïve	2.9054	10.09%**	-11.621	-28,039.5
Constant	2.8516	8.39%**	-11.407	-27,778.8
VECM	2.8531	8.44%**	-11.412	-27,786.0
DCC-GARCH	3.6636	28.70%**	-14.655	-31,486.3
MRS	2.8135	7.15%**	-11.254	-27,592.4
MRS-LR	2.8019	6.77%**	-11.208	-27,535.5
MRS-LR-DCC	**2.6123**	**-**	**-10.449**	**-26,587.5**

Note: Asterisks (***, ** ,*) in the column entitled ‘‘Variance improvement of MRS-LR-DCC” indicate that the MRS-LR-DCC model outperforms the competing model at 1%, 5% and 10%, respectively; the p-values are provided by White’s (2000) reality check using Politis and Romano’s (1994) stationary bootstrap method.

a The in-sample period runs from 3 March, 2008 to 31 May, 2012 (1,109 observations) while the out-of-sample period runs from 1 June 2012 to 30 November 2012 (half a year, 131 observations).

b Variance denotes the variance of the hedged portfolio. Note that the variance corresponds to logarithmic returns multiplied by 100. Figures in bold denote the best performing model for each criterion.

c Variance improvement of MRS-LR-DCC measures the incremental variance reduction of the MRS-LR-DCC model versus the other models. This is estimated using the formula:[Var ($Model_i$)– Var (MRS-LR-DCC)]/Var ($Model_i$).

d Utility is the average daily utility for an investor with a mean-variance utility function and a risk aversion coefficient of 4, using different hedging strategies.

e $VaR_{(5\%)}$ is the value-at-risk estimated with Z_a equal to the normal distribution 5% quantile, i.e. -1.645.

Table 3.5: Effectiveness of long/short hedging positions of Markov regime switching hedge ratios compared to alternative hedge ratios in carbon emission markets[a]

	In-sample hedging effectiveness				Out-of-sample hedging effectiveness			
	Semi-variance[b]	Semi-variance improvement of MRS-LR-DCC[c]	Semi-utility[d]	VaR $_{(5\%)}$[e] (€)	Semi-variance[b]	Semi-variance improvement of MRS-LR-DCC[c]	Semi-utility[d]	VaR $_{(5\%)}$[e] (€)
Panel A: Short hedgers positions								
Unhedged	3.7935	94.00%***	-15.174	-32039.5	4.1018	96.09%***	-16.407	-33,913.1
Naïve	0.3229	29.50%***	-1.292	-9,347.6	0.5734	72.02%***	-2.293	-12,455.9
Constant	0.3103	26.63%***	-1.241	-9,163.1	0.5202	69.17%***	-2.081	-11,864.6
VECM	0.3104	26.66%***	-1.242	-9,164.9	0.5223	69.29%***	-2.089	-11,889.0
DCC-GARCH	0.3059	25.58%***	-1.224	-9,098.1	0.5353	70.03%***	-2.141	-12,035.2
MRS	0.2975	23.48%***	-1.190	-8,972.4	0.4660	65.58%***	-1.864	-11,229.3
MRS-LR	0.2984	23.71%***	-1.194	-8,985.8	0.4468	64.10%***	-1.787	-10,995.5
MRS-LR-DCC	**0.2276**	**-**	**-0.911**	**-7,848.5**	**0.1604**	**-**	**-0.642**	**-6,588.1**
Panel B: Long hedgers positions								
Unhedged	3.1680	90.90%***	-12.672	-29,279.2	5.1951	52.83%***	-20.781	-37,494.2
Naïve	0.3239	14.47%**	-1.347	-9,547.6	2.3099	-6.10%	-9.240	-25,001.5
Constant	0.3250	11.34%**	-1.300	-9,331.9	2.3097	-6.11%	-9.239	-25,000.3
VECM	0.3251	11.37%**	-1.300	-9,379.3	**2.3090**	**-6.14%**	**-9.236**	**-24,996.6**
DCC-GARCH	0.3399	15.23%***	-1.360	-9,590.5	3.1120	21.25%**	-12.448	-29,079.4
MRS	0.3120	7.65%**	-1.248	-9,188.4	2.3266	-5.33%	-9.307	-25,091.7
MRS-LR	0.3064	5.96%**	-1.226	-9,105.3	2.3347	-4.97%	-9.339	-25,135.2
MRS-LR-DCC	**0.2881**	**-**	**-1.153**	**-8,830.0**	2.4508	-	-9.803	-25,752.3

Note: Asterisks (***, **, *) in the column entitled ‘‘Semi-variance improvement of MRS-LR-DCC” indicate that the MRS-LR-DCC model outperforms the competing model at 1%, 5% and 10%, respectively; the p-values are provided by White’s (2000) reality check using Politis and Romano’s (1994) stationary bootstrap method.

a The in-sample period runs from 3 March, 2008 to 31 May, 2012 (1,109 observations) while the out-of-sample period runs from 1 June, 2012 to 30 November, 2012 (six months, 131 observations).

b Semi-variance denotes the semi-variance of the hedged portfolio. Note that the semi-variance corresponds to logarithmic returns multiplied by 100. Figures in bold denote the best performing model for each criterion.

c Semi-variance improvement of MRS-LR-DCC measures the incremental semi-variance reduction of the MRS-LR-DCC model versus the other models. This is estimated using the formula:[SVar (Model$_i$)– SVar (MRS-LR-DCC)]/SVar (Model$_i$).

d Semi-utility is the average daily semi-utility for an investor with a mean-semivariance utility function and a risk aversion coefficient of 4, using different hedging strategies.

e VaR$_{(5\%)}$ is the value-at-risk estimated with Z_a equal to the normal distribution 5% quantile i.e. -1.645 and σ equal to the semi-variance of the hedged portfolio.

Chapter 4

Arbitrage Opportunities and Feedback Trading: Evidence from Emissions and Energy Markets

Abstract

This study extends Sentana and Wadhwani's (1992) feedback trading model by allowing arbitrage opportunities to affect the demand of feedback traders. Using daily spot and futures data in five emissions and energy markets, the results show clear evidence of feedback trading in coal and electricity markets, but not in carbon markets where institutional investors dominate. This finding does not support the view that institutional investors are not necessarily all feedback traders. In addition, the results of the augmented feedback trading models suggest that arbitrage opportunities as proxied by a spot-futures basis and the convenience yield can significantly affect the demand of feedback traders. Furthermore, the effects of arbitrage opportunities on feedback trading are found to vary in different market regimes.

4.1. Introduction

Commodity markets have become more attractive to investors in recent years. Global investment funds increased their commodities holdings from $13 billion in 2003 to $260 billion in mid-2008, which is a twenty-fold rise (Cifarrelli and Paladino, 2010). Motivations for investing in commodity markets include the fact that commodities can offer diversification benefits and protect against inflation (Bodie and Rosansky, 1980). In addition, commodity futures can provide leverage and are not constrained by short-sale restrictions (Miffre and Rallis, 2007). Because of the increasing importance of commodities in global asset allocation, the trading behaviour of commodity markets investors has attracted growing attention in academic research, e.g. regarding momentum or contrarian strategies (Wang and Yu, 2004; Miffre and Rallis, 2007) and other technical trading rules (Marshall, Cahan and Cahan, 2008). However, another important trend chasing strategy, i.e. feedback trading, has not been fully examined in commodity markets.[26]

The design and nature of commodity markets is particularly helpful to feedback trading. For instance, implementing feedback trading strategies requires frequent transactions. There are two types of feedback trading: positive and negative feedback trading. Positive (negative) feedback traders buy the asset after a price rise (drop), where the portfolio manager needs to frequently rebalance their portfolio. The low transaction costs and high liquidity of nearby commodity futures[27] enables investors to pursue profits through feedback trading strategies. In addition, positive feedback traders may sell an asset short after a price drop. In commodity futures markets, short-selling is as easy as taking a long position. Therefore, implementing

[26] A recent paper by Cifarelli and Paladino (2010) examines feedback trading in crude oil markets. However, their results are based on weekly data, while the vast of majority feedback trading studies focus on daily prices or even intraday data. Koutmos (2012) argues that it is more appropriate to use higher frequency data because feedback traders tend to adopt short-run computerised strategies to capture very short-lived trends. The use of weekly data may fail to detect short-run feedback trading activity.

[27] See Miffre and Rallis (2007) for details.

this kind of strategy in commodity markets is feasible, given that the market is not constrained by short-sale restrictions. Furthermore, Culter, Poterba and Summers (1990) argue that margin call-induced selling after a series of negative returns is one of the reasons for positive feedback trading. Therefore, it is likely to detect the margin call-caused feedback trading in commodity futures markets due to the intensive use of leverage.

To this end, this chapter aims to empirically examine the question of whether there is feedback trading in commodity markets, using daily spot and futures prices in the carbon emission market, which was created in 2005 to reduce the emission of greenhouse gases. The market is built on a "cap-and-trade" system launched by the European Union. Only firms in several specified industries can receive a free allocation of carbon assets and individuals cannot claim carbon assets from their emissions reduction. Therefore, almost all the participants in carbon markets are institutional investors.[28] This provides a unique and natural opportunity to investigate the relationship between institutional investors and feedback trading. For completeness and comparison, this chapter also includes four other major energy markets: carbon; coal; natural gas; electricity; and crude oil.

Building on the work of Shiller (1984), Sentana and Wadhwani (1992, hereafter SW) develop a feedback trading model with heterogeneous investors (feedback traders and "smart money" investors) to identify the linkage between volatility and autocorrelation. It is found that, with the presence of significant feedback trading, asset returns exhibit positive autocorrelation in a low volatility period and negative autocorrelation in a high volatility period. The negative relation between autocorrelation and volatility is supported by a number

[28] The data from the European Union Emission Trading Scheme Transaction Log in November, 2012 shows that less than 6% of total accounts are personal holding accounts (2,050 out of a total of 34,492 accounts), suggesting that the vast majority of participants in the European carbon markets are institutional investors. Participants in the EU ETS include the 12,000 installations covered by the scheme, firms investing in the CDM and JI projects, government carbon funds, international organisations, arbitragers, speculators and other environmental investors.

of subsequent studies (e.g. Antoniou et al., 2005; Laopodis, 2005; Salm and Schuppli, 2010; Chau et al., 2011). In addition, recent literature has also focused on extending the original SW feedback trading model. For instance, Faff, Hillier and McKenzie (2005) extend the feedback trading model by including a cross-market feedback trader, whose demand function is sensitive to the price movement in foreign markets. Chau et al. (2011) consider the effect of investor sentiment on the feedback traders' demand function, and further develop a feedback trading model with investor sentiment. Koutmos (2012) incorporates the role of fundamental traders in determining the stock return dynamics.

Nevertheless, the aforementioned literature does not fully take into consideration the effects of arbitrage opportunities on feedback trading behaviour. De Long et al. (1990) argue that rational speculation and arbitrage are among the most important factors contributing to feedback trading. Arbitrage can be regarded as one form of rational speculation. Efficient arbitrage is the main force behind the linkage between spot and futures markets (MacKinlay and Ramaswamy, 1988) and also contributes significantly to price discovery (Garbade and Silber, 1983). One of the most commonly used arbitrage signals is the spot-futures basis (Kumar and Seppi, 1994). If the spot-futures basis moves above the arbitrage window, arbitragers can simultaneously buy futures contracts and sell the spot asset (Miller, Muthuswamy and Whale, 1994), pushing up futures prices. This in turn implies that arbitrage opportunities may contain some predictive value for future price movements (e.g. Khoury and Yourougou, 1991; Knetsch, 2007; Gorton et al., 2013). For this reason, this chapter argues that feedback traders not only trade based on past returns, but are also influenced by the level of arbitrage opportunities. However, no previous research has investigated the impact of arbitrage opportunities on feedback trading. To address this issue, another important objective of this chapter is to extend the SW feedback trading model by allowing the demand of feedback traders to be affected by the level of arbitrage opportunities.

This chapter adds to the existing literature in a number of aspects. Firstly, this study presents the first attempt to study the trading behaviour of investors in the new carbon emission markets. In particular, the baseline SW feedback trading model is adopted to examine the presence of feedback trading in these markets. As nearly all of the investors in carbon markets are institutional investors, the results obtained are significant in understanding the trading behaviour of institutional investors.

Secondly, this work also contributes to a growing number of studies examining the role of arbitrage opportunities in trading behaviour. Arbitrage is a kind of rational speculation, as it is based on rational analysis but speculates on prices adjusting to the equilibrium quickly, while rational speculation is cited as one of the factors contributing to feedback trading (De Long et al., 1990). Arbitrage opportunities could be considered by feedback traders as a signal to trade. This study first extends the SW feedback trading model by allowing arbitrage opportunities to affect the demand of feedback traders, in both additive and multiplicative way. The results of this chapter are important in understanding trading behaviour in futures markets, where arbitrage and hedging are the main purposes of transactions. Thirdly, the augmented feedback trading model is re-estimated using data from different market regimes, i.e. bull and bear markets, to examine whether the level of feedback trading and the effects of arbitrage opportunities on feedback trading change across different market conditions. In addition, unlike previous studies which only assume a particular conditional variance specification, this chapter conducts a detailed specification test to identify the best volatility model for each market.

Using daily spot and futures price data for carbon, coal, electricity, natural gas and crude oil markets, this chapter attempts to examine the following questions:

- Is there feedback trading in the commodity markets? In particular, do the investors in carbon emissions markets (mainly institutional investors) contribute to feedback trading activities or not?
- How do the arbitrage opportunities affect the feedback trading activities?
- Does the relationship between arbitrage opportunities and the level of feedback trading vary across bull/bear market regimes?

The main findings of this chapter can be summarised as follows. First, the results of the feedback trading model show that feedback trading is significantly present 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 view that institutional investors contribute to feedback trading, which differs from the traditional view (e.g. Nofsinger and Sias, 1999). Secondly, the results of the augmented SW feedback trading models show that arbitrage opportunities can affect demand from feedback traders' in the electricity and natural gas markets, in both an additive and a multiplicative way. This supports the view that arbitrage opportunities have an impact on feedback trading. Thirdly, the responses of feedback traders to past returns or arbitrage opportunities vary significantly across bull and bear market regimes. Finally, all the above results are robust to different measures of arbitrage opportunities, including the spot-futures basis and the convenience yield.

The remainder of the chapter is organised as follows: Section 4.2 discusses empirical evidence of feedback trading in financial markets, and the relation between arbitrage opportunities and feedback trading. Section 4.3 describes the basic feedback model and the augmented feedback trading model with arbitrage opportunities. Section 4.4 explains the dataset employed in this study and provides some preliminary results. Section 4.5 analyses the empirical results, while robustness checks are provided in Section 4.6. Conclusions about this research are stated in Section 4.7.

4.2. Related literature: Arbitrage opportunities and feedback trading

Spot-futures arbitrage is a trading strategy that large investors pursue in order to profit from the difference between prices in the futures market and its underlying spot market (Chung, 1991). It is the main mechanism for maintaining the linkage between the two markets (MacKinlay and Ramaswamy, 1988) and also contributes significantly to price discovery (Garbade and Silber, 1983). One of the most commonly used arbitrage signals is the spot-futures basis (Kumar and Seppi, 1994). If the spot-futures basis is greater than a certain threshold, arbitragers can simultaneously buy futures contracts and sell the spot asset (Kumar and Seppi, 1994). To date, research has focused on examining the profitability of arbitrage opportunities (Chung, 1991) and on how limits to arbitrage affect arbitrage activities and spot-futures mispricing (McMillian and Philip, 2012). Intuitively, the presence of arbitrage opportunities is one of the motivations for investors to trade. However, the issue of whether arbitrage opportunities affect investors' trading behaviour has received much less attention. In particular, there is little previous research connecting arbitrage opportunities with feedback trading.

Since the seminal work of SW which develops a heterogeneous feedback trading model, feedback trading has been found in many markets, including the U.S. stock market (SW), other stock markets (Antoniou et al., 2005), foreign exchange markets (Laopodis, 2005), index futures markets (Salm and Schuppli, 2010), and exchange-traded fund (ETF) markets (Chau et al., 2011), as well as the crude oil market (Cifarrelli and Paladino, 2010). Beside the above empirical work in different markets, the baseline feedback trading model has also been augmented in a number of directions. In the SW feedback trading model, there are two groups of investors, namely feedback traders and “smart money” investors. Feedback traders’ demand for shares is dependent on previous price changes while “smart money” investors trade based on risk-return analysis. Faff et al. (2005) extend the feedback trading model by including a cross-market feedback trader. Chau et al. (2011) incorporate the effect of investor sentiment into the feedback traders’ demand function, and develop a feedback trading model that takes into account the role of investor sentiment. A recent study by Koutmos (2012) shows that a feedback trading model with heterogeneous investors should have an additional investors group, consisting of fundamental traders.

This chapter extends the baseline feedback trading model by considering the effects of arbitrage opportunities on feedback trading. Several papers have studied the relations between arbitrage opportunities (measured by the spot-futures basis or convenience yield) and hedging (Lien and Yang, 2008; Millios and Six, 2011), as well as the predictive power of the basis on futures prices and returns, both theoretically (Khoury and Martel, 1989) and empirically (Khoury and Yourougou, 1991). However, little research has been done on whether and how arbitrage opportunities can influence feedback traders’ investment decisions.

Commodity assets have become increasingly important in investors’ asset allocation. The trading strategies used in commodity markets have also attracted increasing attention in academic research. Miffre and Rallis (2007) show that both momentum and contrarian strategies are profitable in commodity markets. Marshall et al. (2008) also suggest that certain groups of technical trading rules can generate abnormal returns in commodity markets. However, there are limited studies on feedback trading strategies in commodity markets. Cifarelli and Paladino (2010) study feedback trading in U.S. crude oil markets using weekly data; however, the vast majority of feedback trading research has focused on daily prices or intraday data. The reason for using high frequency data is that feedback investors are likely to choose short-run computerised strategies to capture those trends which will vanish very quickly (Koutmos, 2012). The use of weekly data may fail to detect short-run feedback trading activity. Therefore, it is plausible to use daily data to examine feedback trading in commodity markets. [29]

Motivated by the aforementioned theories and empirical results, this chapter makes several extensions to the baseline SW feedback trading model, by allowing the potential arbitrage opportunities to affect feedback traders' demand for shares. This study also uses daily data from emission and energy markets to fill the research gap in feedback trading in commodity markets. In the following sections, this chapter shows how the baseline and augmented feedback trading model with arbitrage opportunities can be developed.

4.3. Feedback trading models

4.3.1. The SW feedback trading model

Since the discovery of the relationship between investors' trading behaviour and stock return serial correlation, several forms of feedback trading models have been proposed to theoretically predict the patterns of return autocorrelation. The feedback trading models developed by Shiller (1984) and Cutler et al. (1990) predict a positive serial correlation of stock returns if there is feedback trading, as the feedback traders are able to help maintain the trend, i.e. produce a positive return autocorrelation. However, the SW feedback trading

[29] In addition to the literature summarised in this section, this chapter provides a comprehensive review of previous literature related to arbitrate opportunities, arbitrage proxies, momentum and contrarian strategies in commodity markets, empirical tests and theoretical extensions of the SW feedback trading model, which is shown in Appendix 4A.

model which connects return autocorrelation and volatility, shows that positive feedback trading could lead to negative autocorrelation when volatility is high. This model identifies two distinct styles of investors in the stock market. "Smart money" investors constitute the first type of participants, who are assumed to be rational and make investment decisions based on fundamentals and risk-return trade-off. The second group of investors are known as feedback traders or trend followers, whose demand for stocks is made on the basis of previous stock returns. The SW model posits that the "smart money" investors are more cautious during high volatility periods, and therefore portfolio insurers and stop-loss investors have greater power to affect stock prices, which leads to a higher negative return autocorrelation. The heterogeneous trader model captures both the return autocorrelations and the impacts of volatility on stock returns caused by two different groups of investors. Following SW, by maximising utility in the mean-variance framework, the demand function for the rational "smart money" investors is formulated as:

$$S_t = \frac{E_{t-1}(R_t) - \alpha}{\mu_t} \tag{4.1}$$

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 return when the demand for shares from "smart money" investors is zero, which should be the risk-free rate, and μ_t is the risk premium when all the shares are held by this group of investors. As rational investors are risk averse, the risk premium is further modelled as:

$$\mu_t = \mu(\sigma_t^2) \tag{4.2}$$

where σ_t^2 is the conditional variance of returns at time t and $\mu(x)$ is an increasing function. As the risk associated with returns increases, investors require a higher risk premium. It should be noted that, when all the shares are held by "smart money" investors and the market is in equilibrium (i.e. S_t=1), Equation (1) becomes the classic Capital Asset Pricing Model (CAPM):

$$E_{t-1}(R_t) - \alpha = \mu(\sigma_t^2) \tag{4.3}$$

Feedback traders' demand for shares fluctuates as stock prices change; therefore, their demand function is expressed as:

$$F_t = \gamma R_{t-1} \tag{4.4}$$

where R_{t-1} is the ex-post stock return at time t-1 and γ is the marginal response of feedback traders to stock returns. The sign of γ can help to distinguish between the two types of trend followers in the stock market. A positive value for γ indicates that this group of investors (positive feedback traders) believe the trend will be persistent and consequently they will buy (sell) stocks after a rise (fall) in stock prices. On the contrary, negative feedback traders buy (sell) stocks during a period of falling (increasing) stock prices to reflect their opinion that the trend will reverse. In this case, the value of γ is expected to be less than zero.

When the market is in equilibrium, all the shares are possessed by the two types of investors. Therefore:

$$S_t + F_t = 1 \tag{4.5}$$

Substituting Equations (4.1), (4.2) and (4.4) into Equation (4.5), produces the following:

$$E_{t-1}(R_t) - \alpha = \mu(\sigma_t^2) - \gamma\mu(\sigma_t^2)R_{t-1} \tag{4.6}$$

Assuming that expected stock returns will be rational, i.e.

$$R_t = E_{t-1}(R_t) + \varepsilon_t \tag{4.7}$$

where ε_t is an independently and identically distributed (i.i.d.) error term. Equation (4.6) can then be reformulated as:

$$R_t = \alpha + \mu(\sigma_t^2) - \gamma\mu(\sigma_t^2)R_{t-1} + \varepsilon_t \tag{4.8}$$

However, Equation (4.8) does not consider the return autocorrelation caused by market inefficiency, non-synchronous trading and other market imperfections. Accounting for these possibilities and taking a linear form of risk premium, the empirical version of the SW feedback trading model is:

$$R_t = \alpha + \rho\sigma_t^2 + (\gamma_0 + \gamma_1\sigma_t^2)R_{t-1} + \varepsilon_t \tag{4.9}$$

where γ_0 is the coefficient of first order autocorrelation induced by market imperfections and γ_1=-$\gamma\rho$. Positive (negative) feedback trading indicates that γ_1 should be negative (positive) and statistically significant. The model given by Equation (4.9) is referred to as baseline Model I.

It is interesting to observe from the model that positive feedback trading (negative γ_1) can result in negative return autocorrelations during a high volatility period and positive autocorrelations during low volatility times. The negative relation between autocorrelation and volatility is supported by SW's empirical results using the U.S. data, and is also found in other stock markets (Antoniou et al., 2005), foreign exchange markets (Laopodis, 2005), and index futures markets (Salm and Schuppli, 2010), as well as exchange-traded fund (ETF) markets (Chau et al., 2011).

4.3.2. Feedback trading models with arbitrage opportunities

In the baseline SW feedback trading model, the demand function of feedback traders depends only on past realised returns. However, an increasing amount of literature supports the idea that there is strong link between the presence of arbitrage opportunities and trading behaviour in futures markets. As shown in Section 4.2, the arbitrage opportunities can be measured by the futures basis or convenience yield. Kumar and Seppi (1994) and Miller et al. (1994) indicate that the dynamics of the basis acts as a signal for some arbitragers. If the basis is wide enough or above a certain threshold, arbitragers will exploit the arbitrage opportunity by trading in futures markets. In addition, Lien and Yang (2008) show the importance of incorporating the changes of basis into hedging decisions. The basis affects the minimum variance hedge ratio estimation not only in terms of the mean level but also in terms of the volatility level. Mellios and Six (2011) also demonstrate that the hedging demand is uniquely associated with the convenience yield.

Motivated by the aforementioned literature, this chapter extends the SW feedback trading model by allowing arbitrage opportunities to affect feedback trading in futures markets. Similarly to SW, these feedback traders still do not take risk into consideration; however, they not only respond to the past period returns, but also observe what happens in the spot market and react to the arbitrage opportunities between the spot and futures markets.

Following SW, two distinct types of investors, i.e. “smart money” investors and feedback traders, are assumed to participate in futures markets. The demand function for “smart money” investors remains unchanged. However, the demand function for feedback investors is modified to reflect the important role of arbitrage opportunities. As a substantial amount of literature shows that arbitrage opportunity proxies directly affect futures trading, including both arbitrage and hedging, the first extension of the feedback trading model in this chapter involves allowing the demand function of feedback traders to rely on current arbitrage opportunities, in an additive way. One of the most commonly used arbitrage signals is the spot-futures basis (Kumar and Seppi, 1994). If the spot-futures basis is wider than the threshold, arbitragers can simultaneously buy futures contracts and sell the spot asset (Miller et al., 1994). For this reason, the lagged basis is adopted as a proxy for the arbitrage opportunities. The basis is the logarithm difference between the spot and futures prices $Basis_t = \ln(S_t / F_{t,T})$, where T is the maturity time of the futures contract, St is the spot price at time t and $F_{t,T}$ is the futures price at time t which matures at time T. Therefore, the demand function for feedback traders is:

$$F_t = \gamma R_{t-1} + \delta Basis_{t-1} \tag{4.10}$$

where $Basis_{t-1}$ is the spot-futures basis and δ is the response of feedback traders to arbitrage opportunities (measured by a lagged basis).

Substituting Equations (4.10), (4.2) and (4.4) into Equation (4.5), the first augmented feedback trading model is formulated as follows:

$$E_{t-1}(R_t) - \alpha = \mu(\sigma_t^2) - \gamma\mu(\sigma_t^2)R_{t-1} - \delta Basis_{t-1} \tag{4.11}$$

Following the empirical approximations of SW, and taking $\gamma_2 = -\delta$, the empirical version of the first augmented feedback trading model is:

$$R_t = \alpha + \rho\sigma_t^2 + (\gamma_0 + \gamma_1\sigma_t^2)R_{t-1} + \gamma_2 Basis_{t-1}\sigma_t^2 + \varepsilon_t \tag{4.12}$$

and the model described in Equation (4.12) is referred to as Model II.

It is also noteworthy that the literature has documented that the basis is associated with futures prices and returns, theoretically (Khoury and Martel, 1989) and empirically (Khoury and Yourougou, 1991). In addition, when modelling futures returns, the basis usually acts as the error correction term in the mean equation (Lien and Yang, 2008). Based on the above argument, feedback traders might believe the arbitrage opportunity signal is an indicator of future price movement. They think that the presence of arbitrage opportunities can partly determine the profitability of the feedback trading strategy. Consequently, their reaction to past returns (i.e. the degree of feedback trading) also depends on the arbitrage proxies. The above additive model cannot capture the relation between arbitrage opportunities and the degree of feedback trading; therefore, an alternative model is proposed in which feedback traders' demand for shares is affected by arbitrage proxies in a multiplicative way, as follows:

$$F_t = (\gamma + \delta Basis_{t-1}) R_{t-1} \tag{4.13}$$

where $Basis_{t-1}$ is defined as previously described. δ here represents the effects of arbitrage opportunities on the degree of feedback trading.

Substituting Equations (4.13), (4.2) and (4.4) into Equation (4.5), the second augmented feedback trading model is formulated as follows:

$$E_{t-1}(R_t) - \alpha = \mu(\sigma_t^2) - (\gamma + \delta Basis_{t-1}) \mu(\sigma_t^2) R_{t-1} \tag{4.14}$$

Following the empirical approximations of SW, and taking γ_2=-δ, the empirical version of the second augmented feedback trading model, or Model III, is:

$$R_t = \alpha + \rho\sigma_t^2 + (\gamma_0 + \gamma_1\sigma_t^2 + \gamma_2 Basis_{t-1}\sigma_t^2) R_{t-1} + \varepsilon_t \tag{4.15}$$

4.3.3. Conditional volatility specifications

An important issue within the empirical work on feedback trading involves estimating the conditional variance σ_t^2, which is primarily modelled by generalised autoregressive conditional heteroskedastic (GARCH) processes in the financial literature. SW adopt the exponential GARCH (EGARCH) in their work, but an increasing number of researchers (Antoniou et al., 2005; Chau et al., 2011) have started to use the GJR-GARCH, introduced by Glosten, Jagannathan and Runkle (1993). Both the EGARCH and GJR-GARCH models can capture asymmetric effects in the conditional variance while the standard GARCH model cannot. The standard GARCH model is:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{4.16}$$

and the EGARCH is specified as:

$$\ln \sigma_t^2 = \alpha_0 + \alpha_1 G_{t-1} + \beta \sigma_{t-1}^2 \, ; \; G_{t-1} = \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{2}{\pi}} + \delta \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{4.17}$$

while the GJR-GARCH is modelled as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \delta I_{t-1} \varepsilon_{t-1}^2 \tag{4.18}$$

where σ_t^2 denotes the conditional variance at time *t*, ε_t is the error term from Equations (4.9) (4.12) and (4.15), and I_{t-1} is a dummy variable which takes the value of one if the error term is negative at time *t*-1 and takes the value of zero otherwise.

Cappiello, Engle and Sheppard (2006) show that if the GARCH model is not well specified, the estimation results of the mean model will no longer be consistent. In order to select the most appropriate volatility model for each market, this study includes the following models in the specification tests: standard GARCH; EGARCH; and GJR-GARCH. An AR (1)-GARCH (1, 1) model with the three GARCH specifications is estimated for each market. The most appropriate model is selected based on several criteria, including the value of log-likelihood function (Log L), heteroskedasticity-adjusted mean squared error (HMSE) and Akaike Information Criterion (AIC).

As most of the standard residuals from GARCH models which are assumed to be normally distributed appear to be leptokurtic, the standard t-test will be unreliable (Antoniou et al., 2005). In this chapter, the error terms are assumed to follow the Generalised Error Distribution (GED) which allows for fat tails. Its density function is:

$$f(\mu_t, \sigma_t, \nu) = \frac{\nu}{2}[\Gamma(3/\nu)]^{1/2}[\Gamma(1/\nu)]^{-3/2}(1/\sigma_t)\exp(-[\Gamma(3/\nu)/\Gamma(1/\nu)]^{\nu/2} \mid \varepsilon_t \mid \sigma_t) \tag{4.19}$$

where v is the scale parameter estimated endogenously. When v=2, GED yields normal distribution, and v=1 for the Laplace distribution.

4.4. Data and model selection

The dataset used in this study includes daily spot and futures prices of carbon emission allowances and four main energy commodities within the European market, which are coal, electricity, natural gas and crude oil. In order to examine these commodity markets, the following futures contracts listed on the Intercontinental Exchange (ICE) and their reference spot prices are used: EU Emission Allowance (EUA) futures (carbon emission); Rotterdam coal futures (coal); UK base time electricity futures (electricity); UK natural gas futures (natural gas); Brent crude oil futures (crude oil). These contracts are studied in the previous literature as proxies for each commodity.[30] The starting dates for each commodity vary because of data availability, and are as follows: 03/03/2008 (carbon); 17/07/2006 (coal); 27/12/2006 (electricity); 06/02//2003 (natural gas); and 08/09/2003 (crude oil). The end date for all the markets is 30/09/2012. To construct a continuous series of futures prices, the futures contracts switch over on the first day of a new trading month, for all available trading

[30] For example, see Daskalakis et al. (2009) for the carbon emission market, Borger, Cartea, Kiesel and Schindlmayr (2009) for the coal market, Bunn and Gianfreda (2010) for the electricity market, Hochradl and Rammerstorfer (2012) for the natural gas market, and Ellen and Zwinkels (2010) for the crude oil market.

months. In currency terms, the coal and crude oil prices are denominated in U.S dollars (USD); the carbon emission price is denominated in Euros; while electricity and natural gas prices are denominated in Great British Pounds (GBP). For the estimation of implied convenience yields, following Heaney (2002), the 3-month mid-rate of the Euro-currency (London) USD, Euro and GBP are adopted as the risk-free interest rates for each commodity. The data in this chapter was obtained from DataStream.

[Insert Table 4.1 here]

Daily futures returns are calculated as the logarithmic first differences of futures prices in percentage form. The descriptive statistics of the futures returns are presented in Panel A of Table 4.1. It is shown that coal and crude oil returns are negatively skewed, while carbon, electricity and natural gas returns are positively skewed. All the series exhibit highly leptokurtic and significant deviations from normality (see results of the Jarque-Bera test). Ljung-Box statistics provide clear evidence of serial correlation in all return data except carbon, and in all squared return data except natural gas. A significant ARCH effect is also found in carbon, coal, electricity and crude oil, but not for natural gas. The results of Engle and Ng's (1993) JOINT test designed to test the asymmetries in conditional volatility, indicate that significant asymmetries appear in all futures conditional variances, providing the rationale for using asymmetric GARCH models. It can be observed from Panel B of Table 4.1 that all five markets are significantly correlated.

Panel C in Table 4.1 provides a preliminary idea of the degree of feedback trading in these markets. It shows the estimation results of an autoregressive model of order, AR (5), for futures returns. Consistent with the Ljung-Box Q-test results, all the futures returns except carbon exhibit autocorrelation to some extent. However, the simple autoregressive model cannot capture the interaction between feedback traders and "smart money" investors, as feedback trading can cause a negative relation between autocorrelation and volatility. Therefore, it is useful to further investigate the effect of feedback trading through the SW feedback trading model and its augmented models.

[Insert Table 4.2 here]

The summary statistics for the spot-futures basis and convenience yield is shown in Table 4.2. The means of all futures bases are around zero; however the absolute values of the means of convenience yields are much larger. It is also indicated in the table that the convenience yields of these commodities are more volatile than their basis. All the bases and convenience yields display some degree of skewness and are highly leptokurtic.

[Insert Table 4.3 here]

As described in Section 4.3.3, the conditional variance is modelled by a standard GARCH, EGARCH or GJR-GARCH. A simple AR (1)-GARCH (1, 1) model is estimated to test the fitness of the data to the three GARCH model specifications. Table 4.3 displays the results of the specification tests for the GARCH models. The most appropriate model is selected based on several criteria, including the value of log likelihood function (Log L), heteroskedasticity-adjusted mean squared error (HMSE) and Akaike Information Criterion (AIC). The final GARCH specifications selected for each market are presented in the last column, which are as follows: EGARCH for carbon, electricity, and natural gas; GJR-GARCH for coal and crude oil. It is noteworthy that all the models selected are asymmetric GARCH models, which is consistent with the JOINT test results indicating that there are asymmetries in the conditional variance of all the futures returns.

4.5. Empirical results

4.5.1. Feedback trading evidence in emissions and energy markets

To detect possible feedback trading in the emissions and energy markets, this study first estimates the baseline SW feedback trading model (Model I, Equation 4.9) with the conditional variance specifications stated in Table 4.3. The maximum likelihood estimation results of the baseline model are presented in Table 4.4. From the conditional variance equation, it can be observed that the coefficients α_0, α_1, and β are all statistically significant at the 5% level, indicating that the current conditional variance is dependent on past squared errors and past conditional volatility. δ, which is the asymmetric parameter in the GJR-GARCH and the leverage parameter in the EGARCH, is significant in all cases except the coal market. The results confirm the model selection in Table 4.3. The estimated scale parameter v in the GED function is significant and less than 2 in all cases,[31] showing that all the error terms are not normally distributed and are leptokurtic, which confirms the use of GED distribution. The results also confirm that the temporal first and second moment dependencies of returns cannot fully explain why returns are not normally distributed.

[Insert Table 4.4 here]

The most interesting parameters in the baseline model are the autocorrelation parameters γ_0 and γ_1, which test the existence of feedback trading. The constant term of the return autocorrelation, γ_0, is positive and significant for coal and electricity at the 5% level, and for natural gas at the 10% level, showing a positive return autocorrelation in these markets. The results are generally consistent with the finding in Panel C of Table 4.1. SW argue that this kind of return autocorrelation is caused by non-synchronous trading and other market frictions or inefficiencies. The effects of feedback investors' trading behaviour on return autocorrelation are captured by γ_1. It is shown in Table 4.4 that the feedback trading

[31] When v=2, GED reduces to the standard normal distribution.

parameter γ_1 is insignificant for carbon and natural gas, implying that there is no feedback trading in these markets and investors do not trade based on past returns. As the vast majority of investors in the carbon market are institutions, these results do not support the view that institutional investors contribute to feedback trading, which differs from Nofsinger and Sias's (1999) findings. γ_1 is negative and significant in the coal market at the 5% level, suggesting that positive feedback trading is present in the coal market and its impacts on returns become greater in high volatility periods. Some investors are more inclined to hold a coal futures long position when coal futures prices go up, consistent with the momentum strategy found in commodity markets (Miffre and Rallis, 2007). The presence of positive feedback trading has also been widely discovered in stock markets (Antoniou et al., 2005), foreign exchange markets (Laopodis, 2005), and index futures markets (Salm and Schuppli, 2010), as well as exchange-traded fund (ETF) markets (Chau et al., 2011). Moreover, although not marked in Table 4.4, γ_1 for crude oil is negative and significant at the 10% level (t-statistics is -1.713), showing very weak positive feedback trading in the crude oil market. Cifarrelli and Paladino (2010) document strong positive evidence of feedback in the U.S. crude oil market from 1992 to 2008. However, it is observed that the feedback trading parameter is positive in the electricity market, showing that there is negative feedback trading in that market. Feedback investors in the electricity market sell electricity futures contracts after a rise in the futures price, similarly to the contrarian strategy detected in commodity markets (Wang and Yu, 2004). There is not much evidence of negative feedback trading in the literature. Laopodis (2005) studies the global foreign exchange market using the SW model, and finds that negative feedback trading occurred in the British Pounds market, the South Korean Won market before the 1997-1998 Asian financial crisis, and the Italian Lira market before the Exchange Rate Mechanism (ERM) crisis in 1992-1993. For the diagnostics tests presented in

Panel C of Table 4.4, all the statistics are improved compared to the raw return results and show no evidence of serious model misspecification of the baseline model.

4.5.2. The effects of arbitrage opportunities on feedback trading

This section investigates whether arbitrage proxies have an impact on feedback trading. The influence of arbitrage opportunities on the feedback traders' demand function is modelled in an additive way (Model II) or a multiplicative way (Model III). As the spot-futures basis is a direct signal of arbitrage opportunities (Kumar and Seppi, 1994), this study adopts the basis as the proxy for arbitrage opportunities in the main tests and uses the convenience yield as an alternative measure of arbitrage opportunities for robustness checks.

[Insert Table 4.5 here]

In Model II (Equation 4.12) with a basis, feedback investors not only trade based on the returns from the last period, but also based on the last period's spot-futures basis, which can be an indicator of arbitrage opportunities (Sofianos, 1993) or a factor affecting hedging decisions (Lien and Yang, 2008). The demand function of feedback traders is their additive response to the previous period's return and basis. In this model, a positive γ_2 suggests that feedback traders will sell the asset when the spot price is greater than the futures price on the last trading day while a negative γ_2 implies that feedback investors are more inclined to buy a futures long position when the last period's basis is positive. The estimation results from Model II with a basis are shown in Table 4.5. It can be observed that the directions and significances of the γ_1 parameters are identical to the results in Model I. The magnitude and significance of the parameters in the conditional variance equation are not uncommon. The most interesting parameter in Model II is γ_2, the one governing the additive effect of the basis on feedback trading. The results in Table 4.5 demonstrate that γ_2 is insignificant in the carbon, coal and crude oil markets, showing that feedback traders in these markets do not directly respond to the spot-futures basis. In contrast, γ_2 is negative and significant in the electricity and natural gas markets, indicating that feedback investors hold more long positions of futures contracts when the last period's spot price is higher than the last period's futures prices. Feedback traders in the electricity and natural gas markets believe that futures prices will rise to draw level with the spot prices and therefore they are more likely to buy futures long positions. This trading behaviour can inflate futures prices and reduce the spot-futures basis, which confirms the use of the basis as an arbitrage signal. Miller et al. (1994) argue that when the spot price is too high relative to the futures price and the basis is higher than its theoretical level, arbitragers can simultaneously short-sell the spot asset and buy futures contracts to exploit the arbitrage profit. The results confirm the above arguments and support the linkage between arbitrage opportunities and feedback trading. It is also noteworthy that the diagnostic tests for the electricity and natural gas markets improved significantly from Model I to Model II with a basis, especially for the degree of autocorrelation in the residuals, showing that the significant basis effects in the feedback trading model increase the effectiveness of model specification.

[Insert Table 4.6 here]

Besides predicting arbitrage opportunities, the basis is also claimed to be an indicator of the futures price movement trend (Khoury and Martel, 1989; Khoury and Yourougou, 1991). Therefore the basis can affect the profitability of a feedback trading strategy and thus determine the level of feedback trading. Based on this, Model III (Equation 4.15) is developed, in which the feedback traders' demand function depends on the past basis in a multiplicative way. The results of Model III with a basis are displayed in Table 4.6. In this model, feedback investors do not directly respond to the basis; however, the basis affects their feedback trading in terms of sensitivity to past returns. A positive γ_2 suggests that feedback traders buy short futures contracts when past futures returns are positive and the past basis is positive and a negative γ_2 suggests they buy more long-futures when both past returns and the past basis are negative. However, explaining the results in terms of feedback trading is more complex. In Model III with a basis, $-\gamma_1-\gamma_2*Basis_{t-1}$ is the function parameter of past returns and the basis affects feedback trading in a multiplicative way. A positive γ_2 can only suggest that the degree of negative feedback trading increases or the degree of positive feedback trading decreases, and vice versa. However, we cannot determine the direction of feedback trading. Therefore, it is reasonable to observe γ_1 and γ_2 together. For the carbon emission and crude oil markets, both γ_1 and γ_2 are insignificant, implying that there is no feedback trading in these markets. For the remaining three markets, both parameters are significant. In the coal market, γ_1=-0.0132 and γ_2=0.0913. The results indicate that there is positive feedback trading when the spot price is equal to the futures price, but the degree of positive feedback trading decreases as the basis becomes larger. When the basis is greater than 0.1446, it turns into negative feedback trading. Similarly for γ_1=-0.0001 and γ_2=0.0005 in the natural gas market. When the basis is zero in the natural gas market, feedback investors buy more long position futures when futures prices rise, but the degree of positive feedback trading diminishes and becomes zero when the basis approaches 0.2000. For the electricity market, there is negative feedback trading when the basis is zero (γ_1=0.0009) and the degree of negative feedback trading increases as the basis becomes greater (γ_2=0.0595). However, when the basis decreases to -0.0151 (i.e. the spot price is lower than the futures price by 1.52%), it will become positive feedback trading. It is also very interesting that the γ_2 parameters in all five markets are positive (although some of them are insignificant). The results show that the degree of negative feedback trading increases or the degree of positive feedback trading decreases as the lagged basis becomes larger. The spot-futures basis in the last period provides the threshold point for positive and negative feedback trading, and it can also be viewed as a signal of channel breakouts in technical analysis. When the basis is within certain thresholds, feedback traders believe that the current trend for futures prices will persist; therefore they adopt a positive feedback trading strategy. However, if the basis is wide enough, the current channel will be broken out by arbitragers; consequently, negative feedback trading becomes profitable for investors. The above results are consistent with Marshall et al. (2008), who find some channel breakout trading rules are profitable in the U.S. commodity markets; they are also consistent with the use of a basis as arbitrage signals.

4.6. Robustness checks

4.6.1. Alternative measure of arbitrage opportunities

The difference between spot and futures prices, the basis, is a naïve and widely used signal and measure of arbitrage opportunities. However, the spot-futures basis does not consider the explicit and implicit costs of arbitrage, including borrowing costs and opportunity costs. The convenience yield, which can be derived from the non-arbitrage cost-of-carry model, reflects these costs in addition to the basis. From the equations to calculate the basis and convenience yield (Equations 4.20 and 4.21 below), it can be ascertained that the convenience yield is estimated based on a basis but also considers the effects of dynamic risk-free rates and time-to-maturity. Economically, the convenience yield is the benefit of holding spot inventory rather than buying futures. It shows the economic relationship between spot and futures prices. Therefore, the convenience yield can also be an indicator of future price movements in futures. Bertus, Godbey and Hilliard (2009) and Mellios and Six (2011) also find that the convenience yield can affect the hedging demand and optimal hedge ratio. In this section, the sensitivity of the above results above to an alternative measure of arbitrage opportunities, the convenience yield, is examined.

The convenience yield is estimated from the cost-of-carry model. As suggested by Brennan (1958), the futures price is determined by the spot price, risk-free rate, convenience yield and the time to maturity, which can be expressed as:

$$F_{t,T} = S_t e^{(Rf_t - CY_t)(T-t)} \tag{4.20}$$

where Rf_t is the continuously compounded risk-free rate in the market 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* which matures at time *T*, and CY_t is the convenience yield at time *t*. Rearranging Equation (4.20), the convenience yield can be modelled as:

$$CY_t = Rf_t - \frac{1}{T-t}\ln\left(\frac{F_{t,T}}{S_t}\right) = Rf_t + \frac{1}{T-t} Basis_t \tag{4.21}$$

From Equation (4.21) it can be observed that the convenience yield moves with the basis but also takes into account the effects of the risk-free rate and time-to-maturity. The estimation methods of the convenience yield stated above are extensively used in the literature, for example by Milonas and Henker (2001).

Substituting the basis in the feedback trading models with the convenience yield, and then the feedback trading models II and III with the convenience yield are specified as:

Model II: $$R_t = \alpha + \rho\sigma_t^2 + (\gamma_0 + \gamma_1\sigma_t^2)R_{t-1} + \gamma_2 CY_{t-1}\sigma_t^2 + \varepsilon_t \tag{4.22}$$

Model III: $$R_t = \alpha + \rho\sigma_t^2 + (\gamma_0 + \gamma_1\sigma_t^2 + \gamma_2 CY_{t-1}\sigma_t^2)R_{t-1} + \varepsilon_t \tag{4.23}$$

[Insert Table 4.7 here]

The results of Model II with the convenience yield are presented in Table 4.7. Except for natural gas, the results of γ_1 are consistent with Model I and Model II with a basis. γ_1 is negative and significant for the natural gas market in Model II with the convenience yield, but insignificant in Model I and Model II with a basis. The γ_2 for the natural gas market is also negative and significant. This shows that feedback traders respond positively to the last period's futures return and convenience yield, i.e. they hold more long futures positions when futures returns and the convenience yield is positive in the previous period. Feedback investors buy more long-futures when the convenience yield is positive because they believe that the benefits of holding a spot asset will diminish and futures prices will rise. Similarly to natural gas, the γ_2 of the electricity market in Model II with the convenience yield is negative and significant. For the remaining three markets, carbon, coal and crude oil, the convenience yield parameter is insignificant, indicating that the investors in these markets do not respond to the past convenience yield.

[Insert Table 4.8 here]

Table 4.8 shows the estimation results of Model III with the convenience yield. For the carbon and crude oil markets, both γ_1 and γ_2 are insignificant, implying that there is no feedback trading in these markets. For the remaining three markets, both parameters are significant. In the coal market, γ_1=-0.0127 and γ_2=0.0083. The results indicate that there is positive feedback trading when the convenience yield is zero, but the degree of positive feedback trading decreases as the convenience yield becomes larger. When the convenience yield is greater than 1.5301, it becomes negative feedback trading. Similarly, γ_1=-0.0003 and γ_2=0.00004 in the natural gas market. When the convenience yield is zero in the natural gas market, feedback investors buy more futures long positions when futures prices rise, but the degree of positive feedback trading diminishes and becomes zero when the convenience yield approaches 7.5000. Negative feedback trading occurs in the electricity market when the convenience yield is zero (γ_1=0.0008) and the degree of negative feedback trading increases as the convenience yield becomes greater (γ_2=0.0052). However, when the convenience yield decreases to -0.1538, it becomes positive feedback trading. It is also of interest that the γ_2 parameters in all five markets are positive (although some of them are insignificant). The results show that the degree of negative feedback trading increases or the degree of positive feedback trading decreases as the past convenience yield becomes larger. The results of Model III with the convenience yield and Model III with a basis are strongly consistent. The convenience yield also provides the threshold point for positive and negative feedback trading.

4.6.2. The effects of arbitrage opportunities on feedback trading across different market regimes

The above results thus provide evidence of feedback trading in some of the energy markets, and spot-futures dynamics have a significant impact on feedback trading. The results are consistent with the argument that the basis and convenience yield are related to arbitrage, hedging and other trading activities. However, the sample in this chapter contains both bull and bear market regimes for energy markets. Therefore, following Chau et al. (2011) , it is plausible to examine whether the relation between spot-futures dynamics and feedback trading changes across different market regimes. As shown in the International Monetary Fund and World Bank energy index, energy prices reached a historic peak in July 2008 and have declined since then.[32] For this reason, July 2008 was selected as the cut-off point for

[32] It is not surprising that commodity prices continued to rise after the current financial crisis occurred and stock markets collapsed. Generally speaking, commodities tend to perform well in periods of late expansion and early recessions, because interest rates are cut to boost economic activities when the economy is slowing down, and this could help to increase commodity prices (see Bodie and Rosansky, 1980).

bull and bear markets: the bull market occurred before July 2008 and the bear market happened after July 2008.

[Insert Table 4.9 and Table 4.10 here]

Model III with a basis and Model III with the convenience yield are re-estimated for bull and bear markets, following the same estimation procedure. The results of the robustness checks are summarised in Table 4.9 and Table 4.10. The robust results with a basis and convenience yield are consistent, i.e. the significance and direction of key parameters are identical. Compared with the main tests, the results for carbon and crude oil are consistent with the full sample results, in which both γ_1 and γ_2 are insignificant. For the coal market, the results of the bear market are consistent with the main tests, where γ_1 is negative and significant while γ_2 is positive and significant. The γ_1 of the bull market analysis is still negative and significant but γ_2 becomes insignificant. For the electricity market, the results of the bear market are consistent with the main tests, in which both γ_1 and γ_2 are positive and significant. The γ_1 of the bull market becomes negative and significant but γ_2 remains positive and significant. For the natural gas market, the results of the bull market are consistent with the main tests, in which γ_1 is negative and significant while γ_2 is positive and significant. The γ_1 of the bull market positive and significant but γ_2 is still positive and significant. In addition, two likelihood ratio tests are employed to examine the equality of the parameters in each market regime. LR1 is used to test the equality of γ_1 in each regime and LR2 is used to examine whether γ_2 is the same in a bear market as in a bull market. The Wald-test results show that the feedback trading parameters γ_1, γ_2 are different in each market regime in most of the cases. The different results in bull and bear markets are due to the potential regime switching in these markets.

4.7. Conclusion

Conventional feedback trading models assume that feedback investors trade based on past asset returns. Positive feedback traders purchase more assets after an increase in prices while negative feedback traders sell the asset following a price rise. Commodity markets, however, have long established futures markets along with spot markets. Many empirical studies show that the spot and futures markets are cointegrated and cross-market arbitrage is the main force maintaining the linkage between the two markets (MacKinlay and Ramaswamy, 1988). Arbitrage activity could push futures prices up and down and therefore arbitrage opportunities have some forecasting power for future price movements. For this reason, it is reasonable that some feedback traders not only trade based on past returns, but also pay attention to potential arbitrage opportunities, which can affect the profitability of a feedback trading strategy.

In order to understand how feedback traders respond to arbitrage opportunities, this chapter has developed and estimated several feedback trading models in which the feedback investors' demand for shares is not only depends on previous asset returns, but also on the potential arbitrage opportunities within the spot and futures markets. In particular, arbitrage opportunities can either affect feedback traders' demand in an additive way or in a multiplicative way.

Using recent daily spot and futures data for five emissions and energy markets and the spot-futures basis or convenience yield as the proxy for arbitrage opportunities, this study firstly finds that there is evidence of feedback trading in the coal and electricity markets, but not in the carbon, natural gas and crude oil markets. As most of the investors in the carbon market are institutions, these findings do not support the view that institutional investors contribute to feedback trading, which is not consistent with the common belief, expressed in

Nofsinger and Sias's (1999) study on the U.S. stock market, among others. Secondly, by adopting the spot-futures basis and convenience yield as proxies of arbitrage opportunities, the results show that arbitrage opportunities can affect feedback traders' demand in an additive way, in the electricity and natural gas markets. Thirdly, the results also suggest that arbitrage opportunities can indirectly influence the demand from feedback traders in the coal, electricity and natural gas markets, in a multiplicative way. Finally, this chapter also re-estimates the augmented feedback trading model using data from bull and bear markets, separately. The results show that the degrees of feedback trading to past returns and the effects of arbitrage opportunities on feedback trading are different across bull and bear market regimes.[33]

Overall, the above findings strongly support the claim that feedback traders also take potential arbitrage opportunities into consideration when they make investment decisions. The results in this chapter are important in understanding investors' trading behaviour and trading strategies in commodity markets, particularly the new carbon emission market, where there is no evidence of feedback trading and arbitrage opportunities cannot affect feedback trading. As almost all of the participants in the carbon emission markets are institutional investors, the results also contribute to the debate about whether or not institutional investors contribute to feedback trading.

[33] A summary of key results is presented in Appendix 4B.

Table 4.1: 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(common period)					
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: The table provides descriptive statistics of the emission and energy futures return series. LB(n) and $LB^2(n)$ are the Ljung-Box Q test of autocorrelation for the level and squared emission and energy futures returns; the test statistics follow Chi-squared distribution with n (number of lags) degrees of freedom. ARCH (n) is the Lagrange Multiplier (LM) test for the 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 significant at 1 %, 5 % and 10 % respectively.

Table 4.2: Descriptive statistics of emission and energy 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: The table provides descriptive statistics of the 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 modelled as:

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

Table 4.3: 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: The table shows the results of specification tests for a selection of GARCH models, including standard GARCH, EGARCH and GJR-GARCH. These models are specified as:

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

The most appropriate model is selected based on several criteria, including the value of the log likelihood function (Log L), heteroskedasticity-adjusted mean squared error (HMSE) and Akaike Information Criterion (AIC). For each criterion, the best model is highlighted in bold. The final GARCH specifications for each market are presented in the last column. “-” indicates that is not possible to get convergence results based on that model.

Table 4.4: Maximum likelihood estimates of the SW feedback trading model I

Parameters	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***	-0.009
	(-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)
v	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: The table shows maximum likelihood estimates of the baseline feedback trading model I (i.e. the original SW model) for the emission and energy futures markets. The conditional mean is specified as:

$R_t = \alpha + \rho\sigma_t^2 + (\gamma_0 + \gamma_1\sigma_t^2)R_{t-1} + \varepsilon_t$ (Equation 4.9)

The conditional variance equations are:

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 presumed to follow the Generalised Error Distribution (GED) with a scale parameter of ν. The values of the t-statistics for each parameter (presented in parentheses) are robust to autocorrelation and heteroskedasticity by adopting Bollerslev and Woodridge's (1992) robust standard errors. ***, ** and * denote statistically significant at 1 %, 5 % and 10 % respectively.

Table 4.5: Maximum likelihood estimates of feedback trading model II with basis

Parameters	Carbon (EGARCH)	Coal (GJR-GARCH)	Electricity (EGARCH)	Natural gas (EGARCH)	Crude oil (GJR-GARCH)
Panel A: conditional mean equation					
α	0.0048** (2.107)	0.0475** (2.022)	0.0248 (0.737)	0.0476*** (64.410)	0.1295*** (2.901)
ρ	0.0004 (0.106)	-0.0091 (-0.745)	-0.0095*** (-4.299)	-0.0098*** (-17.143)	-0.0090 (-0.822)
γ_0	0.0048 (0.754)	0.2415*** (10.598)	0.0008 (0.150)	0.0010 (1.260)	-0.0234 (-0.903)
γ_1	-0.0032 (-1.174)	-0.0078** (-2.078)	0.0005*** (9.889)	-0.0000 (-0.874)	-0.0050 (-0.977)
γ_2	0.2175 (0.246)	0.3558* (1.854)	-0.1558*** (-5.110)	-0.0023*** (-149.491)	0.0365 (0.075)
Panel B: conditional variance equation					
α_0	0.0554** (2.251)	0.0284*** (5.054)	0.0550* (1.740)	0.0869*** (7.193)	0.0605** (2.359)
α_1	0.2430*** (3.183)	0.1364*** (20.656)	0.2047*** (10.331)	0.2008*** (67.117)	0.0204** (2.203)
β	0.9727*** (81.106)	0.8708*** (181.365)	0.9761*** (39.372)	0.9770*** (483.135)	0.9414*** (64.231)
δ	-0.2818** (-2.550)	-0.0257** (-2.222)	0.0248 (0.121)	-0.2660*** (-25.459)	0.0452*** (3.111)
v	1.3195*** (14.855)	1.2306*** (24.599)	0.8590*** (14.357)	0.7385*** (24.633)	1.548*** (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: The table shows maximum likelihood estimates of the augmented SW feedback trading model II with a basis for the emission and energy futures markets. The conditional mean is specified as:

$$R_t = \alpha + \rho\sigma_t^2 + (\gamma_0 + \gamma_1\sigma_t^2)R_{t-1} + \gamma_2 Basis_{t-1}\sigma_t^2 + \varepsilon_t \quad \text{(Equation 4.12)}$$

The conditional variance equations are:

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 presumed to follow the Generalised Error Distribution (GED) with a scale parameter of ν. The values of the t-statistics for each parameter (presented in parentheses) are robust to autocorrelation and heteroskedasticity by adopting Bollerslev and Woodridge's (1992) robust standard errors. ***, ** and * denote statistically significant at 1 %, 5 % and 10 % respectively.

Table 4.6: Maximum likelihood estimates of feedback trading model III with basis

Parameters	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)
v	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: The table shows Maximum likelihood estimates of the augmented SW feedback trading model III with a basis for emission and energy futures markets. The conditional mean is specified as:

$$R_t = \alpha + \rho\sigma_t^2 + (\gamma_0 + \gamma_1\sigma_t^2 + \gamma_2 Basis_{t-1}\sigma_t^2)R_{t-1} + \varepsilon_t \quad \text{(Equation 4.15)}$$

The conditional variance equations are:

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 presumed to follow the Generalised Error Distribution (GED) with a scale parameter of v. The values of the t-statistics for each parameter (presented in parentheses) are robust to autocorrelation and heteroskedasticity by adopting Bollerslev and Woodridge’s (1992) robust standard errors. ***, ** and * denote statistically significant at 1 %, 5 % and 10 % respectively.

Table 4.7: Maximum likelihood estimates of feedback trading model II with convenience yield

Parameters	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)
v	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: The table shows maximum likelihood estimates of the augmented SW feedback trading model II with the convenience yield for emission and energy futures markets. The conditional mean is specified as:

$$R_t = \alpha + \rho\sigma_t^2 + (\gamma_0 + \gamma_1\sigma_t^2)R_{t-1} + \gamma_2 CY_{t-1}\sigma_t^2 + \varepsilon_t \quad \text{(Equation 4.22)}$$

The conditional variance equations are:

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 presumed to follow the Generalised Error Distribution (GED) with a scale parameter of v. The values of the t-statistics for each parameter (presented in parentheses) are robust to autocorrelation and heteroskedasticity by adopting Bollerslev and Woodridge’s (1992) robust standard errors. ***, ** and * denote statistically significant at 1 %, 5 % and 10 % respectively.

Table 4.8: Maximum likelihood estimates of feedback trading model III with convenience yield

Parameters	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)	0.00004*** (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)
v	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: The table shows maximum likelihood estimates of the augmented SW feedback trading model III with the convenience yield for emission and energy futures markets. The conditional mean is specified as:

$$R_t = \alpha + \rho\sigma_t^2 + (\gamma_0 + \gamma_1\sigma_t^2 + \gamma_2 CY_{t-1}\sigma_t^2)R_{t-1} + \varepsilon_t \text{ (Equation 4.23)}$$

The conditional variance equations are:

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 presumed to follow the Generalised Error Distribution (GED) with a scale parameter of v. The values of the t-statistics for each parameter (presented in parentheses) are robust to autocorrelation and heteroskedasticity by adopting Bollerslev and Woodridge's (1992) robust standard errors. ***, ** and * denote statistically significant at 1 %, 5 % and 10 % respectively.

Table 4.9: Robustness checks results of model III with basis

Parameters	Bull Market					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	0.4776*** (5.937)	0.0751* (1.690)	0.0867*** (18.251)	0.0467*** (83.348)	0.1669 (0.235)	-0.0043 (-0.191)	0.0069 (0.196)	0.0874*** (8.310)	-0.0346*** (-7.517)	0.0789 (0.862)
ρ	-0.0831*** (-72.253)	0.0287*** (6.720)	-0.0130*** (-36.058)	-0.0110*** (-446.346)	0.0017 (0.008)	-0.0001 (-0.011)	-0.0043 (-0.230)	-0.0469*** (-11.793)	-0.0067*** (-8.637)	-0.0084 (-0.349)
γ_0	0.0056 (0.074)	0.2570*** (12.356)	0.0321*** (95.805)	0.0985*** (196.299)	0.0332 (0.292)	0.0079 (0.989)	0.2403*** (6.769)	-0.0409* (-1.934)	-0.0482*** (-78.476)	0.0265 (0.684)
γ_1	-0.0092 (-1.475)	-0.0203*** (-4.224)	-0.0002*** (-12.319)	-0.0009*** (-187.517)	-0.0287 (-0.925)	-0.0037* (-1.809)	-0.0115*** (-2.784)	0.0162*** (35.415)	0.0031*** (9.336)	-0.0063 (-1.620)
γ_2	-0.0522 (-1.199)	-0.0316 (-1.534)	0.0264*** (220.960)	0.0002*** (363.464)	0.2788 (1.259)	0.0542 (0.211)	0.0852** (2.496)	0.1363*** (2.615)	0.0064*** (7.130)	0.0019 (0.047)
Panel B: conditional variance equation										
α_0	0.2961* (1.674)	0.0676** (2.136)	0.1344*** (190.588)	0.2779*** (912.242)	0.1462 (0.715)	0.0514** (2.464)	0.0249** (2.545)	0.0338 (1.556)	0.0369** (2.150)	0.0466 (0.114)
α_1	0.4009*** (5.777)	0.2204*** (5.347)	0.3097*** (31.075)	0.3670*** (222.132)	0.0201 (1.895)*	0.2375*** (3.464)	0.1161*** (11.377)	0.1485*** (5.153)	0.1706*** (7.545)	0.0103 (0.655)
β	0.7795*** (6.097)	0.8047*** (18.742)	0.9566*** (819.173)	0.9222*** (1302.311)	0.9252*** (12.581)	0.9756*** (100.669)	0.8771*** (112.780)	0.9813*** (50.177)	0.9896*** (203.004)	0.9411*** (32.815)
δ	-0.3510* (-1.743)	-0.0706*** (-3.408)	-0.2263*** (-52.147)	-0.3881*** (-143.684)	0.0286 (0.863)	-0.2927*** (-2.639)	-0.0004 (-0.014)	0.1718 (0.369)	-0.2689** (-2.541)	0.0732*** (2.661)
v	1.6130*** (5.053)	1.1537*** (12.448)	0.7838*** (31.110)	0.6576*** (46.885)	1.7200*** (14.503)	1.2943*** (15.759)	1.250*** (18.014)	0.9073*** (22.795)	0.9741*** (16.197)	1.3754*** (14.457)
Panel C: likelihood ratio tests										
LR1	-	-	-	-	-	7.475***	8.349***	1285.321***	144.494***	33.133***
LR2	-	-	-	-	-	0.171	10.820***	4.447**	47.727***	48.807***

Table 4.9 (Continued)

Parameters	Bull Market					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										
$E(Z_t)$	-0.036	0.031	0.099	0.067	-0.006	-0.036	-0.006	0.057	0.049	-0.020
$E(Z^2_t)$	0.982	1.000	1.013	1.453	0.998	0.996	1.007	1.107	1.115	1.001
LB(12)	22.042***	6.636	17.970**	9.812	4.864	11.213	11.824	13.064	27.274***	8.233
$LB^2(12)$	6.803	3.204	2.112	3.665	16.864	5.074	12.968	2.890	3.198	14.930
ARCH(12)	7.031	2.872	2.156	4.208	17.500	4.776	13.638	2.929	3.159	14.361
JOINT	2.706	3.019	2.106	0.314	17.819***	2.150	2.428	8.945**	4.113	15.990***

Notes: The table shows maximum likelihood estimates of the augmented SW feedback trading model III with a basis for emission and energy futures markets, across different market regimes. The turning point from bull market to bear market is July, 2008. The bull market is defined as the market before 31 July 2008 and bear market is the market after July 2008. The conditional mean is specified as:

$$R_t = \alpha + \rho\sigma_t^2 + (\gamma_0 + \gamma_1\sigma_t^2 + \gamma_2 Basis_{t-1}\sigma_t^2)R_{t-1} + \varepsilon_t \quad \text{(Equation 4.15)}$$

The conditional variance equations are:

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 presumed to follow the Generalised Error Distribution (GED) with a scale parameter of ν. The values of the t-statistics for each parameter (presented in parentheses) are robust to autocorrelation and heteroskedasticity by adopting Bollerslev and Woodridge's (1992) robust standard errors. LR1 is the likelihood ratio test for the equality of γ_1 in each market regime and LR2 is the test for the equality of γ_2 in bull and bear markets. ***, ** and * denote statistically significant at 1 %, 5 % and 10 % respectively.

Table 4.10: Robustness checks results model III with convenience yield

Parameters	Bull Market					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	0.4878**	0.0753*	0.0722***	0.0299***	0.2884	-0.0057	0.0079	0.1080***	-0.0333***	0.0918
	(2.486)	(1.860)	(16.594)	(706.041)	(0.461)	(-0.227)	(0.242)	(14.324)	(-15.896)	(0.995)
ρ	-0.0877	0.0287***	-0.0098***	-0.0074***	-0.0361	-0.0005	-0.0051	-0.0573***	-0.0069***	-0.0131
	(-1.383)	(3.446)	(-47.423)	(-58.493)	(-0.200)	(-0.064)	(-0.364)	(-38.552)	(-44.818)	(-0.555)
γ_0	0.0206	0.2583***	0.0303***	0.0790***	0.0276	0.0092	0.2419***	-0.0370***	-0.0477***	0.0284
	(0.040)	(139.026)	(64.712)	(101.711)	(0.238)	(0.261)	(9.960)	(-262.204)	(-116.127)	(0.816)
γ_1	-0.0052	-0.0203***	-0.0004***	-0.0005***	-0.0286	-0.0037	-0.0115***	0.0164***	0.0032***	-0.0067
	(-0.436)	(-40.681)	(-4.466)	(-53.254)	(-0.957)	(-0.961)	(-4.288)	(93.560)	(40.091)	(-1.645)
γ_2	-0.2528	-0.0032	0.0020***	0.0000	0.0196	0.0160	0.0079***	0.0021**	0.0005***	-0.0016
	(-0.096)	(-1.483)	(144.546)	(0.069)	(0.847)	(0.4487)	(2.7875)	(2.145)	(186.894)	(-0.327)
Panel B: conditional variance equation										
α_0	0.3124	0.0676*	0.14112***	0.300***	0.1659	0.0510**	0.0249***	0.0387***	0.371***	0.0460**
	(0.565)	(1.816)	(62.868)	(81.749)	(0.4126)	(2.217)	(3.159)	(34.744)	(34.378)	(2.001)
α_1	0.3889**	0.2202***	0.3083***	0.3886***	0.0219	0.2361***	0.1159***	0.1651***	0.1714***	0.0104
	(2.294)	(8.772)	(11.994)	(33.088)	(0.651)	(3.050)	(4.525)	(12.969)	(27.437)	(0.753)
β	0.7671***	0.8048***	0.9535***	0.9152***	0.9175***	0.9756***	0.8772***	0.9789***	0.9895***	0.9412***
	(3.001)	(19.085)	(867.714)	(1968.260)	(12.786)	(88.978)	(47.166)	(5983.324)	(548.652)	(48.778)
δ	-0.3614	-0.0705***	-0.2345***	-0.3564***	0.0294	-0.2934***	-0.0001	0.0777***	-0.2656***	0.0731***
	(-0.735)	(-2.959)	(-15.648)	(-25.951)	(0.651)	(-3.091)	(-0.005)	(4.999)	(-3.658)	(3.386)
v	1.5833**	1.1538***	0.7810***	0.6547***	1.7074***	1.301***	1.2507***	0.9131***	0.9740***	1.3744***
	(2.179)	(12.484)	(21.784)	(48.946)	(14.578)	(12.891)	(18.094)	(21.407)	(29.563)	(17.381)
Panel C: likelihood ratio tests										
LR1	-	-	-	-	-	0.276	9.737***	9184.956***	2144.525***	28.403***
LR2	-	-	-	-	-	56.951***	14.145***	0.004	34929.384***	18.436***

Table 4.10 (Continued)

Parameters	Bull Market					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										
$E(Z_t)$	-0.036	0.031	0.109	0.064	-0.006	-0.036	-0.007	0.056	0.048	-0.020
$E(Z^2_t)$	0.982	1.000	1.047	1.455	0.999	0.996	1.007	1.107	1.115	1.001
LB(12)	21.745***	6.613	18.011**	10.606	5.052	10.851	11.914	12.990	27.062***	8.261
$LB^2(12)$	7.014	3.200	2.177	3.497	17.286	5.080	13.225	3.024	3.180	14.901
ARCH(12)	7.185	2.868	2.246	3.990	17.859	4.785	13.883	3.056	3.140	14.318
JOINT	2.480	3.021	2.649	0.691	16.945***	2.242	2.481	9.131**	4.100	16.009***

Notes: The table shows maximum likelihood estimates of the augmented SW feedback trading model III with the convenience yield for emission and energy futures markets, across different market regimes. The turning point from bull market to bear market is July, 2008. The bull market is defined as the market before 31 July 2008 and the bear market is after July 2008. The conditional mean is specified as:

$$R_t = \alpha + \rho\sigma_t^2 + (\gamma_0 + \gamma_1\sigma_t^2 + \gamma_2 CY_{t-1}\sigma_t^2)R_{t-1} + \varepsilon_t \quad \text{(Equation 4.23)}$$

The conditional variance equations are:

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 presumed to follow the Generalised Error Distribution (GED) with a scale parameter of ν. The values of the t-statistics for each parameter (presented in parentheses) are robust to autocorrelation and heteroskedasticity by adopting Bollerslev and Woodridge's (1992) robust standard errors. LR1 is the likelihood ratio test for the equality of γ_1 in each market regime and LR2 is the test for the equality of γ_2 in bull and bear markets. ***, ** and * denote statistically significant at 1 %, 5 % and 10 % respectively.

Appendix 4A: An overview of related literature on arbitrage opportunities and feedback trading

In addition to the literature summarised in Section 4.2, this chapter conducts a comprehensive review of the relevant literature, presented in Table 4A.1. This includes the empirical tests for feedback trading in various financial markets using the SW feedback trading model (Panel A); theoretical extensions of the original SW model (Panel B); why arbitrage is important in futures markets (Panel C); the performances of technical trading rules other than feedback trading (e.g. momentum or contrarian strategies) in commodity markets (Panel D); and the importance and usefulness of arbitrage opportunities measured by the spot-futures basis or convenience yield (Panel E). The literature shows why this chapter examines feedback trading in commodity markets and what the linkage is between arbitrage opportunities and feedback trading.

Table 4A.1: Summary of literature on arbitrage opportunities and feedback trading

Panel A: Empirical tests of SW feedback trading model in financial markets	
Papers	Key or relevant arguments
Koutmos (1997)	Provides additional evidence of feedback trading in some developed stock markets, including Australia, Belgium, Germany, Italy, Japan and UK. Note: Sentana and Wadhwani (1992) only study the U.S. market.
Aguirre and Saidi (1999)	Studies feedback trading of exchange rates within and across three economics areas: EU; ASEAN (southeast Asia); and NAFTA (north America). No feedback trading is found across economic areas, but provides evidence of feedback trading within ASEAN area.
Koutmos and Saidi (2001)	Provides empirical evidence of positive feedback trading in emerging markets, including HK, Malaysia, Philippines, Singapore, Taiwan and Thailand.
Watanabe (2002)	Provides evidence of positive feedback trading in Japan. Adjusts the empirical model by allowing asymmetric feedback trading parameter, i.e., for positive and negative past returns, there are different feedback trading parameters or sensitivity of feedback traders’ demand to the last period’s return.
Laopodis (2005)	Tests feedback trading in exchange rates of 17 industrial and emerging currencies with respect to USD or Euro.

Antoniou et al. (2005)	Tests feedback trading in major stock spot indexes before and after the introduction of index futures and compares the difference. The empirical results support the view that the futures markets stabilise the spot markets as feedback trading in spot markets disappeared after the introduction of futures markets. Finds no evidence of feedback trading in futures markets.
Bohl and Reitz (2006)	Provides evidence of positive feedback trading in Germany's Neuer market (young company market).
Chau et al. (2008)	Investigates the impact of the introduction of Universal Stock Futures on the underlying level of feedback trading in UK.
Dean and Faff (2008)	Provides empirical extension of feedback trading model by allowing Markov switching in the conditional mean equation, using Australian Equity and bond market data.
Bohl and Siklos (2008)	Provides evidence of feedback trading in both emerging and mature stock markets.
Laopodis (2008)	The paper is similar to Laopodis' (2005), but adds some variance specification tests and robustness tests.
Schuppli and Bohl (2010)	Compares the level of feedback trading in China's A share and B share markets.
Salm and Schuppli (2010)	Provides empirical tests of positive feedback trading in 32 emerging and mature index futures markets.

Antoniou (2011)	Provides evidence of feedback trading from major index futures markets.
Panel B:Theoretical extension of SW feedback trading model	
Faff et al. (2005)	Extends the SW feedback trader model by including a cross-market feedback trader. Feedback traders are then divided into two groups: "own-market" feedback traders who respond to past own markets returns; and "cross-market" feedback traders who respond to the past returns of other related markets.
Cifarrelli and Paladino (2010)	Provides evidence of positive feedback trading in oil markets. Extends the SW model by using Merton's (1973) ICAPM instead of conventional CAPM. Thus the "smart money" investors' risk premium does not only depend on systematic risk but also other "state variables". The feedback trading model is then transformed from a univariate model to a multivariate model. However, this does not significantly extend the feedback trading model; instead, it extends the rational CAPM model.
Dean and Faff (2011)	Introduces a similar extension to that of Cifarrelli and Paladino (2010). SW model is extended to a multivariate framework, and the two variables used are equity and bond returns.
Chau et al. (2011)	Extends the SW model by allowing investor sentiment to affect feedback traders' demand function, in both an

	additive way and a multiplicative way.
Koutmos (2012)	Extends the SW feedback trader model by including a group of fundamental traders, whose demand function depends on the difference between market prices and fundamental prices.
Panel C: Papers about the importance of arbitrage in futures market	
Garbade and Silber (1983)	"Risk transfer and price discovery are two of the major contributions of futures markets to the organization of economic activity (Working (1962), Evans (1978, p. 80), and Silber (1981))." Risk transfer is connected to hedging and price discovery is related to arbitrage.
Working (1984)	Continuous effectiveness of arbitrage between cash and futures prices is the driving force behind price discovery.
MacKinlay and Ramaswamy (1988)	"It is generally agreed that linkage in prices between the underlying basket of stocks and the futures is maintained by arbitrageurs".
Panel D: Papers about momentum/contrarian strategies in commodity markets	
Wang and Yu (2004)	Studies the short-horizon (1-8 weeks) return predictability in 24 U.S futures, including financial, currency and commodity markets. The results provide strong evidence of futures returns reversals over the 1-week horizon. However, further examination of return predictability for holding horizons spanning from 2 to 8 weeks shows no

	evidence of contrarian profits.
Pirrong (2005)	Provides evidence of short-run momentum (less than 3-months) and long-run reversal (more than 1 year) in futures markets, including both U.S. and international, and both financial and commodity futures. Futures momentum is related to, but not subsumed by, equity momentum.
Shen, Szakmary and Sharma (2007).	Finds momentum profit in 28 commodity futures markets in the U.S. from 2-month up to 9-month holding periods. The profit is large enough to account for transaction costs and the market factor model. Reversal happens after 24-month horizon, but the profitability of the contrarian strategy is not significant.
Miffre and Rallis (2007)	The paper studies the profitability of 56 momentum (<=1 year) and contrarian strategies (> 1 year) in U.S. commodity futures markets. It finds 13 profitable momentum strategies with an average return of 9.38% p.a., but no profitable contrarian strategy. The authors argue that, "momentum strategy is related to the backwardation and contango theories. The results indicate that the momentum strategy is to buy backwardated contracts and sell contangoed contracts". Contango and backwardation are related to basis.

Marshall et al. (2008)	Examines the profitability of 7846 technical trading strategies in 15 commodities in the U.S. market using robust statistics. These rules are divided into five groups: filter rules (similar to feedback trading); moving average rules; support and resistance rules, channel breakouts; and on-balance volume rules. The results indicate there is evidence that certain rules generate profits, but the statistical significance of these profits disappears once the data-snooping bias is accounted for.
Fuertes, Miffre and Rallis (2010)	Firstly, provides evidence of the profitability of using the momentum strategy and term structure signal rules in U.S. commodity markets, separately. Finds that combining the two strategies can generate much higher abnormal returns than a single strategy. The results cannot be explained by illiquidity, transaction costs or data mining.
Panel E: Papers about arbitrage proxies, i.e. the basis and convenience yield	
Khoury and Martel (1989)	Theoretically proves that "the basis is positively correlated with the average future change in spot prices and negatively correlated with that of futures prices".
Khoury and Yourougou (1991)	Provides empirical evidence for Khoury and Martel's (1989) model.
Kumar and Seppi (1994)	Claims that naïve comparison of spot and index futures prices (i.e. looking at the basis) could suggest arbitrage

	opportunities.
Sofianos (1993)	Argues that when spot-futures basis is wide enough, arbitragers exploit this arbitrage opportunity and it can be profitable.
Miller et al. (1994)	Claims that arbitrage strategy for index futures is as follows: “when the basis widens beyond its theoretical level, arbitragers simultaneously sell index futures and buy the index portfolio, pulling the difference between the futures and index”.
Chartrath, Christie-David, Dhanda and Koch (2002)	Provides empirical evidence to show that there is a positive relationship between basis and futures return volatility.
Roll, Schwartz and Subrahmanyam (2007)	Produces empirical evidence to show that there is two-way Granger causality between the short-term absolute basis and liquidity (measured by quoted and effective spread), and that liquidity Granger-causes longer-term absolute basis.
Lien and Yang (2008)	Shows importance of incorporating the dynamics of basis into hedging decisions since Working (1953, 1961), but only in the mean equation level. Argues that basis also has an asymmetric effect on the variance and covariance structure, and hence affects the minimum variance hedge ratios. Also provides empirical support for the new hedging model.

Kogan, Livdan and Yaron (2009)	Provides a theoretical model showing that there is a V-shaped relationship between oil futures price volatility and the slope of the forward curve (like the basis).
Gorton et al. (2013)	Provides empirical evidence suggesting that the futures risk premium (expected excess return) is related to the basis.
Mellios and Six (2011)	Provides a theoretical model showing that the hedging demand for futures contracts is uniquely related to the estimate of the convenience yield.
Knetsch (2007)	Forecasts oil prices through present value model. Convenience yield prediction outperforms the approach which uses futures prices as direct predictors of future spot prices.
Godbey and Hilliard (2007)	Claims that convenience yield in hedge ratio determination can help to improve the hedging performance of staked hedge.
Bertus Godbey and Hilliard, (2009)	Provides simulations whose empirical results show that horizon-sensitive hedging models using stochastic convenience yields systematically outperform other hedging strategies, especially for longer horizons.

Appendix 4B: Summary of Key Results

In order to observe and compare the empirical results in this chapter comprehensively and intuitively, this chapter summarises all the key results from Table 4.4 to Table 4.10 in this appendix. Parameter estimates and t-statistics are shown in Table 4B.1. ***, ** and * denote that an item is statistically significant at 1%, 5% and 10% respectively. The key parameters are γ_1, which governs the response of feedback traders to the last period's returns, and γ_2, which shows the sensitivity of feedback traders to the arbitrage opportunities in the last period, in an additive or a multiplicative ways.

Table 4B.1: Summary of feedback trading coefficients estimates in Table 4 to Table 10

Parameters	Carbon (EGARCH)	Coal (GJR-GARCH)	Electricity (EGARCH)	Natural gas (EGARCH)	Crude oil (GJR-GARCH)
Model I					
γ_1	-0.0033 (-0.971)	-0.0093** (-2.020)	0.0009*** (28.966)	-0.0002 (-1.336)	-0.0054* (-1.713)
Model II Basis					
γ_1	-0.0032 (-1.174)	-0.0078** (-2.078)	0.0005*** (9.889)	-0.0000 (-0.874)	-0.0050 (-0.977)
γ_2	0.2175 (0.246)	0.3558* (1.854)	-0.1558*** (-5.110)	-0.0023*** (-149.491)	0.0365 (0.075)
Model II CY					
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)
Model III Basis					
γ_1	-0.0033 (-0.751)	-0.0132*** (-3.274)	0.0009*** (19.289)	-0.0001*** (-25.101)	-0.0050 (-1.279)
γ_2	0.0034 (0.010)	0.0913** (2.515)	0.0595*** (26.703)	0.0005*** (72.152)	0.0262 (0.569)
Model III CY					
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)	0.00004*** (188.229)	0.0000 (0.004)
Model III Basis Bull					
γ_1	-0.0092 (-1.475)	-0.0203** (-4.224)	-0.0002** (-12.319)	-0.0009** (-187.517)	-0.0287 (-0.925)
γ_2	-0.0522 (-1.199)	-0.0316 (-1.534)	0.0264** (220.960)	0.0002** (363.464)	0.2788 (1.259)
Model III Basis Bear					
γ_1	-0.0037 (-1.809)	-0.0115*** (-2.784)	0.0162*** (35.415)	0.0031*** (9.336)	-0.0063 (-1.620)
γ_2	0.0542 (0.211)	0.0852** (2.496)	0.1363*** (2.615)	0.0064*** (7.130)	0.0019 (0.047)
Model III CY Bull					
γ_1	-0.0052 (-0.436)	-0.0203*** (-40.681)	-0.0004*** (-4.466)	-0.0005*** (-53.254)	-0.0286 (-0.957)
γ_2	-0.2528 (-0.096)	-0.0032 (-1.483)	0.0020*** (144.546)	0.0000 (0.069)	0.0196 (0.847)
Model III CY Bear					
γ_1	-0.0037 (-0.961)	-0.0115*** (-4.288)	0.0164*** (93.560)	0.0032*** (40.091)	-0.0067 (-1.645)
γ_2	0.0160 (0.4487)	0.0079*** (2.7875)	0.0021** (2.145)	0.0005*** (186.894)	-0.0016 (-0.327)

Chapter 5

The impact of allowance submission in the European carbon emission markets

Abstract

This chapter studies the impact of the allowance submission deadline (on 30 April every year), set by the European Union emission trading scheme (EU ETS), on the relationship between spot and futures markets in the European carbon markets. Specifically, utilising high-frequency data from the second phase of the EU ETS, this study examines whether the mean-reverting process of the carbon spot and futures relationship, price discovery and volatility spillovers of the carbon spot and futures markets are different before and after the submission deadline. The results suggest that the spot and futures price are cointegrated before and after the submission deadline, which shows that the mixed results found for the cointegration relationship in previous studies are not due to the allowance submission. However, the equilibrium level, adjustment speed and no-arbitrage boundaries of the spot and futures relationship shift after the submission deadline, implying that there is a change in the mean-reverting process. In addition, the results also show that the allowance submission deadline does not have a significant influence on the price discovery process of the European carbon markets, in which both the spot and futures markets Granger-cause each other.

Furthermore, by using the heterogeneous autoregressive (HAR) realised volatility model, it is found that there is a change in volatility spillovers after the submission deadline, particularly from the spot market to the futures market. Finally, the above findings are robust to different intraday time frequencies. The results suggest that, when modelling the relationship between carbon spot and futures prices, the change in the mean-reverting process of the carbon spot and futures relationship and volatility spillovers between spot and futures markets before and after the submission deadline should be taken into account.

5.1. Introduction

Carbon emission markets, which are designed to reduce emissions of global greenhouse gases (GHGs), have experienced rapid ongoing development even during the recent recession and have attracted considerable attention from policy makers and investors. Accounting for 83% of global carbon markets' value, the European carbon markets under the European Union emission trading scheme (EU ETS) is the most influential and successful emission trading market in the world (World Bank, 2010). The financial instruments traded in the carbon emission markets are known as carbon allowances. According to the EU ETS regulations, 30 April of the year succeeding the year when the emissions occur is the last date for operating firms to submit their carbon allowances. This date is also known as the submission deadline for the European carbon emission markets. After the submission, the carbon allowances surrendered to the EU are no long available to trade in the markets. Therefore the inventory level of carbon allowances in the markets decreases significantly after the submission deadline each year. The inventory level is related to the costs and constraints of arbitrage. Firstly, it has been argued that market markers require additional compensation for inventory risk (e.g, Ho and Stoll, 1981; Biais, 1993). A high inventory level will lower the inventory risk and narrow down the bid-ask spread. Therefore the transaction costs of arbitrage activities are lower in a high inventory state. Secondly, it is easier for arbitragers to borrow and short-sell financial assets when the inventory level is higher. For the above reasons, arbitragers in the European carbon markets are expected to behave differently before and after the submission deadline each year, causing a shift in the pattern of the mean-reverting process of carbon futures mispricing derived from the cost-of-carry model.

[Insert Figure 5.1 here]

Figure 5.1 displays the time series of carbon futures mispricing, i.e. the logarithmic difference between the observed futures prices and the theoretical futures (also known as the basis) at the frequency of 15 minute intervals. It can be observed that the patterns of the time series before the submission deadline of 30 April differ from those after the deadline, at least in 2009 and 2011. In particular, the graph in Figure 5.1, Panel C (year 2011), clearly shows that, except for several outliers, the observed futures prices are persistently higher than the theoretical futures prices by around 2%-8% before 04/05/2011, which is the first trading day after the submission deadline of 30/04/2011. By contrast, the futures mispricing hovers just above and below zero after 04/05/2011. This implies that there may be a change in the time series characteristics of carbon futures mispricing after the submission deadline and provides a strong motivation for examining the impact of allowance submission on the time series dynamics of carbon emission markets. Therefore, this chapter aims to investigate the time series properties of the carbon spot and futures relationship before and after the submission deadline and compare the differences.

In particular, the first objective of this chapter is to examine the impact of the submission deadline on the mean-reverting process of the carbon futures mispricing. Some previous papers have studied whether the cost-of-carry relationship holds between the carbon spot and futures prices and they have produced mixed results (e.g. Uhrig-Homburg and Wagner, 2009; Joyeux and Milunovich, 2010; Chevallier, 2010; Rittler, 2012). However, these papers do not take the impact of allowance submission into account. The mixed results for the cost-of-carry relationship may be due to the effects of allowance submission. Therefore, it is important to compare the mean-reverting characteristics of the spot and futures relationship before and after the submission deadline.

Secondly, the submission of allowances may also have an influence on the transmission of information between spot and futures markets. The EU ETS regulations require firms that fail to surrender enough carbon allowances by the deadline to pay a heavy penalty (see Section 5.2 for details). Therefore, operating firms which have insufficient carbon allowances in-hand want to acquire the uncovered allowances in the spot market before the submission deadline in order to avoid the penalty. For this reason, trading activities in the spot market are likely to be more active before the submission deadline than after. In addition, it is possible that the spot market responds to new information more quickly than futures market before the submission deadline, due to the active trading in the spot market. This may change the underlying data generation process (DGP) of the carbon allowance prices after the submission deadline. Rittler (2012) studies the price discovery and volatility spillovers of the European carbon markets and finds that the futures market incorporates new information first and transmits it to the spot market afterwards. However, the paper ignores the potential impact of allowance submission, which may cause distinct information transmission processes before and after the submission deadline. This leads to the second purpose of this chapter, which is to examine whether the transmission of information between the spot and futures markets before the submission deadline is different before and after the submission deadline. This involves examining the first and second moments of information transmission, i.e. the price discovery process, and volatility spillovers.

Overall, this chapter represents the first attempt to examine the impact of the allowance submission deadline on carbon emission markets. It contributes to the existing literature in a number of respects. Firstly, few studies, if any, have studied the mean-reverting properties of the carbon spot and futures relationship. Therefore, this constitutes the first attempt to study the mean-reverting process of the relationship in the European carbon markets and the effects of allowance submission on the process. The results obtained are important for understanding arbitrage activities in the European carbon markets at market microstructure level, and will also help to shed light on the mixed results for the cost-of-carry relationship between spot and futures prices found in previous studies. Secondly, this chapter is the first to incorporate the impact of allowance submission into the examination of the causal relationship between spot and futures returns in the European carbon markets. Thirdly, this study also examines whether the submission of allowances has an impact on the volatility spillovers between the spot and futures markets, for the first time. This study differs from Rittler's (2012) investigation of the volatility spillovers in the European carbon emission markets by considering the impact of the allowance submission deadline and by using realised volatility instead of conditional volatility, which is preferable, as previous studies have shown that the realised measure of volatility is model-free and performs well in out-of-sample forecasting (e.g. Andersen, Bollerslev, Diebold and Labys, 2003). Chevallier and Sevi (2011) support the merit of using realised volatility in carbon emission markets.

This study employs tick-by-tick order flow data for spot and futures contracts in the leading European carbon exchanges. In order to examine the mean-reverting properties of the spot and futures relationship, this chapter adopts a series of cointegration tests, ranging from the standard augmented Dickey-Fuller (ADF) test to threshold models and smooth-transition models. The smooth-transition model enables not only the speed of adjustment to be examined but also the no-arbitrage boundaries. In order to analyse information transmission, Granger causality tests are used for price discovery and the heterogeneous autoregressive (HAR) model is employed for the realised volatility spillovers. All the above models are augmented with dummy variables which account for the effects of allowance submission.

The results of this chapter show that there is a cointegration relationship between spot and futures price before and after the submission deadline, which suggests that the mixed results found for the cointegration relationship in previous studies is not due to the allowance submission. More importantly, it is found that the long-run equilibrium level, the speed of adjustment, and the upper and lower bands of the no-arbitrage area all change after the submission deadline. Therefore, the mean-reverting process of the spot and futures relationship is different before and after the deadline. The findings are consistent with the hypothesis that arbitrage behaviours alter because of the submission of allowances. The above effects are prominent in 2009 and 2011, but not very significant in 2010. This is because the financial crisis made industrial production in the EU drop significantly in 2009, causing an unexpectedly sharp decrease in carbon emissions in the EU in the same year. According to World Bank (2012), carbon emissions in the EU decreased by 11% from 2008 to 2009, following a 15% reduction in industrial production in the same period. As firms emitted less than the excepted amount in 2009, they had sufficient carbon allowances to surrender by 30/04/2010 and thus did not need to trade in the carbon market before the submission deadline. Therefore the impact of allowance submission in 2010 was not very significant.[34] Industrial productions and carbon emission in the EU recovered to previous levels in 2010; therefore the impact of allowance submission in 2011 is significant. Moreover, the results of Granger causality tests reveal that the causal relation between spot and futures returns in the European carbon markets does not shift significantly after the submission deadline each year. Spot and futures returns generally Granger-cause each other, which is in line with Rittler’s (2012) claims. However, the values of the F-test statistics indicate that the spot market leads the futures markets in the periods before the submission deadline but the futures market leads the spot market after the deadline. Nonetheless, in terms of volatility spillovers, the results of the bivariate HAR model using realised volatility show that the volatility spillovers between spot and futures markets are significantly different before and

[34] For further details of the explanations, please see the last paragraph of Section 5.4.1.

after the submission deadline, particularly from the spot market to the futures market. This supports the assertion that trading activities in the spot market should be more active before the submission deadline than after, and therefore new information may be incorporated into the dynamics of volatility in the spot market first during the periods before the deadline. The effects of allowance submission on volatility spillovers are also more significant in 2009 and 2011 than in 2010. The results of the HAR model also suggest that volatility spillovers from the futures market to the spot market are only significant in the periods after the submission deadline. However, Rittler's (2012) results show that volatility spillovers are significant from the futures market to the spot market but not vice versa. This is because the author ignores the impact of allowance submission and uses the conditional measures of volatility instead of realised measures. All the above findings are robust to different intraday time frequencies.

The remainder of the chapter is organised as follows. Section 5.2 introduces the key elements of the EU ETS, and the submission deadline in particular. Section 5.3 briefly reviews the related literature. Section 5.4 describes how to construct the intraday spot and futures price series, and the estimation methodology of futures mispricing, as well as presenting the summary statistics of mispricing. Section 5.5 explains the methodology employed in this chapter, analyses the empirical results and provides robustness checks. The findings are summarised and conclusions presented in Section 5.6.

5.2. The European Union emission trading scheme and the submission deadline

The EU ETS was launched in 2005 to comply with the Kyoto Protocol, which requires industrial countries and countries in transition covered by the protocol to reduce their collective greenhouse gas emissions by 5.2% of the level reached in 1990 before 2012

(UNFCCC, 1997).[35] In order to reduce emissions efficiently and economically, the EU ETS developed a "cap-and-trade" system. Under this system, central authorities set up a standard or "cap" on the total amount of greenhouse gases that a country or region is allowed to emit within a year. The authorities then allocate the allowance of emission units, which is the right to emit a certain amount of GHGs. Firms' GHGs emission should not exceed the allocated allowance represented by their in-hand allowances; otherwise they must deliver the missing carbon allowances in the next year and also pay a heavy penalty. The total amount of allowances should not exceed the cap. Consequently, the total amount of emissions can be controlled and kept under a target level. If a company needs to emit more than its allocated allowance, it can buy carbon allowances from another company which has some emission allowances remaining. According to the Coase theorem (Coase, 1937, 1960), under the assumption of zero transaction costs, and if the authorities allocate and protect the rights of allowance holders very effectively, the "cap-and-trade" system can completely solve the externalities problem of market failure. Because the carbon emission markets are futures-dominated markets and always a sub-market of energy exchanges, carbon allowances are commonly viewed as a special type of commodities.

By adopting the "cap-and-trade" mechanism, the total value of European Union allowances (EUAs)[36] transactions has risen to 118.5 billion U.S. dollars with an 18% growth rate, which is considerably faster than the growth rate of the global carbon markets (World Bank, 2010). Accounting for 83% of the market value of global carbon emission markets, the EU ETS is the most influential and successful emission trading programme in the world. The firms covered by the EU ETS comprise approximately 12,000 installations which have a net

[35] There are 41 countries defined as industrialised countries and countries in transition under the Kyoto Protocol. See UNFCCC (1997) for details.

[36] EUA is the carbon allowance traded under EU ETS.

generating capacity of more than 20 megawatts (MW) in 28 countries in the EU and 3 non-EU European countries (Iceland, Liechtenstein and Norway). The sectors included are power stations, mineral or oil refineries, ferrous metal, glass production, coke ovens, ceramic productions, cement manufactures and the aviation industry which joined in 2012. All the operators which hold allowances and trade in carbon allowances are registered in the EU ETS Transaction Log. The data shows that less than 6% of total accounts were personal holding accounts (2,050 out of a total of 34,492 accounts) in November 2012, indicating that the vast majority of the participants in the European carbon emission markets are institutional investors. This is because individuals cannot claim a carbon allowance from their personal emission reduction, disadvantaging them from participating in carbon emission trading compared to firms. The participants in the EU ETS include the 12,000 installations covered by the scheme, firms investing in the CDM and JI projects, government carbon funds, international organisations, arbitragers, speculators and other environmental investors.

The EU ETS has three phases, each with different mechanisms. Phase I spans the period from January 2005 to the end of 2007, and did not permit banking and borrowing of carbon allowances between different phases. The period from January 2008 to December 2012 constitutes the second phase of the EU ETS; interphase banking and borrowing restrictions were relaxed to some extent and more countries, such as Norway, Iceland, and Liechtenstein are covered by the scheme. The aviation industry has also been included in the scheme since 2012. In Phase III of EU ETS (2013–2020), a series of changes will be made by the European Union. For example, a proportion of carbon allowances will be moved from free allocation to auctioning; and more restrictions will be imposed on using carbon offsets outside of the EU as a substitute for EUAs. This chapter only considers the data from EU ETS Phase II for the following reasons. Firstly, the second phase of EU ETS is the most recent commitment period and has not been fully investigated. Secondly, the mechanisms of EU ETS Phase I and Phase

II had been significantly changed between Phase I and Phase II; therefore, it is not reasonable to examine the Phase I and Phase II data together. Thirdly, due to inter-phase banking restrictions, the spot prices are close to zero at the end of Phase I, i.e. the second half of 2007 (Chevellier, 2011a). Therefore, it is not appropriate to use the spot prices at that stage to study the relationship between spot and futures markets.

On 30 April each year, the EU ETS regulations require all firms covered by the scheme to surrender a quantity of EUAs or other accepted carbon financial instruments[37] corresponding to the GHG emissions in the previous year. GHG emissions not covered by the surrendered carbon allowances incurred a fine of €40 per CO_2 ton in Phase I and €100 per CO_2 ton in Phase II and Phase III. In addition, the uncovered carbon allowance should also be surrendered in the next compliance year. In order to avoid the penalty, firms which do not have enough carbon allowances to surrender have to purchase the uncovered allowances in the spot market before the submission deadline. Thus, firms with spare carbon allowances have an incentive to sell these allowances for cash, especially in the current financial crisis when the costs of borrowing are high. For the above reasons, trading in the carbon spot market is expected to be more active in the period before the submission deadline than after the deadline. This implies that the transmission of information may be different before and after the submission deadline. The allowances surrendered to the EU are no longer available to be traded on the markets. Therefore, the total amount of carbon allowance drops dramatically after the submission deadline each year, which can affect trading behaviour in the carbon markets, including arbitrage and hedging. To summarise, the submission of allowances by 30 April each year could result in changes in the behaviour of arbitrage

[37] These eligible carbon financial instruments include Certified Emission Reductions (CERs) developed from Clean Development Mechanisms (CDM) and Emission Reduction Units (ERUs) from Joint Implementation (JI). CDM and JI are flexible mechanisms under the Kyoto Protocol. CERs and ERUs only account for a very small proportion of carbon allowances under EU ETS while the vast majority of allowances are EUAs.

activities and the process of information transmission. This chapter will provide empirical evidence with regard to whether the shift is significant.

5.3. Related Literature

Given the novel features and rapid growth of the carbon emission market, an increasing number of studies have been conducted in this field. The existing literature includes research into pricing carbon spot and derivatives assets (e.g. Benz and Trück, 2009; Daskalakis et al., 2009); the relationship between carbon allowance prices and macroeconomic variables (e.g. Chevellier, 2011a, b); the econometric properties of carbon allowance prices (e.g. Paolella and Taschini, 2008); and the market efficiency of carbon emission markets (e.g. Daskalakis and Markellos, 2008; Charles et al., 2011).

An important group of studies on carbon emission markets have examined the cointegration relationship between carbon spot and futures prices. Previous studies have shown mixed results regarding this relationship. For example, by using daily data from EU ETS Phase I, Uhrig-Homburg and Wagner (2009) provide evidence that there is a cointegration relationship between observed futures prices and theoretical futures prices which is derived from the cost-of-carry model. Charles et al. (2013) confirm the existence of cointegration relationship between spot and futures prices in the EU ETS Phase II by using daily data. In contrast, Joyeux and Milunovich (2010) show that the cost-of-carry model may not hold during the first commitment period of EU ETS at daily level. Chevallier (2010) and Chevallier (2012) support Joyeux and Milunovich’s (2010) arguments in EU ETS Phase II, by using linear and nonlinear vector error correction (ECM) models with structural breaks. In order to explain the mixed results for the cointegration relationship, Rittler (2012) re-examines this relationship by using high-frequency data in EU ETS Phase II, and find that the cointegration relationship holds at the intraday level. The author argues that the previous mixed results regarding the cointegration relationship are caused by the use of low frequency daily data, which can induce an identification problem.

In terms of information transmission in the carbon emission markets, most previous studies have focused on the causal relationship between spot and futures returns or the leadership of spot/futures markets in the price discovery process. Uhrig-Homburg and Wagner (2009) and Chevallier (2010) find the futures market leads the spot market in the price discovery process at daily level. The daily data results produced by Rittler (2012) support the leadership of the futures markets and suggest a unidirectional causality from futures returns to spot returns. However, Rittler's (2012) results for high frequency analysis indicate bidirectional feedback in the spot and futures returns. For the second moment of the information transmission process, i.e. volatility spillovers, little research has been conducted into carbon emission markets. Only Rittler (2012) has investigated the volatility spillovers in the European carbon emission markets using high frequency data and multivariate GARCH models, and shown that there are volatility spillovers from the futures market to the spot market. However, with the availability of high frequency data, realised volatility is preferred over conditional measures of volatility in modelling and forecasting the dynamics of volatility. Chevallier and Sevi (2011) examine the statistical properties and forecasting performance of realised volatility in carbon emission markets, and show that the model which uses realised volatility significantly outperforms GARCH specifications in one step ahead forecasting. Therefore, it is better to use realised volatility as a measure for studying volatility spillovers in the carbon emission markets.

5.4. The Data

5.4.1. Constructing futures and spot price series

To examine the effects of allowance submission on the European carbon markets, the spot and futures price series are constructed based on order flow data from spot and futures markets. The spot market tick-by-tick data is provided by BlueNext Exchange while the futures markets data is obtained from the Intercontinental Exchange (ICE).[38] As shown in the previous section, this study only analyses the impact of the allowance submission deadline based on EU ETS Phase II data, which runs from 2008 to 2011. Because the allowance submission deadline for the previous year's emission falls on 30 April of the following year, the first submission deadline in EU ETS Phase II is not 30/04/2008 but 30/04/2009. For this reason, the data for the year 2008 is excluded from the analysis. The final sample in this chapter runs from 2009 to 2011. For each year, this study uses futures contracts which expire in December of that year, which are the most liquid contracts. For example, when studying futures mispricing in 2009, the futures contract which expires in December 2009 will be used. The trading hours of the ICE and BlueNext exchanges are from 07:00 to 17:00 GMT. However, trading is not active in the spot market at the beginning and end of the trading day. To avoid these illiquid trading hours, only the transactions which occurred from 09:00 to 16:00 GMT are used. In order to convert irregular transaction data into equidistant price data at frequencies of h-minutes, for each h-minute interval, this study computes the mean of the log prices of the immediate preceding and following transactions at that time interval as the log price at the h-minute mark. This chapter uses an h=15 minutes interval in the main tests.[39] To avoid the intraday effects, the log price of the first trade immediately following 09:00 is

[38] Carbon futures were initially listed on the European Climate Exchange (ECX) from 2005. In 2010, the ICE acquired ECX as its emission markets. Therefore, the carbon futures data in this paper is obtained from the ICE.

[39] As well as the frequency of 15 minutes, this study also examines other intraday frequencies, i.e. 10 minutes and 30 minutes. The results are qualitatively similar to those in Section 5.4 and are shown in Appendix 5B.

used as the price at the 09:00 time interval each day, and the log price of the last trade immediately preceding 16:00 is taken as the price at the 16:00 time interval each day.

5.4.2. Estimating spot-futures mispricing

Most studies about futures mispricing assume that the theoretical price of a futures contract is determined by Brennan's (1958) cost-of-carry model. In the cost-of-carry model, the theoretical futures price is determined by the spot price, risk-free rate, storage costs, convenience yield and the time to maturity, which can be expressed as:

$$F_{t,T}^{*} = S_t e^{(Rft + u_t - CYt)(T-t)} \tag{5.1}$$

where $F_{t,T}{}^{*}$ is the theoretical futures price at time t, which matures at time T. S_t is the spot price at time t, Rf_t is the annualised risk-free rate, u_t is the annualised cost of storage at time t, CY_t is the annualised convenience yield for the commodity, and T is the expiration date of the futures contract. The difference between the observed futures price and the theoretical futures price is the futures mispricing. Therefore, the futures mispricing, Z_t, at any time point of t is computed as:

$$Z_t = \ln(F_{t,T}) - \ln(F_{t,T}^{*}) = \ln(F_{t,T}) - \ln(S_t e^{(Rft + u_t - CYt)(T-t)}) \tag{5.2}$$

where $F_{t,T}$ is the observed futures price at time t, which matures at time T.

A number of studies have examined the cost-of-carry model for the European carbon markets. For example, Rittler (2012) employs the cost-of-carry model to calculate the theoretical prices of carbon futures, and Joyeux and Milunovich (2010) use the cost-of-carry model to investigate the market efficiency of European carbon futures markets. As carbon assets in the EU ETS are electronically registered and incur little cost, most of the previous studies assume that the cost of storage (u_t) for carbon allowances is zero. For the risk-free rate in the model, following Rittler (2012), this study adopts the monthly EURIBOR on a daily basis as Rf_t, which is obtained from DataStream.

However, previous studies offer different views on whether there is a convenience yield in carbon emission markets. In economics, the convenience yield is the benefit from holding a spot commodity rather than entering forward or futures contracts, because it is more convenient to have some inventory in-hand than to purchase it when needed. Therefore, from a valuation standpoint, the convenience yield is similar to the dividend yield, but it is not observable. Daskalakis et al. (2009) and Uhrig-Homburg and Wagner (2009) argue that firms only need the carbon allowance annually to meet the regulatory requirements, and thus the convenience yield in carbon markets should be insignificant. Joyeux and Milunovich (2010) and Rittler (2012) also assume that the convenience yield is zero in the cost-of-carry model. Conversely, Paolella and Taschini (2006) argue that, because the GHG emissions are uncertain during each year, and due to the high transaction costs and illiquidity in carbon markets compared to major stock exchanges, there should be significant benefit to be gained from holding a spot carbon allowance, and thus the convenience yield in carbon markets is not zero. Borak, Härdle, Trück and Weron (2006) and Chevallier (2009) show that carbon futures in European markets have a significant convenience yield. Frunza and Guegan (2010) and Lin, Chen and Li (2012) also include a non-zero convenience yield term in their cost-of-carry model. Furthermore, Rittler (2012) shows that the theoretical carbon futures prices with zero convenience yield are persistently higher than the observed futures prices, which could constitute evidence for the existence of a convenience yield. [40] For the above reason, a non-zero convenience yield is assumed in this study, by employing an option implied methodology recently developed by Hochradl and Rammerstorfer (2012) to estimate the

[40] Daskalakis et al. (2009) also find similar results which support the non-zero convenience yield in carbon emission markets.

convenience yield. The method is based on the original economic idea of a convenience yield, where the convenience yield is defined as the benefit of holding spot assets rather than futures assets. The convenience yield is estimated as the difference between a put option on a spot contract and another put option on a futures contract. Further details about Hochradl and Rammerstorfer's (2012) methodology are provided in Appendix 5A.

[Insert Table 5.1 here]

The summary statistics of futures mispricing using 15 min data are presented in Table 5.1. The statistics for the full year sample periods are shown in Panel A. All the series in Panel A display non-zero skewness and excess kurtosis, and the results of Jarque-Bera tests show that they significantly deviate from normal distribution. In Panel B, two samples are provided for each year, which run from three months before and after the submission deadline, in order to comparatively analyse the effects of allowance submission.[41] The results of the mean statistics show that the average scales of mispricing reduce significantly after the submission deadlines for 2009 and 2011, while the means of futures mispricing in 2010 are small and do not change much. A similar pattern can also be observed for the standard deviation statistics. The skewness of futures mispricing changes from negative to positive after the submission deadline for 2009 and 2011; however, in 2010 the skewness does not change much. The values for kurtosis also reduce significantly after the submission deadline in 2009 and 2011 but not in 2010.

5.5. Impact of allowance submission

5.5.1. Impact of allowance submission on mispricing mean-reverting process

[41] Chen, Chou and Chung (2009) study the effect of decimalization on index futures pricing efficiency, by splitting the total sample into two equal-length subsamples before and after the date of decimalization. This chapter follows Chen et al.'s (2009) methodology.

From the observation of Figure 5.1 and the analysis of Table 5.1, it is found that the last date of allowance submission for each year is a potential point of structural change for futures mispricing. To further analyse the characteristics of the distribution of the futures mispricing, the kernel density for the same sample periods in Table 5.1, Panel B is estimated and presented in Figure 5.2. The graphs in Panel A (year 2009) show a clear shift in distribution to the left after the submission deadline. The figures in Panel C (year 2011) demonstrate a similar pattern to that in Panel A, and the distribution of the sample period before the submission deadline strongly deviates to the right, indicating that almost all the observations are above zero. However, the kernel density estimations in 2010 hardly change. This is because of the low industrial production and carbon emissions in 2009. The above findings are consistent with the time series of futures mispricing plotted in Figure 5.1 and the summary statistics in Table 5.1.

[Insert Figure 5.2 here]

This chapter starts the analysis of the spot and futures relationship from the linear cointegration framework. If the cost-of-carry model holds, spot and futures prices should be cointegrated with each other and accordingly the futures mispricing (or the basis) will be stationary. For this reason, the linear adjustment of futures mispricing, Z_t,, is assumed to follow the standard Engle and Granger (1987) process. In order to examine the effect of allowance submission on the dynamics of the mean-reverting process, this study augments the standard ADF test with a dummy variable to account for the period before the submission deadline, which is shown as:

$$\Delta Z_t = \alpha + \delta D_t + \rho_1 Z_{t-1} D_t + \rho_2 Z_{t-1}(1-D_t) + \sum_{i=1}^{k} \lambda_i \Delta Z_{t-i} + \varepsilon_t \tag{5.3}$$

where ε_t is the white noise error term, ΔZ_{t-i} are the lags of the dependent variable included in the regression to eliminate the autocorrelation of the dependent variable, D_t is a dummy variable set to be 1 during the period before 30 April each year and equal to 0 for the period after the submission deadline, δ captures the difference in equilibrium levels of the two periods so that $\alpha+\delta$ and δ are the equilibrium levels during the period before 30 April and after 30 April, respectively; ρ_1 and ρ_2 are related to the speed of mean-reverting before and after the submission deadline, respectively. The null hypothesis of non-cointegration is rejected if ρ_1 (or ρ_2) is statistically significant and lies between -2 and 0.

[Insert Table 5.2 here]

The results of the ADF test with dummy variables (Equation 5.3) using 15 min data are summarised in Table 5.2. The analysis starts by using a whole sample period running from February to July each year (split into two equal-length subsamples before and after the submission deadline), and then extends the end of the sample to August and October, respectively, to examine whether the effect of allowance submission declines as time passes. It is found that the results for the same year but with different lengths of sample periods are strongly consistent, showing that the changes in the dynamics of equilibrium reversion are permanent. It is observed from Table 5.2 that all the intercept terms are positive and significant, suggesting that the equilibrium level is positive in all cases. One of the key parameters is the one governing the difference in the mean-reverting level for the two subperiods, δ, which is positive and significant for 2009 and 2011, but not for 2010. This indicates that the equilibrium level shifts downward after the submission deadline in 2009 and 2011,[42] which is consistent with the summary statistics showing that the mean of mispricing decreases after the submission deadline. The other key parameters, ρ_1 and ρ_2,

[42] The intercept terms for the period before and after the submission deadline are $\alpha+\delta$ and α, respectively. If δ is positive and significant, the equilibrium level after the submission deadline would be lower than that before the deadline.

which are related to the speed of adjustment, are all significant and lie between -2 and 0, providing strong evidence of mean-reversion and cointegration before and after the submission deadline. This confirms Rittler's (2012) results and suggests that the mixed results found for the cointegration relationship in previous studies is not because of the allowance submission but due to the identification problem caused by using low frequency data. This study further examines whether there is a change in the mean-reverting speed after the submission deadline by using a Wald-test of $\rho_1=\rho_2$. The results show that the speed of adjustment is statistically different for the two sub-periods in 2009, but not in 2010 and 2011. To summarise, the overall results of the ADF test with dummy variables confirm the theory that allowance submission has an impact on the mean-reverting process of mispricing in 2009 and 2011, but not in 2010.

The linear ADF model assumes that the adjustment process is symmetric when the variable deviates from its long-run equilibrium. However, the futures mispricing always fluctuates within its upper and lower no-arbitrage boundaries due to transaction costs, illiquidity, and other market imperfections. When the futures mispricing deviates beyond the no-arbitrage boundaries, arbitrage activities can quickly correct the relative pricing inefficiency and pull the futures mispricing back within the no-arbitrage boundaries. In contrast, if the futures mispricing fluctuates within the no-arbitrage boundaries, arbitragers cannot fully eliminate the relative mispricing because of the costs and constraints of arbitrage. In this case, arbitrage normally takes place outside the no-arbitrage boundaries when there is a large deviation from the equilibrium, while the small mispricing that takes place within the no-arbitrage boundaries remains uncorrected. Therefore, various nonlinear mean-reverting models are adopted to capture the asymmetries in futures mispricing. Monoyios and Sarno (2002) first introduce several threshold and smooth transition models to capture the nonzero transaction costs. The first nonlinear model is Tong's (1978, 1990) threshold autoregressive

(TAR) model for the cointegration test, which enforces abrupt changes of dynamic behaviour in each regime and assumes that all the arbitragers behave instantaneously in an identical style (McMillan and Ülkü, 2009). In the case examined in this thesis, the submission of allowances should have a stronger impact on one side of the market, when the theoretical futures price induced from the spot price is too high relative to the observed futures price. Under this circumstance, arbitragers would short-sell the spot asset. However, it is more difficult to short-sell spot carbon allowances after the submission deadline because the total amount of carbon allowances in the markets decreases significantly after that date. This thesis does not use other non-linear models, such as the Markov regime switching model used in Chapter 3, because the unobservable Markov chain in the Markov regime switching model lacks an economicbasis, unlike the threshold models, when analysing the cointegration between spot and futures prices. For the above reasons, the TAR model is used for the cointegration test, which can identify the asymmetric effects in the mispricing series. With an augmented dummy variable for the submission deadline, the TAR model with dummy variables is shown as:

$$\begin{aligned}\Delta Z_t &= \alpha + \delta D_t + \rho_1 Z_{t-1} I_t D_t + \rho_2 Z_{t-1} I_t (1-D_t) + \rho_3 Z_{t-1}(1-I_t) D_t \\ &+ \rho_4 Z_{t-1}(1-I_t)(1-D_t) + \sum_{i=1}^{k} \lambda_i \Delta Z_{t-i} + \varepsilon_t\end{aligned} \tag{5.4}$$

where I_t is a dummy variable taking the value of 1 if Z_{t-1} is greater than or equal to the threshold, and 0 otherwise; D_t is a dummy variable set to be 1 during the period before 30 April and equal to 0 for the period after the submission deadline; ρ_1, ρ_2, ρ_3 and ρ_4 are the parameters for the speed of mean-reversion. More specifically, ρ_1 and ρ_2 govern the speed of adjustment in the upper regimes, while ρ_3 and ρ_4 are related the speed of adjustment in the lower regimes. Symmetric adjustment holds if $-2<\rho_1=\rho_2<0$, or $-2<\rho_3=\rho_4<0$ in each subsample, and asymmetric adjustment happens when $\rho_1 \neq \rho_2$ or $\rho_3 \neq \rho_4$ and both lie between -2 and 0.

Therefore the ADF model described in Equation (5.4) is a special case of Equation (5.3). The asymmetric adjustment process shown in Equation (5.4) is consistent with non-zero transaction costs and the presence of short-sale constraints. The estimation results of the TAR model with dummy variables (Equation 5.4) using 15 min data are presented in Table 5.3.

[Insert Table 5.3 here]

Several approaches are adopted in order to determine the value of the threshold. The simplest method is to set the threshold at zero. This is an economically meaningful value, and therefore the underlying cointegration vector derived from the TAR model attractor would correspond to the attractor. However, the value of the threshold should be permitted to differ from the attractor (McMillan and Dennis, 2012). For this reason, two alternative methods are selected to determine the threshold value. The first approach involves a recursive estimation based on Chan's (1993) procedure. The regression of Equation (5.4) is run over a number of possible threshold values and the most appropriate value is selected based on the conditional least squares (CLS) methodology. The advantage of this approach is that the estimator of the threshold parameter is strongly consistent. Nonetheless, Chan's (1993) procedure can only produce a single threshold value for the whole sample period, which does not allow for the variation of the threshold over time. The second method entails using a simple 10-day moving average of the futures mispricing Z_t as the time-varying threshold values. The results reported in Table 5.3 are based on Chan's (1993) procedure, while the results obtained by using the 10-day moving average are qualitatively similar and are presented in Appendix 5C.

The results in Table 5.3 illustrate several interesting points. Firstly, the results of the Wald-tests of $\rho_1=\rho_3$ and $\rho_2=\rho_4$ are significant in most cases, showing that the speed of adjustment is different in the two regimes. This supports the use of the TAR model instead of the linear cointegration model. Secondly, similarly to the results in Table 5.2, all the intercept terms are positive and significant, suggesting a positive long-run equilibrium. The coefficient of the dummy variable is significant and positive in all the sub-periods in 2009 and 2011, showing that the allowance submission can significantly decrease the equilibrium level. However, contrary to the results in Table 5.2, the dummy variable in 2010 is negative and significant in the subsamples which run from February to July (at 1% level) and February to August (at 10% level), but insignificant in the subsample which runs from February to October. The results suggest that the submission of allowances can affect the mean-reversion equilibrium in 2010 if the asymmetries of futures mispricing are taken into account, but the effect diminishes as time passes. The parameters related to the speed of mean-reversion, ρ_1, ρ_2, ρ_3 and ρ_4, are all negative and significant, showing that the futures mispricing, Z_t, is stationary in all the subsamples. Because this chapter is mainly concerned with the effects of allowance submission, it further examines whether the speed of adjustment is the same before and after the deadline, for both the upper and lower regimes, by using two Wald-tests. The null hypotheses of $\rho_1=\rho_2$ and $\rho_3=\rho_4$ are rejected in all the subsamples in 2009, which suggests the speed of mean-reversion changes after the submission deadline in both regimes. $\rho_1=\rho_2$ and $\rho_3=\rho_4$ are also rejected in the sample running from February to July 2010, but cannot be rejected in the other subsample for 2010. This shows that the impact of allowance submission on the mean-reverting speed also lessens over time. Only the hypothesis $\rho_3=\rho_4$ is rejected for all the subsamples in 2011, indicating that the submission of allowances can only affect the speed of adjustment in the lower regime. The above results suggest that allowance submission can influence the equilibrium level and adjustment speed of futures mispricing in all three years. The effects are persistent in 2009 and 2011 but weaker in 2010.

The TAR model used above imposes an abrupt regime change which requires a number of unrealistic assumptions, including that all the agents hold homogeneous expectations, and incur the same interest rates and transaction costs (Monoyios and Sarno, 2002). However, asset returns also normally display smooth mean-reverting characteristics. Consequently, smooth-transition models have been preferred over threshold models, such as the aforementioned TAR model. In order to allow for a smooth change of regimes, this chapter employs the quadratic-logistic smooth-transition (QLSTR) model developed by Jansen and Teräsvirta (1996), in which the adjustment of a small deviation from the equilibrium is different from that of a large deviation, and the shift between regimes is smooth. In addition, unlike the single threshold for each side in the TAR model, the QLSTR model allows for different threshold points to be set for both sides of the attractor. This makes it possible to examine how the allowance submission influences the no-arbitrage boundaries as well as the speed of transition between the two regimes. Taking the effects of allowance submission into consideration, the QLSTR model with dummy variables is given as follows:

$$\begin{aligned}\Delta Z_t &= \left(\alpha_{0,1} + \alpha_{1,1} Z_{t-1} + (\beta_{0,1} + \beta_{1,1} Z_{t-1})(1 + \exp(-\gamma_1 (Z_{t-1} - c_{1,1})(Z_{t-1} - c_{2,1})))^{-1}\right) D_t \\ &+ \left(\alpha_{0,2} + \alpha_{1,2} Z_{t-1} + (\beta_{0,2} + \beta_{1,2} Z_{t-1})(1 + \exp(-\gamma_2 (Z_{t-1} - c_{1,2})(Z_{t-1} - c_{2,2})))^{-1}\right)(1 - D_t) + \sum_{i=1}^{k} \lambda_i \Delta Z_{t-i} + \varepsilon_t\end{aligned} \tag{5.5}$$

where D_t is the dummy variable for the submission deadline with the same definition as before, γ_i is the parameter for the speed of transition between the two regimes, $c_{1,i}$ is the lower boundary and $c_{2,i}$ is upper boundary of the inner regime, which determines the locations where the adjustment process changes regimes, and $\alpha_{1,i}$ and $\beta_{1,i}$ govern the speed of adjustment in the inner and outer regimes. More precisely, the speed of mean-reversion in the outer regime is determined by the sum of $\alpha_{1,i}$ and $\beta_{1,i}$, i=1 for the period before 30 April each year, and i=2 for the sample period after 30 April. If $\gamma_i \to 0$, the model becomes a linear ADF model, while if $\gamma_i \to \infty$, the formula becomes 0 if $c_{1,i} < Z_t < c_{2,i}$ and is equal to 1 if $Z_t < c_{1,i}$ and $Z_t > c_{2,i}$. At the point of transition, the model allows different adjustment behaviours for positive and negative deviations. Therefore the model contains Balke and Fomby's (1997) three-regime threshold model. The estimation results of the QLSTR model with dummy variables (Equation 5.5) using 15 min data are displayed in Table 5.4.

[Insert Table 5.4 here]

The parameters of interest in Equation (5.5) are those that determine the speed of regime transition, the speed of mean-reversion and the upper and lower boundaries of the no-arbitrage space. Five Wald-tests are conducted to examine whether the speed of adjustment in the inner and outer regimes, the speed of transition, and the location of the upper and lower no-arbitrage boundaries are the same before and after the submission deadline. It can be observed from Table 5.4 that the null hypotheses $\alpha_{1,1}=\alpha_{1,2}$ and $\beta_{1,1}=\beta_{1,2}$ are rejected for all the samples in 2009 and 2011, except for the subsample running from February to July in 2011 for the test of $\alpha_{1,1}=\alpha_{1,2}$. However, the hypotheses $\alpha_{1,1}=\alpha_{1,2}$ and $\beta_{1,1}=\beta_{1,2}$ cannot be rejected for any of the samples in 2010. The results indicate that allowance submission can affect the speed of mean-reversion in the inner and outer regimes in 2009 and 2011, but not in 2010. The results of Table 5.4 also show that the parameter related to the speed of regime transition, γ, does not change significantly after the submission deadline as the test of $\gamma_1=\gamma_2$ cannot be rejected for all the samples for the three years in question. The most interesting parameters in the model are the threshold parameters, c_1 and c_2. The results shown in Table 5.2 and Table 5.3 suggest that the long-run equilibrium shifts after the submission deadline for all three years; nevertheless, if the upper and lower no-arbitrage boundaries do not change, the movement of the equilibrium level does not necessarily induce the change in arbitrage behaviour. The results shown in the last two columns in Table 5.4 signify that both the upper and lower boundaries of the no-arbitrage space alter after the submission deadline for 2009 and 2011, as nearly all the tests for $c_{1,1}=c_{1,2}$ and $c_{2,1}=c_{2,2}$ are rejected (except the test for $c_{1,1}=c_{1,2}$ in the subsample from February to October 2009 and the subsample from February to July 2011). In 2010, there is a significant change for the lower boundaries in the subsample running from February to July only, but the effect lessens very rapidly in the next subsample (from February to August). This provides evidence of the effect of the submission deadline on the no-arbitrage bands, although the effect in 2010 is not strong and persistent.

Overall, the results presented in Section 5.4.1 suggest several important findings regarding the mean-reverting process of the spot and futures relationship before and after the submission deadline, although it is found that the cointegration relationship between spot and futures prices holds for all the subperiods, confirming the results obtained by Rittler (2012). Firstly, the equilibrium level of mean-reversion shifts after the submission deadline for all three years. Secondly, the speed of mean-reversion in each regime is different before and after the submission deadline. Thirdly, the no-arbitrage bands have also changed after the submission deadline. These findings support the view that the submission of carbon allowances can affect arbitrage activities and therefore shift the mean-reverting process of the futures mispricing Z_t.

The above effects are more prominent in 2009 and 2011 than in 2010, because the global financial crisis deepened in 2009, and the European sovereign debt crisis happened in the same year. This caused a 15% reduction in industrial production in the EU from 2008 to 2009 and an 11% drop in GHG emissions in the same period (World Bank, 2012). It should be noted that the emissions in 2009 determine the amount of carbon allowance which should be surrendered in 2010. Therefore, the total amount of carbon allowances that should be surrendered by 30/04/2010 also decline considerably while the amount of carbon allowances allocated to firms are based on a smooth industrial production. In this case, firms would have more carbon allowances than those should be submitted, and thus they do not need to purchase more carbon allowances from the markets before 30/04/2010. Trading and arbitrage activities before and after the submission deadline in 2010 may not change as much as those in 2009, and therefore the impact of allowance submission is not very significant in 2010. Economic activities recovered in 2010, causing industrial production and carbon emissions to recover to previous levels in 2010. For this reason, trading and arbitrage activities before and after the submission deadline in 2011 should be significantly different and the results of this study support the above arguments.

5.5.2. Impact of allowance submission on price discovery

In the previous section, it is shown that the submission of carbon allowances has an impact on arbitrage and the mean-reverting process of the spot and futures relationship. However, the allowance submission may also affect the transmission of information. Operating firms with insufficient carbon allowances in-hand have to purchase the uncovered allowance before the submission deadline in order to avoid severe financial punishment. Thus, trading activities in the spot market should be more vigorous before the submission deadline than after. It is possible that the first market (spot or futures markets) to react to the new information would be different before and after the submission deadline. Motivated by the aforementioned reasons, this section examines whether the price discovery process changes after the submission deadline. The analysis of price discovery is conducted to determine how the newly arrived information is incorporated into the price dynamics of several closely related markets, such as the spot and futures market for the same asset. The central question of price discovery is to identify whether one market reacts to new information more quickly than the other market, such that the prices in the two markets would differ temporarily after the arrival of new information. Subsequently, the market which responds more slowly to the new information would also respond to the prices changes in the first market due to arbitrage activities. Therefore, the market which absorbs new information more quickly can lead the other market in terms of price changes. The Granger causality test developed by Granger (1969) can be used to test the lead-lag relationship. The Granger causality test is based on a vector autoregressive (VAR) model to examine whether the lagged returns in one market are jointly significant in the equation of the other market in the VAR system. The null hypothesis is that one market does not Granger-cause another, and thus the rejection of the null hypothesis would show that the related market Granger-causes the other market.

[Insert Table 5.5 here]

In the Granger causality test, sub-sampling analysis is employed instead of using dummy variables. The estimation results of the Granger causality tests using 15 min data are presented in Table 5.5. The results in Panel A (year 2009) show that spot returns Granger-cause futures returns while futures returns do not Granger-cause spot returns in the subsample before the submission deadline. Thus, the spot market leads the futures market in the price discovery process before the deadline. Meanwhile, spots and futures Granger-cause each other in the samples that come after the submission deadline in 2009. The above findings are consistent with the view that the spot carbon market is more active before the submission deadline because operating firms are likely to purchase spot carbon allowances to fulfil their obligations. However, the results for 2010 and 2011 do not support the above argument. Spots and futures Granger-cause each other in all the samples before and after the submission deadlines in 2010 and 2011, showing no evidence of changes in the price discovery process caused by the submission of carbon allowances. Consequently, the effect of allowance submission on price discovery is not significant and persistent, and the two markets Granger-cause each other in most cases. The results are in line with Rittler's (2012) finding that there is a bidirectional causality relationship between the results of spot and futures returns before and after the submission deadline. However, although there is a bidirectional causality relationship between the results of spot and futures returns before and after the submission deadline, it is found that the spot market leads the futures markets in the periods before the submission deadline but the futures market leads the spot market after the deadline (indicated by the larger F-test statistics). The results are inconsistent with those of Uhrig-Homburg and Wagner (2009), Chevallier (2010) and Rittler (2012) who claim that carbon futures contracts lead in the price discovery process. However, they overlook the impact of allowance submission, which can induce intensive trading before the submission deadline in the spot market.

5.5.3. Impact of allowance submission on volatility spillovers

In addition to analysing the first moment of information transmission in the return level, it is of interest to examine whether allowance submission can affect the second moment of information transmission, namely volatility spillovers. The volatility of an asset is driven by the latent information in the market such that the transmission of information within markets can induce a lead-lag relationship in corresponding markets' volatility dynamics (Andersen, 1996). Multivariate GARCH models are normally used to study cross-market volatility spillovers; however, due to the availability of high-frequency data the realised measure of volatility is prevalent in studies on volatility spillovers because of its nonparametric nature and excellent performance in out-of-sample forecasting. For example, Bubák, Kočenda, and Žikeš (2011) examine volatility spillovers in East European foreign exchange markets by using realised volatility. Next, this section will briefly introduce the theory of realised volatility and the model for realised volatility spillovers.

Following Andersen, Bollerslev and Diebold (2007), it is assumed that the logarithmic asset price p_t follows a continuous-time jump diffusion process, which is shown as:

$$dp_t = \mu_t dt + \sigma_t dW_t + \kappa_t dq_t \tag{5.6}$$

where μ_t denotes a finite variation process, W_t denotes a Wiener process, σ_t represents a positive definite stochastic volatility process independent of W_t , κ_t is the size of jumps in the logarithmic prices, and q_t is a counting process. The quadratic variation (QV_t) for the cumulative return process, p_t-p_0, can be shown as:

$$QV_t = \int_0^t \sigma^2(\omega)d\omega + \sum_{0<\omega\leq t} \kappa^2(\omega) \tag{5.7}$$

The first part of Equation (5.7) relates to the diffusion while the second component captures the jumps in the stochastic process. As proved by the seminal work of Andersen, Bollerslev, Diebold and Labys (2001), the above quadratic variation can be estimated by the summation of the intraday squared returns, which is defined as realised volatility (RV). The daily realised volatility is calculated as:

$$RV_{t+1}(\Delta) = \sum_{j=1}^{1/\Delta} r^2_{r+j\Delta,\Delta} \tag{5.8}$$

where Δ denotes the intraday frequency and $r_{t,\Delta}=p(t)-p(t-\Delta)$ shows the compounded Δ-period return at time *t*. The advantages of the realised volatility measure are that it is non-parametric and model-free. In addition, Andersen et al. (2003) show that modelling using realised volatility strongly outstrip a series of GARCH models and stochastic volatility models in terms of out-of-sample forecasting. Therefore, in this chapter, the realised volatility approach is adopted to examine the volatility spillover in European carbon markets.[43]

Long-memory dependency is one of the most important issues to be considered in regard to financial market volatility. Some early studies on realised volatility employ complicated

[43] This chapter also tries some Multivariate GARCH models (e.g. Vech-GARCH, CCC-GARCH, DCC-GARCH, etc.) for the conditional volatility spillover but failed to get convergence results due to the limited number of observations.

fractional integrated models (such as ARFIMA) in the empirical estimations, for example those by Areal and Taylor (2002), and Andersen et al. (2003), among others. However, Corsi (2009) proposes a simple heterogeneous autoregressive (HAR) model with realised volatility (HAR-RV) to capture the main features of long-memory. The HAR model is motivated by the heterogeneous ARCH (HARCH) model developed by Müller, Dacorogna, Davé, Olsen, Pictet and von Weizsäcker (1997), in which the conditional variance is dependent on a series of squared returns over different time horizons. To examine the effects of the submission deadline on volatility spillovers in carbon spot and futures markets, this study augments the bivariate HAR-RV models by including a dummy variable for the submission deadline, which is shown as:

$$\begin{aligned} RVF_t = {} & (\alpha_1 + \beta_{1,1}RVF_{t-1} + \beta_{1,5}RVF_{(t-1|t-5)} + \beta_{1,22}RVF_{(t-1|t-22)} + c_{1,1}RVS_{t-1} + c_{1,5}RVS_{(t-1|t-5)} + c_{1,22}RVS_{(t-1|t-22)})D_t \\ & + (\alpha_2 + \beta_{2,1}RVF_{t-1} + \beta_{2,5}RVF_{(t-1|t-5)} + \beta_{2,22}RVF_{(t-1|t-22)} + c_{2,1}RVS_{t-1} + c_{2,5}RVS_{(t-1|t-5)} + c_{2,22}RVS_{(t-1|t-22)})(1-D_t) + \varepsilon_t \end{aligned} \quad (5.9)$$

$$\begin{aligned} RVS_t = {} & (\alpha_1 + \beta_{1,1}RVF_{t-1} + \beta_{1,5}RVF_{(t-1|t-5)} + \beta_{1,22}RVF_{(t-1|t-22)} + c_{1,1}RVS_{t-1} + c_{1,5}RVS_{(t-1|t-5)} + c_{1,22}RVS_{(t-1|t-22)})D_t \\ & + (\alpha_2 + \beta_{2,1}RVF_{t-1} + \beta_{2,5}RVF_{(t-1|t-5)} + \beta_{2,22}RVF_{(t-1|t-22)} + c_{2,1}RVS_{t-1} + c_{2,5}RVS_{(t-1|t-5)} + c_{2,22}RVS_{(t-1|t-22)})(1-D_t) + \varepsilon_t \end{aligned} \quad (5.10)$$

where RVF_t is the daily realised volatility for futures returns while RVS_t is the daily realised volatility for spot returns at time *t*, $RVF_{(t-1|t-k)} = \frac{1}{k}\sum_{j=1}^{k} RVF_{t-j}$, $RVS_{(t-1|t-k)} = \frac{1}{k}\sum_{j=1}^{k} RVS_{t-j}$, and D_t is the dummy variable for the submission deadline with the same definition as described earlier. In the above model, $c_{i,k}$ are the parameters governing the volatility spillovers from spot markets to futures markets, while the volatility spillovers from futures markets to spot markets are determined by the parameters of $\beta_{i,k}$. The three volatility components in this model, the first lag of realised variance and the average of 5-day and 22-day lagged realised variance, reflect daily, weekly and monthly realised volatility. Each component corresponds to various response times of different groups of investors to the arrival of new information.

An intuitive interpretation of the HAR-RV model is that the model allows the volatility patterns over longer intervals to associate with those over shorter intervals (Corsi, 2009). Bubák et al. (2011) suggest that the multivariate version of the HAR model can be adopted to study the impact of long-run and/or short-run volatility terms in one financial market on another. This chapter employs the bivariate framework of the HAR-RV model to study volatility spillovers in European carbon markets. In carbon emission markets, Chevallier and Sevi (2011) show that the HAR-RV model is more accurate than a number of GARCH models in one step ahead volatility forecasting. The HAR-RV model is also adopted by Andersen et al. (2007), Chen and Ghysels (2011) and a number of other realised volatility studies.

[Insert Table 5.6 here]

Table 5.6 displays the results of the bivariate HAR-RV model with dummy variables (Equation 5.9 and 5.10). This study employs the longest available sample period each year (from February to November), rather than different sub-samples, because of the limited number of observations. The key parameters are $c_{i,k}$ for the futures market and $\beta_{i,k}$ for the spot market. For the futures market, it is shown in Table 5.6 that $c_{1,1}$ and $c_{1,22}$ are strongly significant while $c_{2,1}$, $c_{2,5}$, and $c_{2,22}$ are all insignificant in 2009, indicating that there are volatility spillovers from the spot market to the futures market before the submission deadline, while the effect disappears after the deadline. This is confirmed by the rejection of the likelihood ratio (LR) test for the joint hypotheses $c_{1,1}=c_{2,1}$, $c_{1,5}=c_{2,5}$, and $c_{1,22}=c_{2,22}$, which provides evidence of change in the volatility spillover property of the futures market. The results for 2010 and 2011 are consistent with those for 2009, where the volatility parameters shift from significant to insignificant after the submission deadline and the joint test of $c_{1,1}=c_{2,1}$, $c_{1,5}=c_{2,5}$, and $c_{1,22}=c_{2,22}$ is also rejected. As suggested in Section 5.4.2, transactions in the spot market are more active before the submission deadline. Thus, new information could be incorporated into the spot market first and thereby induce the change in the volatility dynamics of spot returns. Subsequently, the futures market would respond to the new information. This results in a causal relationship between the volatility from the spot market to the futures market before the submission deadline. The results in Table 5.6 strongly support the above analysis, as there is evidence of volatility spillovers from the spot market to the futures market before the submission deadline but no spillover effect is found afterwards. Furthermore, it is found that the joint LR test of $c_{1,1}=c_{2,1}$, $c_{1,5}=c_{2,5}$, and $c_{1,22}=c_{2,22}$ is rejected at the 1% level for 2009 and 2011, while the LR test for 2010 is only rejected at the 10% level. The results show that the effects of allowance submission on volatility spillovers are more significant in 2009 and 2011 than in 2010, which is consistent with the analysis presented in Section 5.4.1.

In the case of the spot market, only weak evidence of volatility spillovers is found from the futures market to the spot market in the subsamples taken after the submission deadline. This implies that the futures market incorporates new information first in the periods after the submission deadline, in line with the common belief that the futures market plays a key role in the information transmission in commodity markets. However, the joint test of $\beta_{1,F,1}= \beta_{2,F,1}$, $\beta_{1,F,5}= \beta_{2,F,5}$, and $\beta_{1,F,22}= \beta_{2,F,22}$ cannot be rejected for 2009 and 2010, which shows that the submission of allowances has limited impact on volatility spillovers from the futures market to the spot market. These results differ from those of Rittler (2012) that find a strong spillover effect from the futures market to the spot market but not vice versa due to the omission of the allowance submission deadline effect.

5.6. Conclusion

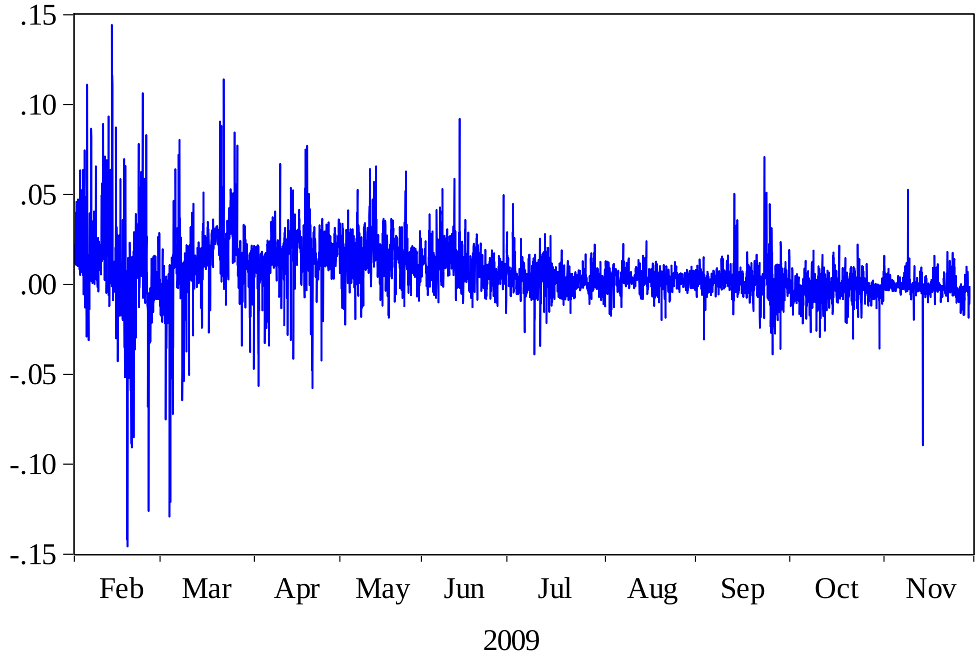
The chapter studies the effects of allowance submission on the relationship between the spot and the futures markets under EU ETS. In particular, the mean-reverting process of carbon futures mispricing, the causal relationship between spot and futures returns, as well as the volatility spillovers between the two markets, are different before and after the submission deadline, resulting from the decrease in the total amount of spot carbon assets available. This research provides evidence with regard to whether the impact is significant.

Using high-frequency data for the second commitment period of the EU ETS, the results firstly show that there is a cointegration relationship between spot and futures prices before and after the submission deadline. However, it is found that the long-run equilibrium level, the speed of mean-reverting, and the upper and lower boundaries of no-arbitrage space shift, due to the submission of carbon allowances. Thus the mean-reverting process of the futures mispricing is different before and after the deadline. This confirms the claim that allowance submission can change the behaviour of arbitrage activities. Moreover, previous studies, such as those by Uhrig-Homburg and Wagner (2009), Joyeux and Milunovich (2010) and Chevallier (2010) have produced mixed results regarding the cost-of-carry relationship between carbon spot and futures prices. Rittler (2012) suggests that the mixed results are due to the use of low frequency daily data, which causes an identification problem in the two markets. The results in this chapter indicate that the mixed results found for the cointegration relationship in previous studies is driven by the allowance submission, but is due to the identification problem caused by using low frequency data. Secondly, the results of the Granger causality tests demonstrate inconsistent evidence for the change in the causal relationship between spot and futures returns in the European carbon markets after the submission deadline each year. Spot and futures returns generally Granger-cause each other. The change in the price discovery process due to the allowance submission is insignificant. However, by comparing the F-test statistics of the Granger causality tests, it is found that the leading market shifts from the spot market to the futures market after the submission deadline. Nonetheless, in terms of volatility spillovers, the results of the bivariate HAR model using realised volatility reveal that the change in volatility spillovers between the spot and the futures markets is significant after the submission deadline, particularly from the spot market to the futures market. This is because trading activities in the spot market should be more active before the submission deadline than after, and new information may be incorporated into the dynamics of volatility in the spot market first in the sub-periods before the deadline. These results conflict with those of Rittler (2012) because his results overlook the impact of allowance submission and the author uses conditional measures of volatility instead of realised measures. The impact of allowance submission in European carbon markets found in this chapter is more prominent in 2009 and 2011 than in 2010, due to the drop in GHG emission in 2009 caused by the global financial crisis and the European sovereign debt crisis.

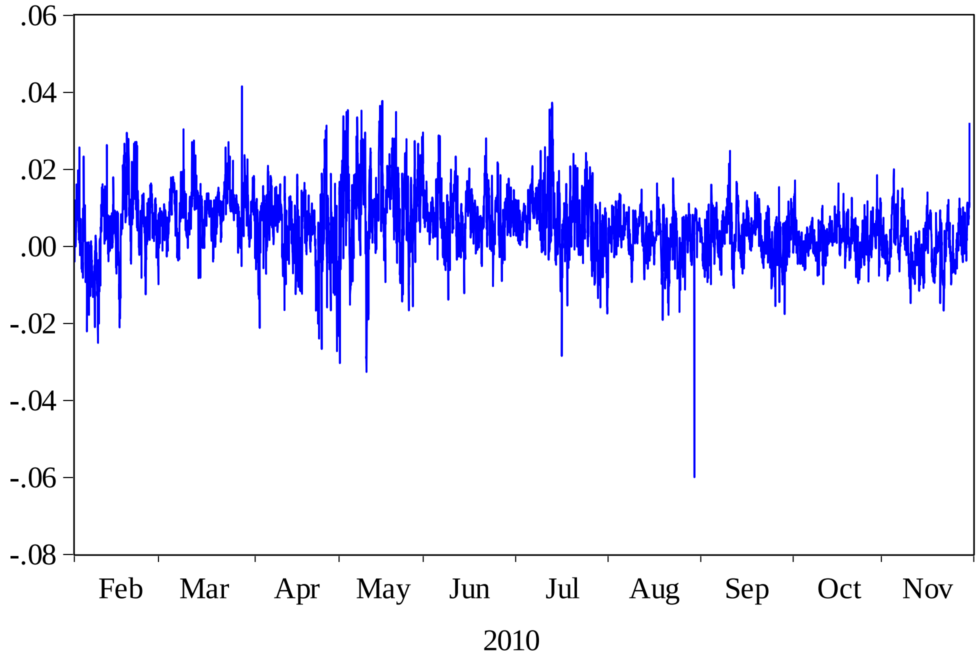
In conclusion, this chapter finds that the submission of allowances has a significant impact on the mean-reverting process of the spot and futures relationship and the transmission of information between spot and futures markets under EU ETS. The above findings are robust to different intraday time frequencies. The results indicate that, in modelling the relationship between carbon spot and futures prices (e.g. for arbitrage purpose), the difference in the mean-reverting process of futures mispricing before and after the submission deadline should be accounted for. The findings of this thesis are of interest to investors and arbitragers operating in the carbon emission market and could aid regulators in improving the EU ETS mechanisms used in the next commitment period.

Figure 5.1: Time series of carbon futures mispricing using 15 min data

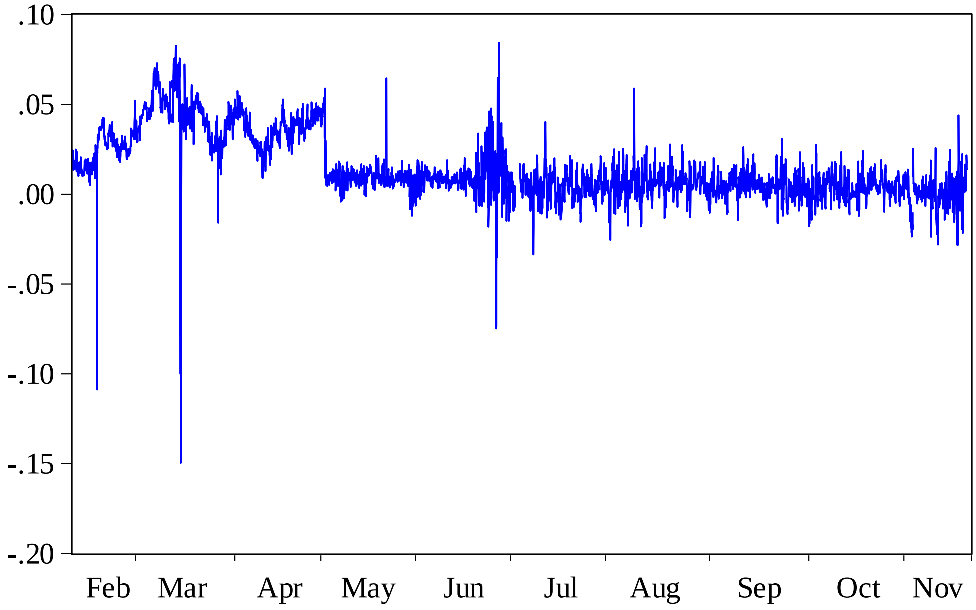
Panel A. Year 2009



Panel B. Year 2010



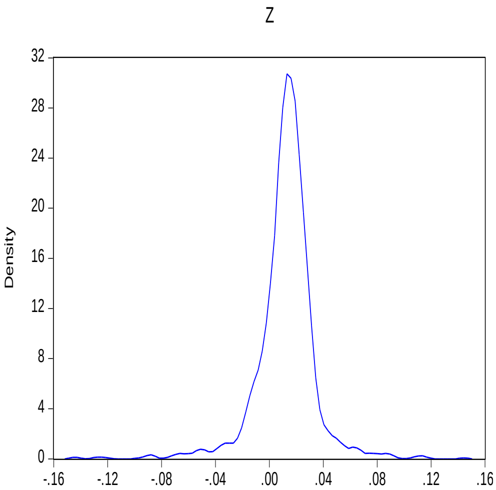
Panel C.   Year 2011

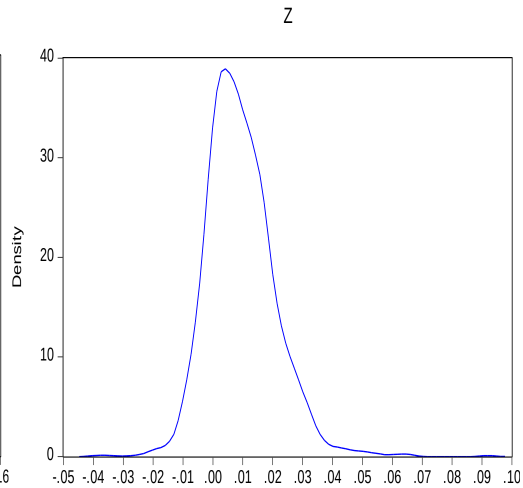


Note: The figure shows the time series of carbon futures mispricing from February to November each year, using 15 min intervals. The series for 2009, 2010 and 2011 are shown in Panel A, Panel B and Panel C, respectively. The carbon futures mispricing, Z_t, is computed as the difference between the observed futures prices and the theoretical futures prices: $Z_t = \ln(F_{t,T}) - \ln(F^*_{t,T}) = \ln(F_{t,T}) - \ln(S_t e^{(Rft + u_t - CYt)(T-t)})$

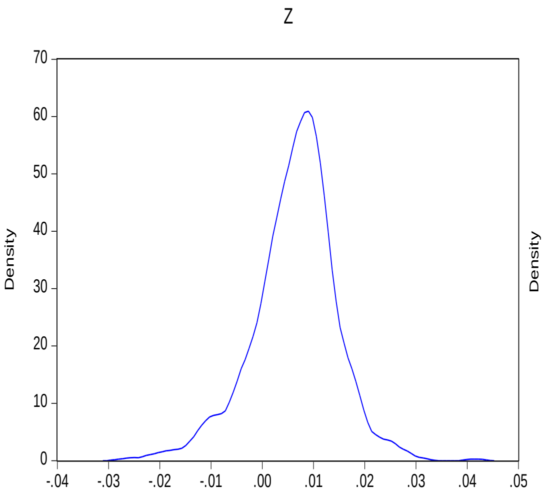
Figure 5.2: Kernel density estimation of carbon futures mispricing using 15 min data

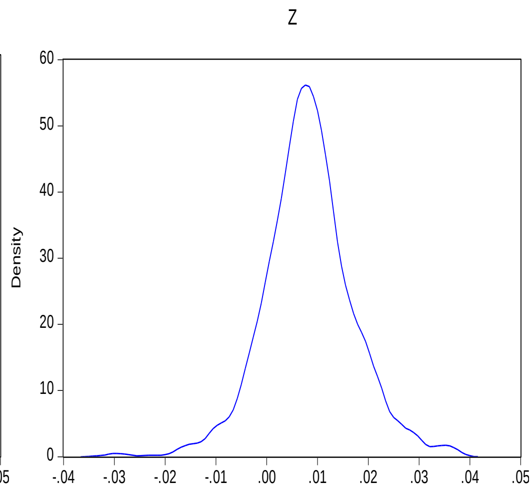
Panel A. 2009 February to April 2009 May to July



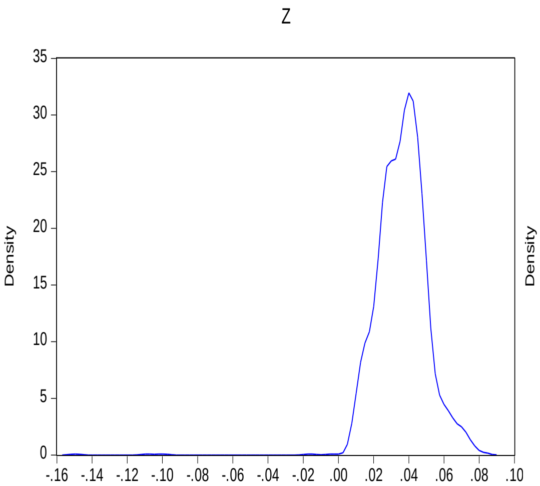


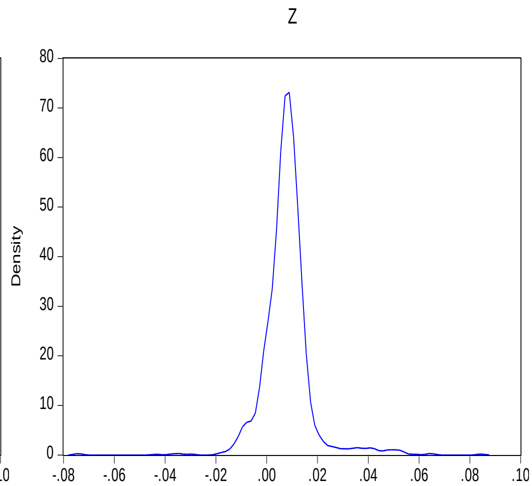
Panel B. 2010 February to April 2010 May to July





Panel C. 2011 February to April 2011 May to July





Note: The figure shows kernel density estimates of carbon futures mispricing before and after the submission deadline each year. The results for 2009, 2010 and 2011 are shown in Panel A, Panel B and Panel C, respectively.

Table 5.1: Summary statistics of carbon futures mispricing using 15 min data

Panel A: Full year sample periods			
	2009	2010	2011
Mean	0.0066	0.0052	0.0143
Std. Dev.	0.0154	0.0079	0.0174
Skewness	-0.062	0.095	0.649
Kurtosis	16.188	5.105	5.710
Jarque-Bera	43924.180***	1149.384***	2148.784***

Panel B: Before and after submission deadline subsample periods						
	2009 02-04	2009 05-07	2010 02-04	2010 05-07	2011 02-04	2011 05-07
Mean	0.0124	0.0094	0.0063	0.0083	0.0362	0.0080
Std. Dev.	0.0223	0.0114	0.0082	0.0088	0.0148	0.0098
Skewness	-0.918	0.847	-0.433	-0.029	-2.114	0.701
Kurtosis	11.980	6.174	4.383	4.471	28.086	16.276
Jarque-Bera	6294.107***	969.689***	202.835***	167.672***	43011.170***	13352.160***

Note: The table provides summary statistics of carbon futures mispricing using 15 min data. Panel A shows the full year sample results, i.e. from February to November each year. Panel B displays the summary statistics of the sample periods before and after the submission deadline. 2009 02-04 indicates the sample period covering February 2009 to April 2009; and by analogy for the rest of the sample periods. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 5.2: Estimation results of ADF tests with dummy variables using 15 min data

	α	δ	ρ_1	ρ_2	$\rho_{1=}\rho_2$
Panel A: Year 2009					
2009 02-07	0.0017***	0.0021***	-0.3019***	-0.1793***	11.919***
	(3.414)	(3.338)	(-13.234)	(-5.150)	
2009 02-08	0.0013***	0.0024***	-0.3023***	-0.1691***	17.967***
	(3.478)	(4.598)	(-14.326)	(-5.572)	
2009 02-10	0.0009***	0.0028***	-0.2977***	-0.1786***	23.403***
	(3.606)	(6.433)	(-15.815)	(-7.818)	
Panel B: Year 2010					
2010 02-07	0.0013***	-0.0004	-0.1433***	-0.1511***	0.128
	(6.720)	(-1.482)	(-8.324)	(-9.288)	
2010 02-08	0.0010***	-0.0001	-0.1411***	-0.1468***	0.079
	(6.946)	(0.531)	(-8.452)	(-10.323)	
2010 02-10	0.0008***	0.0001	-0.1411***	-0.1414***	0.000
	(7.297)	(0.604)	(-9.075)	(-11.851)	
Panel C: Year 2011					
2011 02-07	0.0008***	0.0035***	-0.1195***	-0.1106***	0.151
	(3.419)	(6.200)	(-8.539)	(-5.384)	
2011 02-08	0.0009***	0.0042***	-0.1411***	-0.1324***	0.179
	(4.838)	(7.717)	(-10.558)	(-7.869)	
2011 02-10	0.0008***	0.0043***	-0.1405***	-0.1260***	0.640
	(5.226)	(8.807)	(-11.230)	(-8.146)	

Note: The table shows the estimation results of the augmented Dickey-Fuller (ADF) tests with dummy variables using 15 min data. The ADF test with dummy variables is specified as:

$$\Delta Z_t = \alpha + \delta D_t + \rho_1 Z_{t-1} D_t + \rho_2 Z_{t-1}(1 - D_t) + \sum_{i=1}^{k} \lambda_i \Delta Z_{t-i} + \varepsilon_t$$

where D_t is a dummy variable set to be 1 during the period before 30 April and 0 otherwise. 2009 02-07 indicates the sample period covering February 2009 to July 2009; and by analogy for the rest of the sample periods. The results for 2009, 2010 and 2011 are shown in Panel A, Panel B and Panel C, respectively. $\alpha + \delta$ and α are the intercept terms during the period before 30 April and after 30 April, respectively. The coefficients ρ_1 and ρ_2 are related to the first-order lagged mispricing during the period before and after 30 April, respectively. The values of the t-statistics for each parameter are presented in parentheses. $\rho_{1=}\rho_2$ is the Wald-test for equality. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 5.3: Estimation results of TAR model with dummies using 15 min data (Chan's (1993) procedure)

	α	δ	ρ_1	ρ_2	ρ_3	ρ_4	$\rho_1=\rho_2$	$\rho_3=\rho_4$
Panel A: Year 2009								
2009 02-07	0.0016***	0.0023***	-0.3631***	-0.2357***	-0.2696***	-0.1551***	6.245**	6.983***
	(3.120)	(3.561)	(-12.370)	(-4.882)	(-10.814)	(-3.805)		
2009 02-08	0.0012***	0.0026***	-0.3363***	-0.2127***	-0.2796***	-0.1400***	8.270***	12.190***
	(3.105)	(4.869)	(-12.835)	(-5.308)	(-11.787)	(-3.786)		
2009 02-10	0.0009***	0.0028***	-0.3027***	-0.1720***	-0.2918***	-0.1877***	17.140***	8.666***
	(3.628)	(6.357)	(-13.682)	(-6.158)	(-12.322)	(-6.071)		
Panel B: Year 2010								
2010 02-07	0.0011***	-0.0011***	-0.0617***	-0.1402***	-0.3385***	-0.1955***	7.149***	5.080**
	(4.904)	(-3.270)	(-2.593)	(-7.186)	(-7.898)	(-4.085)		
2010 02-08	0.0005***	-0.0005*	-0.0616***	-0.1040***	-0.3386***	-0.3053***	2.360	0.357
	(3.039)	(-1.672)	(-2.663)	(-6.090)	(-8.108)	(-7.967)		
2010 02-10	0.0004***	-0.0004	-0.0598***	-0.0967***	-0.3408***	-0.3408***	2.393	0.519
	(3.040)	(-1.283)	(-2.893)	(-7.019)	(-8.888)	(-9.523)		
Panel C: Year 2011								
2011 02-07	0.0009***	0.0057***	-0.1357***	-0.1721***	-0.2035***	-0.1122***	1.151	11.099***
	(3.637)	(8.682)	(-9.845)	(-5.370)	(-10.752)	(-5.157)		
2011 02-08	0.0009***	0.0064***	-0.1497***	-0.1804***	-0.2248***	-0.1264***	0.933	15.771***
	(4.632)	(10.147)	(-11.215)	(-6.063)	(-12.284)	(-6.731)		
2011 02-10	0.0012***	0.0074***	-0.2080***	-0.2028***	-0.5952***	-0.1872***	0.057	184.840***
	(7.977)	(14.661)	(-16.867)	(-10.650)	(-22.167)	(-10.620)		

Note: The table shows the estimation results of the threshold autoregressive (TAR) model with dummy variables using 15 min data. The model is specified as:

$$\Delta Z_t = \alpha + \delta D_t + \rho_1 Z_{t-1} I_t D_t + \rho_2 Z_{t-1} I_t (1-D_t) + \rho_3 Z_{t-1}(1-I_t) D_t + \rho_4 Z_{t-1}(1-I_t)(1-D_t) + \sum_{i=1}^{k} \lambda_i \Delta Z_{t-i} + \varepsilon_t$$

where D_t is a dummy variable set to be 1 during the period before 30 April and 0 otherwise. I_t is also a dummy variable taking the value of 1 if Z_{t-1} is greater than or equal to the threshold, and 0 otherwise. The thresholds are determined by using Chan's (1993) procedure. 2009 02-07 indicates the sample period covering February 2009 to July 2009; and by analogy for the rest of the sample periods. The results for 2009, 2010 and 2011 are shown in Panel A, Panel B and Panel C, respectively. $\alpha+\delta$ and α are the intercept terms during the period before and after 30 April, respectively. The values of the t-statistics for each parameter are presented in parentheses. $\rho_1=\rho_2$ and $\rho_3=\rho_4$ are the Wald-tests for equality. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 5.4: Estimation results of QLSTR model with dummy variables using 15 min data

	α_0	α_1	β_0	β_1	γ	c_1	c_2	$\alpha_{1,1}=\alpha_{1,2}$	$\beta_{1,1}=\beta_{1,2}$	$\gamma_1=\gamma_2$	$c_{1,1}=c_{1,2}$	$c_{2,1}=c_{2,2}$
Panel A: Year 2009												
2009 02-07	0.0036***	-0.2514***	-0.0052***	-0.2096***	108246.900	-0.0014***	0.0668***	7.938***	3.753*	0.102	11.853***	58.389***
i=1	(4.769)	(-6.693)	(-4.520)	(-5.137)	(0.258)	(-2.587)	(91.915)					
2009 02-07	0.0008	-0.1009**	0.0035	-0.3866***	17284.640	-0.0088***	0.0453***					
i=2	(1.430)	(-2.374)	(1.357)	(-4.711)	(0.810)	(-4.567)	(17.682)					
2009 02-08	0.0036***	-0.2530***	-0.0053***	-0.2093***	108246.900	-0.0014***	0.0668***	10.858***	4.460**	0.117	14.394***	69.530***
i=1	(5.157)	(-7.242)	(-4.870)	(-5.503)	(0.277)	(-2.780)	(96.892)					
2009 02-08	0.0006	-0.0964***	0.0031	-0.3822***	17284.640	-0.0087***	0.0452***					
i=2	(1.453)	(-2.650)	(1.453)	(-5.248)	(0.915)	(-5.108)	(19.191)					
2009 02-10	0.0036***	-0.2482***	-0.0052***	-0.2089***	108246.900	-0.0014***	0.0668***	15.230***	6.726***	0.135	0.300	134.840***
i=1	(5.534)	(-7.816)	(-5.252)	(-5.983)	(0.298)	(-2.992)	(107.114)					
2009 02-10	0.0001	-0.0856***	-0.0006	-0.3754***	17284.51	-0.0042	0.0453***					
i=2	(0.393)	(-2.822)	(-0.621)	(-6.923)	(0.917)	(-0.948)	(27.943)					
Panel B: Year 2010												
2010 02-07	-0.0014	-0.0897	0.0121	-0.4747*	5421.904	-0.0219***	0.0156***	0.527	1.543	0.002	7.345***	0.008
i=1	(-0.572)	(-0.713)	(1.626)	(-1.713)	(1.300)	(-5.200)	(2.586)					
2010 02-07	0.0081	-0.4406	-0.0070	0.2177	9277.955	0.0142	0.0499					
i=2	(0.570)	(-0.944)	(-0.499)	(0.450)	(0.115)	(1.125)	(0.127)					
2010 02-08	-0.0014	-0.0912	0.0122*	-0.4814*	5419.885	-0.0219***	0.0157***	0.025	0.263	1.402	0.127	0.003
i=1	(-0.589)	(-0.745)	(1.697)	(-1.788)	(1.354)	(-5.420)	(2.669)					
2010 02-08	0.0198	0.4571	-0.0330	-1.3828	668.347**	0.0221	0.0221					
i=2	(0.084)	(0.131)	(-0.093)	(-0.796)	(2.544)	(0.179)	(0.179)					
2010 02-10	-0.0014	-0.0910	0.0121*	-0.4796*	5418.831	-0.0219***	0.0157***	0.008	0.005	0.884	0.011	0.000
i=1	(-0.626)	(-0.790)	(1.801)	(-1.897)	(1.436)	(-5.752)	(2.837)					
2010 02-10	0.2700	-4.8778	-0.3143	3.5576	4.0154	0.0411	10.8871					
i=2	(0.073)	(-0.098)	(-0.098)	(0.062)	(0.001)	(0.069)	(0.001)					
Panel C: Year 2011												
2011 02-07	0.0018	-0.0437	0.0100***	-0.8005***	3263.053	0.0136***	0.0917***	2.470	10.993***	0.087	2.648	19.691***
i=1	(1.117)	(-1.438)	(3.982)	(-17.025)	(1.447)	(10.886)	(10.886)					
2011 02-07	-0.0095**	0.1324	0.0115***	-0.4060***	111991.900	0.0229***	0.0539***					
i=2	(-2.317)	(1.226)	(2.805)	(-3.673)	(0.305)	(8.662)	(29.435)					
2011 02-08	0.0018	-0.0449	0.0106***	-0.8393***	3260.655	0.0917***	0.0131***	5.487**	12.360***	0.124	3.824*	21.827***
i=1	(1.192)	(-1.543)	(4.205)	(-18.850)	(1.507)	(11.501)	(2.634)					
2011 02-08	-0.0126***	0.1943**	0.0145***	-0.4592***	111991.900	0.0233***	0.0539***					
i=2	(-3.432)	(1.984)	(3.937)	(-4.588)	(0.382)	(22.694)	(33.575)					
2011 02-10	0.0019	-0.0481*	0.0108***	-0.8721***	3260.623*	0.0131***	0.0918***	6.368**	19.254***	0.196	4.725**	26.721***
i=1	(1.368)	(-1.778)	(4.680)	(-21.245)	(1.678)	(2.971)	(12.684)					
2011 02-10	-0.0124***	0.1836**	0.0140***	-0.4463***	11991.900	0.0231***	0.0539***					
i=2	(-3.804)	(2.091)	(4.301)	(-4.996)	(0.447)	(26.014)	(38.232)					

Note: The table shows the estimation results of the quadratic-logistic smooth transition (QLSTR) model with dummy variables using 15 min data. The model is specified as:

$$\Delta Z_t = \left(\alpha_{0,1} + \alpha_{1,1} Z_{t-1} + (\beta_{0,1} + \beta_{1,1} Z_{t-1})(1 + \exp(-\gamma_1 (Z_{t-1} - c_{1,1})(Z_{t-1} - c_{2,1})))^{-1}\right) D_t + \left(\alpha_{0,2} + \alpha_{1,2} Z_{t-1} + (\beta_{0,2} + \beta_{1,2} Z_{t-1})(1 + \exp(-\gamma_2 (Z_{t-1} - c_{1,2})(Z_{t-1} - c_{2,2})))^{-1}\right)(1 - D_t) + \sum_{i=1}^{k} \lambda_i \Delta Z_{t-i} + \varepsilon_t$$

D_t is the dummy variable set to be 1 during the period before 30 April and 0 otherwise. 2009 02-07 indicates the sample period covering February 2009 to July 2009; and by analogy for the rest of the sample periods. The results for 2009, 2010 and 2011 are shown in Panel A, Panel B and Panel C, respectively. $\alpha_{1,i}$ and $\beta_{1,i}$ are the parameters used to determine the speed of mean-reversion; γ_i is the speed of regime transition; $c_{1,i}$ is the lower boundary and $c_{2,i}$ is upper boundary of the inner regime. i=1 for the period before 30 April each year, and i=2 for the sample period after 30 April. The values of the t-statistics for each parameter are presented in parentheses. $\alpha_{1,1=}\ \alpha_{1,2}$, $\beta_{1,1=}\ \beta_{1,2}$, $\gamma_1 = \gamma_2$, $c_{1,1}=c_{1,2}$ and $c_{2,1}=c_{2,2}$ are the Wald-tests for equality. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 5.5: Estimation results of Granger causality tests using 15 min data

	Optimal lags	Null hypothesis	F-statistics	P-value
Panel A: Year 2009				
2009 02-04	8	Spot≠>Futures	23.845***	0.000
		Futures≠>Spot	0.476	0.874
2009 05-07	7	Spot≠>Futures	3.328***	0.002
		Futures≠>Spot	21.854***	0.000
2009 05-08	8	Spot≠>Futures	5.540***	0.000
		Futures≠>Spot	26.348***	0.000
2009 05-10	12	Spot≠>Futures	11.440***	0.000
		Futures≠>Spot	30.561***	0.000
Panel B: Year 2010				
2010 02-04	4	Spot≠>Futures	13.201***	0.000
		Futures≠>Spot	5.717***	0.000
2010 05-07	4	Spot≠>Futures	14.799***	0.000
		Futures≠>Spot	14.263***	0.000
2010 05-08	18	Spot≠>Futures	24.167***	0.000
		Futures≠>Spot	4.290***	0.000
2010 05-10	29	Spot≠>Futures	32.190***	0.000
		Futures≠>Spot	5.109***	0.000
Panel C: Year 2011				
2011 02-04	2	Spot≠>Futures	9.731***	0.000
		Futures≠>Spot	7.340***	0.001
2011 05-07	8	Spot≠>Futures	3.487***	0.001
		Futures≠>Spot	32.638***	0.000
2011 05-08	8	Spot≠>Futures	2.881***	0.003
		Futures≠>Spot	47.397***	0.000
2011 05-10	8	Spot≠>Futures	3.834***	0.000
		Futures≠>Spot	57.652***	0.000

Note: The table shows the results of Granger causality tests using 15 min data. 2009 02-04 indicates the sample period covering February 2009 to April 2009; and by analogy for the rest of the sample periods. The results for 2009, 2010 and 2011 are shown in Panel A, Panel B and Panel C, respectively. The optimal lags are selected based on the Schwarz information criterion (SIC). The null hypothesis Spot≠>Futures indicates that spot returns do not Granger cause futures returns and Futures≠>Spot shows that futures returns do not Granger cause spot returns. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 5.6: Estimation results of HAR model for volatility spillovers using 15 min data

	2009		2010		2011	
	RVF	RVS	RVF	RVS	RVF	RVS
α_1	-0.0305***	0.0005**	0.0005	-0.0002	0.0386***	0.0010
	(-5.877)	(2.342)	(0.592)	(-1.115)	(7.192)	(1.251)
$\beta_{1,1}$	-0.0710	-0.0013	0.0647	0.0270	-0.5961***	-0.0035
	(-0.870)	(-0.372)	(0.398)	(0.774)	(-6.859)	(-0.275)
$\beta_{1,5}$	-0.2795	-0.0107	-0.1457	0.1480	0.3503	0.0001
	(-1.419)	(-1.234)	(-0.246)	(1.167)	(1.012)	(0.002)
$\beta_{1,22}$	-2.8771***	0.0326	-1.6741	0.0118	2.7737***	0.0602
	(-5.180)	(1.341)	(-1.028)	(0.034)	(4.446)	(0.661)
$c_{1,1}$	7.5414***	0.0124	3.5519***	-0.3860	91.7453***	0.6070
	(3.024)	(0.113)	(2.964)	(-1.506)	(13.679)	(0.620)
$c_{1,5}$	5.9514	0.2123	2.1715	0.9343	-63.4115**	-0.7180
	(1.016)	(0.828)	(0.562)	(1.130)	(-2.500)	(-0.194)
$c_{1,22}$	81.7784***	-0.4255	1.5743	1.2957	-316.8747***	-6.5017
	(6.006)	(-0.714)	(0.175)	(0.672)	(-6.384)	(-0.897)
α_2	0.0010	0.0000	0.0003*	0.0000	0.0006	0.0002**
	(1.011)	(0.413)	(1.862)	(0.073)	(0.850)	(2.035)
$\beta_{2,1}$	0.1333	0.0095	-0.0087	-0.0011	0.3995*	0.1456***
	(0.684)	(1.114)	(-0.091)	(-0.056)	(1.690)	(4.218)
$\beta_{2,5}$	-0.4089	-0.0085	0.3245	0.0644	0.0969	-0.1753***
	(-0.870)	(-0.411)	(1.539)	(1.428)	(0.222)	(-2.748)
$\beta_{2,22}$	0.5380	0.0471*	-0.5567	0.2065*	0.1589	0.0104
	(0.905)	(1.811)	(-0.996)	(1.718)	(0.238)	(0.106)
$c_{2,1}$	-0.9468	0.0921	0.7303*	-0.0035	1.0174	0.3759***
	(-0.282)	(0.627)	(1.704)	(-0.038)	(1.610)	(4.074)
$c_{2,5}$	6.9261	0.4671*	0.9574	0.2008	-0.3868	0.4049*
	(1.127)	(1.736)	(0.999)	(0.980)	(-0.254)	(1.822)
$c_{2,22}$	-3.976	-0.1609	1.1522	-0.2853	-1.8174	-0.2367
	(-0.567)	(-0.524)	(0.701)	(-0.810)	(-0.610)	(-0.544)
LR	41.517***	2.064	7.026*	1.377	269.044***	17.155***

Note: The table shows the estimation results of the heterogeneous autoregressive (HAR) model with dummy variables for volatility spillovers using 15 min data. The model is specified as:

$$RVF_t = (\alpha_1 + \beta_{1,1}RVF_{t-1} + \beta_{1,5}RVF_{(t-1|t-5)} + \beta_{1,22}RVF_{(t-1|t-22)} + c_{1,1}RVS_{t-1} + c_{1,5}RVS_{(t-1|t-5)} + c_{1,22}RVS_{(t-1|t-22)})D_t$$
$$+(\alpha_2 + \beta_{2,1}RVF_{t-1} + \beta_{2,5}RVF_{(t-1|t-5)} + \beta_{2,22}RVF_{(t-1|t-22)} + c_{2,1}RVS_{t-1} + c_{2,5}RVS_{(t-1|t-5)} + c_{2,22}RVS_{(t-1|t-22)})(1-D_t) + \varepsilon_t$$

$$RVS_t = (\alpha_1 + \beta_{1,1}RVF_{t-1} + \beta_{1,5}RVF_{(t-1|t-5)} + \beta_{1,22}RVF_{(t-1|t-22)} + c_{1,1}RVS_{t-1} + c_{1,5}RVS_{(t-1|t-5)} + c_{1,22}RVS_{(t-1|t-22)})D_t$$
$$+(\alpha_2 + \beta_{2,1}RVF_{t-1} + \beta_{2,5}RVF_{(t-1|t-5)} + \beta_{2,22}RVF_{(t-1|t-22)} + c_{2,1}RVS_{t-1} + c_{2,5}RVS_{(t-1|t-5)} + c_{2,22}RVS_{(t-1|t-22)})(1-D_t) + \varepsilon_t$$

RVF_t is the daily realised volatility for futures returns while RVS_t is the daily realised volatility for spot returns at time *t*. $RVF_{(t-1|t-k)} = \frac{1}{k}\sum_{j=1}^{k} RVF_{t-j}$; $RVS_{(t-1|t-k)} = \frac{1}{k}\sum_{j=1}^{k} RVS_{t-j}$. The sample period runs from February to November each year (longest available), because of the limited observations available for each year. D_t is the dummy variable set to be 1 during the period before 30 April and 0 afterwards. The results for 2009, 2010 and 2011 are shown in Panel A, Panel B and Panel C, respectively. The values of the t-statistics for each parameter are presented in parentheses. LR is the likelihood ratio test for the equality of volatility spillover parameters before and after 30 April each year. Specifically, it is the joint test of $c_{1,1}= c_{2,1}$, $c_{1,5}= c_{2,5}$, $c_{1,22}= c_{2,22}$ for futures realised volatility spillovers; and the joint test of $\beta_{1,1}= \beta_{2,1}$, $\beta_{1,5}= \beta_{2,5}$, $\beta_{1,22}= \beta_{2,22}$ for spot realised volatility spillovers. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Appendix 5A: Hochradl and Rammerstorfer's (2012) Methodology

Based on the economic implications that the convenience yield represents the advantages of holding spot commodities over futures contracts, Heaney (2002) first models the convenience yield as the difference between a lookback put option on a spot asset and another lookback put option on a futures contract. The advantage of this methodology over the traditional approach based on the cost-of-carry model is that it releases the condition of no short-sale constraints and other restrictions. Therefore, even if the market is imperfect, investors can still use the option implied approach to estimate the convenience yield. Hochradl and Rammerstorfer (2012) further develop Heaney's (2002) approach by using Asian options instead of European options. In this case, investors can sell the asset at the average price over a period, rather than using Heaney's (2002) assumption that assets can only be sold at the maximum price. For this reason, Hochradl and Rammerstorfer's (2012) methodology is adopted to estimate the convenience yield and calculate the mispricing in European carbon markets.

In Hochradl and Rammerstorfer's (2012) model, the convenience yield is calculated as the difference between an Asian style put option on a spot asset and an Asian style put option on a futures contract[44]:

$$y_{t,T} = y_{t,T}^{S} - y_{t,T}^{F} \tag{5A1}$$

Take the Asian style put option on a spot asset as an example. Assume that the investor can sell the asset at its average price during the period of [*t*, *T*]. Therefore, the amount of money the investor can obtain is (geometrically):

[44] Please see Hochradl and Rammerstorfer (2012) for detailed explanation.

$$M_T^S = (\prod_{t=0}^{T} S_t)^{1/T} \tag{5A2}$$

If the investor misses the chance to sell the asset, the payoff is then the value of a geometric average strike Asian style put option:

$$\max(0, M_T^S - S_T) \tag{5A3}$$

The present value of the option can then be modelled using the standard no-arbitrage principle, which can be shown as[45]:

$$PV_t^S = e^{\mu_M + 0.5\sigma_M^2 - rT} N(-y_2) - S_t N(-y_1) \tag{5A4}$$

where y_1 and y_2 is shown as (following the same definitions used by Levy (1997)):

$$\left\{ \begin{array}{l} y_1 = \dfrac{\ln S_t + rT - \mu_M - 0.5\sigma_M^2 + 0.5\sum^2}{\sum} \\ y_2 = y_1 - \sum \\ \sum^2 = \sigma_M^2 + \sigma_S^2 T - 2\sigma_{M,T} \\ \mu_M = \dfrac{m}{M}\ln M_t + \dfrac{N-m}{N}\{\ln S_t + (r - \dfrac{\sigma_s^2}{2})[(t_{m+1} - t) + \dfrac{t_N - t_1}{2(N-1)}(N-m-1)]\} \\ \sigma_M^2 = \sigma_S^2 (\dfrac{N-m}{N})^2 [(t_{m+1} - t) + \dfrac{\dfrac{(t_N - t_1)}{(N-1)}(2N-2m-1)(N-m-1)}{6(N-m)} \\ \sigma_{M,T} = \sigma_S^2 \dfrac{N-m}{N}[(t_{m+1} - t) + \dfrac{t_N - t_1}{2(N-1)}(N-m-1)] \end{array} \right\} \tag{5A5}$$

Next, the same procedure is repeated for the futures contract, and the present value of the Asian style put option on futures can also be estimated. The difference between the two present values (PV_t^S-PV_t^F) is the option implied convenience yield (CY_t):

[45] Please see Levy (1997) for details of the derivation.

$$CY_t = PV_t^S - PV_t^F \qquad (5A6)$$

Appendix 5B: Robustness checks using different time frequencies

The results in Section 5.5 demonstrate that allowance submission has effects on changing the mean-reverting process of the spot and futures relationship and volatility spillovers between the spot and futures markets. However, these findings may have arisen because of the selection of intraday time frequencies. For this reason, the models in Section 5.5 are re-estimated by using data at frequencies of h=10 and 30 minute intervals. The results are shown in Table 5B.1 to Table 5B.5 in this appendix.

The results for the robustness checks are generally consistent with those obtained by using 15 min data. The estimation results using 10 min data are shown in Part A while the results using 30 min data are displayed in Part B in each table. In Table 5B.1, the spot and futures prices are cointegrated in the periods before and after the submission deadline, for all three years and different time frequencies. In addition, the equilibrium level shifts for all three years due to the fact that the allowance submission and the speed of mean-reverting are different before and after the deadline for 2009 and 2011, for both 10 minute and 30 minute intervals. Table 5B.2 provides further evidence that the speed of adjustment also changes in the lower regime after the submission deadline in 2010 by using 10 min data. Turning to Table 5B.3, the results of the QLSTR model for 10 min data are consistent with previous findings that the speed of mean-reverting and no-arbitrage bands alters after the deadline in 2009 and 2011, and show that the speed of regime transition also changes due to the submission of allowances in 2011. For the 30 min data results, it is found that the adjustment speed and no-arbitrage boundaries shift after the submission deadline in 2011, but the effect of allowance submission on the mean-reverting process is not very significant in 2009 and 2010. Furthermore, there is evidence that the effect of allowance submission is not significant in the price discovery process from the results of the Granger causality tests in Table 5B.4, for both 10 minute and 30 minute intervals. However, the values of the F-test statistics also show the switch in the leading market from the spot market to the futures market. Finally, the 10 min and 30 min data results in Table 5B.5 provide additional evidence for the view that volatility spillovers from the spot market to the futures market shift from being significant before the submission deadline to insignificant after the deadline. To summarise, all the results are consistent with the findings in Section 5.4.

Table 5B.1: Estimation results of ADF tests with dummy variables

Part A: 10 min data results					
	α	δ	ρ_1	ρ_2	$\rho_1 = \rho_2$
Panel A: Year 2009					
2009 02-07	0.0014***	0.0020***	-0.2733***	-0.1493***	17.442***
	(3.392)	(3.876)	(-15.136)	(-5.148)	
2009 02-08	0.0011***	0.0023***	-0.2747***	-0.1411***	25.965***
	(3.470)	(5.250)	(-16.443)	(-5.583)	
2009 02-10	0.0007***	0.0027***	-0.2773***	-0.1464***	41.276***
	(3.577)	(7.495)	(-18.629)	(-7.752)	
Panel B: Year 2010					
2010 02-07	0.0014***	-0.0003*	-0.1667***	-0.1793***	0.412
	(9.863)	(-1.717)	(-11.651)	(-13.096)	
2010 02-08	0.0011***	-0.0001	-0.1625***	-0.1699***	0.188
	(10.006)	(-0.354)	(-11.667)	(-14.292)	
2010 02-10	0.0008***	0.0003*	-0.1637***	-0.1578***	0.153
	(10.320)	(1.776)	(-12.646)	(-16.125)	
Panel C: Year 2011					
2011 02-07	0.0010***	0.0018***	-0.0758***	-0.1218***	7.543***
	(5.415)	(4.235)	(-7.208)	(-8.430)	
2011 02-08	0.0009***	0.0021***	-0.0836***	-0.1250***	7.286***
	(6.282)	(5.291)	(-8.280)	(-9.762)	
2011 02-10	0.0008***	0.0025***	-0.0921***	-0.1303***	8.169***
	(7.756)	(6.857)	(-9.872)	(-12.145)	

Part B: 30 min data results					
	α	δ	ρ_1	ρ_2	$\rho_1 = \rho_2$
Panel A: Year 2009					
2009 02-07	0.0020***	0.0021**	-0.3267***	-0.2161***	4.502**
	(2.773)	(2.309)	(-9.457)	(-4.130)	
2009 02-08	0.0015***	0.0026***	-0.3248***	-0.2014***	7.221***
	(2.789)	(3.284)	(-10.180)	(-4.444)	
2009 02-10	0.0010***	0.0031***	-0.3195***	-0.1996***	11.259***
	(2.739)	(4.752)	(-11.250)	(-5.849)	
Panel B: Year 2010					
2010 02-07	0.0006**	0.0008*	-0.1286***	-0.1038***	0.886
	(2.521)	(1.907)	(-6.020)	(-5.810)	
2010 02-08	0.0007***	0.0007*	-0.1261***	-0.1181***	0.097
	(3.245)	(1.746)	(-5.986)	(-7.075)	
2010 02-10	0.0005***	0.0009***	-0.1251***	-0.1121***	0.323
	(3.089)	(2.609)	(-6.402)	(-8.042)	
Panel C: Year 2011					
2011 02-07	0.0020***	-0.0004	-0.0412**	-0.2529***	46.539***
	(6.339)	(-0.573)	(-2.295)	(-9.192)	
2011 02-08	0.0020***	-0.0003	-0.0453**	-0.2703***	57.202***
	(7.298)	(-0.3713)	(-2.501)	(-10.471)	
2011 02-10	0.0018***	0.0000	-0.0490***	-0.2801***	72.859***
	(8.592)	(0.060)	(-2.799)	(-12.314)	

Note: The table shows the estimation results of the augmented Dickey-Fuller (ADF) tests with dummy variables using alternative time frequencies. The results using 10 min data are shown in Part A and the results using 30 min data are displayed in Part B. The ADF test with dummy variables is specified as:

$$\Delta Z_t = \alpha + \delta D_t + \rho_1 Z_{t-1} D_t + \rho_2 Z_{t-1}(1 - D_t) + \sum_{i=1}^{k} \lambda_i \Delta Z_{t-i} + \varepsilon_t$$

where D_t is a dummy variable set to be 1 during the period before 30 April and 0 otherwise. 2009 02-07 indicates the sample period covering February 2009 to July 2009; and by analogy for the rest of the sample periods. The results for 2009, 2010 and 2011 are shown in Panel A, Panel B and Panel C, respectively. $\alpha + \delta$ and α are the intercept terms during the period before and after 30 April, respectively. The coefficients ρ_1 and ρ_2 are related to the first-order lagged mispricing during the period before and after 30 April, respectively. The values of the t-statistics for each parameter are presented in parentheses. $\rho_1 = \rho_2$ is the Wald-test for equality. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 5B.2: Estimation results of TAR model with dummies (Chan's (1993) procedure)

	α	δ	ρ_1	ρ_2	ρ_3	ρ_4	$\rho_1=\rho_2$	$\rho_3=\rho_4$
Part A: 10 min data results								
Panel A: Year 2009								
2009 02-07	0.0013***	0.0022***	-0.3456***	-0.2213***	-0.2335***	-0.1289***	6.656***	9.149***
	(3.107)	(4.086)	(-14.797)	(-4.803)	(-11.760)	(-3.964)		
2009 02-08	0.0010***	0.0025***	-0.3413***	-0.2124***	-0.2363***	-0.1199***	8.963***	14.352***
	(3.160)	(5.495)	(-15.880)	(-5.200)	(-12.781)	(-4.218)		
2009 02-10	0.0007***	0.0027***	-0.2724***	-0.1654***	-0.2830***	-0.1241***	16.284***	30.537***
	(3.502)	(7.249)	(-15.662)	(-6.996)	(-14.867)	(-4.932)		
Panel B: Year 2010								
2010 02-07	0.0012***	-0.0004	-0.1383***	-0.1596***	-0.2590***	-0.2934***	0.873	0.356
	(7.207)	(-1.608)	(-7.681)	(-10.224)	(-6.935)	(-6.519)		
2010 02-08	0.0008***	0.0000	-0.1393***	-0.1371***	-0.2579***	-0.3693***	0.011	4.901**
	(6.417)	(0.195)	(-8.167)	(-10.440)	(-7.044)	(-10.264)		
2010 02-10	0.0006***	0.0003*	-0.1412***	-0.1272***	-0.2607***	-0.3724***	0.578	6.193**
	(6.464)	(1.721)	(-8.893)	(-12.010)	(-7.623)	(-12.218)		
Panel C: Year 2011								
2011 02-07	0.0015***	-0.0001	-0.0420***	-0.1898***	-0.9333***	-0.1508***	62.777***	189.330***
	(7.987)	(-0.185)	(-4.046)	(-11.904)	(-18.504)	(-4.817)		
2011 02-08	0.0014***	0.0002	-0.0451***	-0.1838***	-0.9815***	-0.1661***	67.632***	233.691***
	(8.625)	(0.468)	(-4.502)	(-13.138)	(-20.429)	(-6.019)		
2011 02-10	0.0012***	0.0006	-0.0480***	-0.1791***	-1.0288***	-0.1696***	80.234***	317.079***
	(9.716)	(1.356)	(-5.175)	(-15.344)	(-23.399)	(-7.195)		
Part B: 30 min data results								
	α	δ	ρ_1	ρ_2	ρ_3	ρ_4	$\rho_1=\rho_2$	$\rho_3=\rho_4$
Panel A: Year 2009								
2009 02-07	0.0020***	0.0023**	-0.3384***	-0.2007***	-0.3168***	-0.4288***	5.696**	0.653
	(2.781)	(2.294)	(-8.177)	(-3.780)	(-6.535)	(-3.157)		
2009 02-08	0.0016***	0.0027***	-0.3387***	-0.1858***	-0.3167***	-0.4024***	8.852***	0.588
	(2.930)	(3.104)	(-8.827)	(-4.041)	(-7.032)	(-3.695)		
2009 02-10	0.0008**	0.0035***	-0.3333***	-0.1594***	-0.3102***	-0.3508***	15.794***	0.323
	(2.099)	(4.693)	(-9.678)	(-4.294)	(-7.596)	(-5.372)		
Panel B: Year 2010								
2010 02-07	0.0007**	0.0005	-0.1201***	-0.1109***	-0.1788**	-0.0881**	0.069	0.947
	(1.972)	(0.971)	(-4.756)	(-4.304)	(-2.173)	(-1.964)		

Table 5B.2 (Continued)

	α	δ	ρ_1	ρ_2	ρ_3	ρ_4	$\rho_1=\rho_2$	$\rho_3=\rho_4$
2010 02-08	0.0004*	0.0008**	-0.1206***	-0.0973***	-0.2157**	-0.1945***	0.668	0.038
	(1.801)	(1.999)	(-5.426)	(-4.987)	(-2.136)	(-4.827)		
2010 02-10	0.0003*	0.0009***	-0.1196***	-0.0939***	-0.2140**	-0.1876***	1.054	0.070
	(1.723)	(2.709)	(-5.928)	(-5.928)	(-2.274)	(-5.523)		
Panel C: Year 2011								
2011 02-07	0.0018***	0.0002	-0.0509**	-0.2664***	-0.1117	-0.2134***	40.304***	1.514
	(5.015)	(0.262)	(-2.414)	(-9.221)	(-1.490)	(-5.292)		
2011 02-08	0.0017***	0.0007	-0.0606***	-0.2940***	-0.1362**	-0.2259***	47.236***	1.476
	(5.787)	(0.744)	(-2.797)	(-10.430)	(-2.018)	(-6.495)		
2011 02-10	0.0016***	0.0010	-0.0654***	-0.3073***	-0.1453**	-0.2452***	56.775***	2.058
	(7.199)	(1.113)	(-3.125)	(-11.776)	(-2.226)	(-8.699)		

Note: The table shows the estimation results of the threshold autoregressive (TAR) model with dummy variables using alternative time frequencies. The results using 10 min data are shown in Part A and the results using 30 min data are displayed in Part B. The model is specified as:

$$\Delta Z_t = \alpha + \delta D_t + \rho_1 Z_{t-1} I_t D_t + \rho_2 Z_{t-1} I_t (1-D_t) + \rho_3 Z_{t-1}(1-I_t) D_t + \rho_4 Z_{t-1}(1-I_t)(1-D_t) + \sum_{i=1}^{k} \lambda_i \Delta Z_{t-i} + \varepsilon_t$$

where D_t is a dummy variable set to be 1 during the period before 30 April and 0 otherwise. I_t is also a dummy variable taking the value of 1 if Z_{t-1} is greater than or equal to the threshold, and 0 otherwise. The thresholds are determined by using Chan's (1993) procedure. 2009 02-07 indicates the sample period covering February 2009 to July 2009; and by analogy for the rest of the sample periods. The results for 2009, 2010 and 2011 are shown in Panel A, Panel B and Panel C, respectively. $\alpha+\delta$ and α are the intercept terms during the period before and after 30 April, respectively. The values of the t-statistics for each parameter are presented in parentheses. $\rho_{1=}\rho_2$ and $\rho_{3=}\rho_4$ are the Wald-tests for equality. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 5B.3: Estimation results of QLSTR model with dummy variables

						Part A: 10 min data results						
	α_0	α_1	β_0	β_1	γ	c_1	c_2	$\alpha_{1,1}=\alpha_{1,2}$	$\beta_{1,1}=\beta_{1,2}$	$\gamma_1=\gamma_2$	$c_{1,1}=c_{1,2}$	$c_{2,1}=c_{2,2}$
Panel A: Year 2009												
2009 02-07	0.0072**	0.4918***	-0.0044	0.3060***	-2092.992	-0.1123***	0.0629***	0.005	3.713*	0.172	17.340***	18.710***
i=1	(2.475)	(14.776)	(-1.490)	(8.979)	(-1.070)	(-4.569)	(23.335)					
2009 02-07	0.0116	0.4770**	-0.0222	0.9001***	-1213.055	0.0040	0.0040					
i=2	(1.008)	(2.405)	(-1.018)	(2.935)	(-1.487)	(0.302)	(0.302)					
2009 02-08	0.0072***	0.4894***	-0.0043	0.3063***	-2092.989	-0.1123***	0.0628***	0.004	4.961**	0.205	21.842***	27.758***
i=1	(2.650)	(15.820)	(-1.582)	(9.651)	(-1.155)	(-4.912)	(25.154)					
2009 02-08	0.0111	0.4784***	-0.0216	0.9241***	-1213.078*	0.0054	0.0054					
i=2	(1.172)	(2.875)	(-1.124)	(3.351)	(-1.726)	(0.509)	(0.509)					
2009 02-10	0.0069***	0.4903***	-0.0041	0.3046***	-2093.203	-0.1122***	0.0629***	0.000	5.907**	0.255	18.829***	19.315***
i=1	(2.804)	(17.535)	(-1.631)	(10.517)	(-1.270)	(-5.215)	(27.781)					
2009 02-10	0.0103	0.4887**	-0.0201	0.8388***	-1212.358**	-0.0003	-0.0003					
i=2	(0.878)	(2.517)	(-0.856)	(3.846)	(-2.105)	(-0.024)	(-0.024)					
Panel B: Year 2010												
2010 02-07	0.0011***	-0.1555***	-0.0034***	-0.3623***	13419.620	-0.0040*	0.0405***	0.531	2.302	0.562	2.476	0.020
i=1	(3.027)	(-5.427)	(-3.096)	(-5.488)	(1.367)	(-1.927)	(17.472)					
2010 02-07	0.0060	-0.3219	-0.0057	-0.0622	4817.511	0.0091	0.0437**					
i=2	(0.826)	(-1.419)	(-0.683)	(-0.333)	(0.816)	(1.136)	(1.989)					
2010 02-08	0.0011***	-0.1552***	-0.0034***	-0.3627***	13345.360	-0.0040**	0.0406***	1.449	0.099	1.332	2.014	2.636
i=1	(3.087)	(-5.547)	(-3.158)	(-5.601)	(1.406)	(-1.966)	(17.806)					
2010 02-08	0.0097	-0.3526**	-0.0132	-0.3068*	2295.332**	0.0059	0.0558***					
i=2	(1.227)	(-2.181)	(-1.406)	(-1.852)	(1.972)	(0.885)	(6.147)					
2010 02-10	0.0012***	-0.1571***	-0.0034***	-0.3649***	13247.910	-0.0040**	0.0405***	2.621	0.245	1.446	4.487**	3.904**
i=1	(3.314)	(-5.990)	(-3.396)	(-6.024)	(1.521)	(-2.111)	(19.213)					
2010 02-10	0.0085*	-0.3547***	-0.0116*	-0.2965**	2699.710***	0.0057	0.0554***					
i=2	(1.661)	(-2.969)	(-1.873)	(-2.382)	(2.634)	(1.364)	(7.685)					
Panel C: Year 2011												
2011 02-07	0.0008*	-0.0225**	0.0363***	-0.5701***	16797.290**	0.0045***	0.0720***	27.328***	0.000	4.277**	0.047	0.041
i=1	(1.843)	(-2.047)	(15.737)	(-17.997)	(2.100)	(8.273)	(36.136)					
2011 02-07	0.0067	-0.1919***	22.7182	-236.638	317.271**	-0.1325	0.1990					
i=2	(1.572)	(-6.285)	(-0.016)	(-0.016)	(2.123)	(-0.211)	(0.316)					
2011 02-08	0.0009**	-0.0251**	0.0382***	-0.5968***	16797.740**	0.0044***	0.0719***	28.449***	0.000	4.850**	0.047	0.137
i=1	(2.125)	(-2.358)	(17.311)	(-19.730)	(2.246)	(8.909)	(37.260)					
2011 02-08	0.0067*	-0.1859***	-22.6235	-236.6952	321.482**	-0.1327	0.1953					
i=2	(1.801)	(-6.571)	(-0.016)	(-0.016)	(2.379)	(-0.211)	(0.310)					
2011 02-10	0.0009**	-0.0275***	0.0400***	-0.6231***	16797.770**	0.0044***	0.0719***	29.022***	0.000	6.010**	0.138	0.040
i=1	(2.509)	(-2.783)	(19.776)	(-22.464)	(2.500)	(9.976)	(39.828)					
2011 02-10	0.0067**	-0.1805***	-22.5152	-236.716	321.715***	-0.1336	0.1927					
i=2	(2.099)	(-6.761)	(-0.016)	(-0.016)	(2.725)	(-0.221)	(0.319)					

Table 5B.3 (Continued)

Part B: 30 min data results												
	α_0	α_1	β_0	β_1	γ	c_1	c_2	$\alpha_{1,1}=\alpha_{1,2}$	$\beta_{1,1}=\beta_{1,2}$	$\gamma_1=\gamma_2$	$c_{1,1}=c_{1,2}$	$c_{2,1}=c_{2,2}$
Panel A: Year 2009												
2009 02-07	0.0037***	-0.2557***	-0.0002	-0.2518***	20438.380	-0.1210***	0.0552**					
i=1	(5.350)	(-6.828)	(-0.052)	(-4.247)	(0.024)	(-117.910)	(2.167)	2.650	0.388	0.000	1.817	0.000
2009 02-07	0.0012	-0.1513**	0.0041	-0.3328***	36806.030	-0.0073***	0.0442***					
i=2	(1.449)	(-2.504)	(1.323)	(-2.862)	(0.424)	(-4.361)	(10.803)					
2009 02-08	0.0037***	-0.2548***	-0.0003	-0.2519***	20438.500	-0.1210***	0.0552**					
i=1	(5.740)	(-7.341)	(-0.061)	(-4.557)	(0.025)	(-121.512)	(2.304)	4.276**	0.392	0.000	1.773	0.000
2009 02-08	0.0008	-0.1368***	0.0031	-0.3252***	36805.950	-0.0062***	0.0442***					
i=2	(1.260)	(-2.601)	(1.336)	(-3.132)	(0.437)	(-3.797)	(12.360)					
2009 02-10	0.0036***	-0.2484***	-0.0004	-0.2491***	20438.540	-0.1210***	0.0553**					
i=1	(6.167)	(-7.947)	(-0.101)	(-4.901)	(0.028)	(-125.369)	(2.299)	6.097**	0.011	0.000	1.838	0.000
2009 02-10	0.0004	-0.1335***	0.0015	-0.2587***	36805.870	-0.0072***	0.0436***					
i=2	(0.840)	(-3.244)	(1.021)	(-3.419)	(0.501)	(-4.888)	(12.457)					
Panel B: Year 2010												
2010 02-07	0.0012***	-0.1138***	0.0121	-0.3715	9454.080	-0.0254***	0.0357*					
i=1	(3.658)	(-4.359)	(0.412)	(-0.546)	(0.731)	(-3.240)	(1.719)	0.264	0.178	0.000	0.000	0.192
2010 02-07	0.0006**	-0.0969***	0.0214***	-0.6735***	1084.086	-1.7938	0.0266***					
i=2	(2.433)	(-4.442)	(2.828)	(-3.019)	(0.000)	(-0.000)	(19.071)					
2010 02-08	0.0012**	-0.1136***	0.0094	-0.3031	6179.036	-0.0251**	0.0352					
i=1	(2.456)	(-3.355)	(0.430)	(-0.607)	(0.806)	(-2.199)	(1.488)	0.000	0.000	0.047	0.000	0.000
2010 02-08	-0.0874	14.0708	0.1754	-28.2265	20.043	0.0052	0.0052					
i=2	(-0.000)	(0.001)	(0.000)	(-0.001)	(0.001)	(0.000)	(0.000)					
2010 02-10	0.0012***	-0.1121***	0.0093	-0.3003	6179.748	-0.0251**	0.0352					
i=1	(2.604)	(-3.565)	(0.449)	(-0.636)	(0.856)	(-2.304)	(1.581)	0.000	0.000	0.042	0.000	0.000
2010 02-10	-0.0875	14.0573	0.1753	-28.2141	18.813	0.0061	0.0061					
i=2	(-0.000)	(0.001)	(0.000)	(-0.001)	(0.001)	(0.000)	(0.000)					
Panel C: Year 2011												
2011 02-07	0.0024	-0.0553*	0.0288**	-3.1193*	2817.490	0.0032	0.0998***					
i=1	(1.302)	(-1.730)	(2.050)	(-1.699)	(1.027)	(0.364)	(4.794)	23.370***	0.096	0.572	45.187***	6.402**
2011 02-07	0.0021***	-0.2689***	0.1949***	-3.7063***	7222.873	-0.0758***	0.0471***					
i=2	(6.534)	(-8.433)	(7.176)	(-7.522)	(1.402)	(-44.265)	(41.935)					
2011 02-08	0.0024	-0.0564*	0.0291**	-3.135*	2869.210	0.0034	0.0995***					
i=1	(1.319)	(-1.744)	(2.213)	(-1.833)	(1.041)	(0.412)	(4.933)	31.324***	0.061	0.024	48.187***	6.403**
2011 02-08	0.0022***	-0.3027***	0.1888***	-3.5820**	3357.697**	-0.0785***	0.0481***					
i=2	(7.792)	(-9.673)	(5.621)	(-6.043)	(2.089)	(-30.505)	(20.535)					
2011 02-10	0.0025	-0.0593*	0.0304**	-3.2779*	2810.234	0.0032	0.0997***					
i=1	(1.408)	(-1.870)	(2.253)	(-1.861)	(1.120)	(0.408)	(5.274)	38.087***	0.038	0.021	49.774***	7.438***
2011 02-10	0.0021***	-0.3297***	0.1928***	-3.6364***	3222.853**	-0.0787***	0.0478***					
i=2	(9.872)	(-12.688)	(5.871)	(-6.281)	(2.429)	(-33.400)	(22.052)					

Note: The table shows the estimation results of the quadratic-logistic smooth transition (QLSTR) model with dummy variables using alternative time frequencies. The results using 10 min data are shown in Part A and the results using 30 min data are displayed in Part B. The model is specified as:

$$\Delta Z_t = \left(\alpha_{0,1} + \alpha_{1,1} Z_{t-1} + (\beta_{0,1} + \beta_{1,1} Z_{t-1})(1 + \exp(-\gamma_1 (Z_{t-1} - c_{1,1})(Z_{t-1} - c_{2,1})))^{-1}\right) D_t + \left(\alpha_{0,2} + \alpha_{1,2} Z_{t-1} + (\beta_{0,2} + \beta_{1,2} Z_{t-1})(1 + \exp(-\gamma_2 (Z_{t-1} - c_{1,2})(Z_{t-1} - c_{2,2})))^{-1}\right)(1 - D_t) + \sum_{i=1}^{k} \lambda_i \Delta Z_{t-i} + \varepsilon_t$$

D_t is the dummy variable set to be 1 during the period before 30 April and 0 otherwise. 2009 02-07 indicates the sample period covering February 2009 to July 2009; and by analogy for the rest of the sample periods. The results for 2009, 2010 and 2011 are shown in Panel A, Panel B and Panel C, respectively. $\alpha_{1,i}$ and $\beta_{1,i}$ are the parameters for determining the speed of mean-reversion; γ_i is the speed of regime transition; $c_{1,i}$ is the lower boundary and $c_{2,i}$ is the upper boundary of the inner regime. i=1 for the period before 30 April each year, and i=2 for the sample period after 30 April. The values of the t-statistics for each parameter are presented in parentheses. $\alpha_{1,1}=\alpha_{1,2}$, $\beta_{1,1}=\beta_{1,2}$, $\gamma_1=\gamma_2$, $c_{1,1}=c_{1,2}$ and $c_{2,1}=c_{2,2}$ are the Wald-tests for equality. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 5B.4: Estimation results of Granger causality tests

	Optimal lags	Null hypothesis	F-value	P-value
Part A: 10 min data results				
Panel A: Year 2009				
2009 02-04	7	Spot≠>Futures	28.584***	0.000
		Futures≠>Spot	2.440**	0.017
2009 05-07	8	Spot≠>Futures	4.674***	0.000
		Futures≠>Spot	20.325***	0.000
2009 05-08	8	Spot≠>Futures	6.279***	0.000
		Futures≠>Spot	27.071***	0.000
2009 05-10	14	Spot≠>Futures	11.295***	0.000
		Futures≠>Spot	28.180***	0.000
Panel B: Year 2010				
2010 02-04	3	Spot≠>Futures	1.488	0.216
		Futures≠>Spot	7.561***	0.000
2010 05-07	2	Spot≠>Futures	6.352***	0.002
		Futures≠>Spot	9.957***	0.000
2010 05-08	3	Spot≠>Futures	3.247**	0.021
		Futures≠>Spot	6.917***	0.000
2010 05-10	23	Spot≠>Futures	18.449***	0.000
		Futures≠>Spot	9.141***	0.000
Panel C: Year 2011				
2011 02-04	5	Spot≠>Futures	2.728**	0.018
		Futures≠>Spot	6.620***	0.000
2011 05-07	11	Spot≠>Futures	4.631***	0.000
		Futures≠>Spot	21.363***	0.000
2011 05-08	11	Spot≠>Futures	3.943***	0.000
		Futures≠>Spot	31.381***	0.000
2011 05-10	11	Spot≠>Futures	4.994***	0.000
		Futures≠>Spot	41.074***	0.000
Part B: 30 min data results				
	Lags	Null hypothesis	F-value	P-value
Panel A: Year 2009				
2009 02-04	2	Spot≠>Futures	99.903***	0.000
		Futures≠>Spot	2.312*	0.100
2009 05-07	3	Spot≠>Futures	8.226***	0.000
		Futures≠>Spot	39.590***	0.000
2009 05-08	6	Spot≠>Futures	6.600***	0.000
		Futures≠>Spot	33.031***	0.000
2009 05-10	7	Spot≠>Futures	15.499***	0.000
		Futures≠>Spot	40.875***	0.000
Panel B: Year 2010				
2010 02-04	5	Spot≠>Futures	3.977***	0.001
		Futures≠>Spot	10.321***	0.000
2010 05-07	4	Spot≠>Futures	1.726	0.142
		Futures≠>Spot	16.112***	0.000
2010 05-08	4	Spot≠>Futures	1.160	0.169
		Futures≠>Spot	21.488***	0.000
2010 05-10	5	Spot≠>Futures	4.100***	0.001
		Futures≠>Spot	26.187***	0.000
Panel C: Year 2011				
2011 02-04	4	Spot≠>Futures	5.830***	0.000
		Futures≠>Spot	14.331***	0.000
2011 05-07	4	Spot≠>Futures	7.945***	0.000
		Futures≠>Spot	51.726***	0.000
2011 05-08	4	Spot≠>Futures	4.216***	0.002
		Futures≠>Spot	91.957***	0.000
2011 05-10	5	Spot≠>Futures	5.389***	0.000
		Futures≠>Spot	100.300***	0.000

Note: The table shows the results of the Granger causality tests using alternative time frequencies. The results using 10 min data are shown in Part A and the results using 30 min data are displayed in Part B. 2009 02-04 indicates the sample period covering February 2009 to April 2009; and by analogy for the rest of the sample periods. The results for 2009, 2010 and 2011 are shown in Panel A, Panel B and Panel C, respectively. The optimal lags are selected based on the Schwarz information criterion (SIC). The null hypothesis Spot≠>Futures indicates that spot returns do not Granger cause futures returns and Futures≠>Spot shows that futures returns do not Granger cause spot returns. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 5B.5: Estimation results of HAR model for volatility spillovers

Part A: 10 min data results						
	2009		2010		2011	
	RVF	RVS	RVF	RVS	RVF	RVS
α_1	-0.0645***	0.0012***	0.0004	-0.0000	-0.0005	0.0005
	(-6.952)	(2.939)	(0.496)	(-0.136)	(-0.122)	(0.8110)
$\beta_{1,1}$	-0.3503***	-0.0033	-0.1345	0.0282	0.0231	-0.0020
	(-4.569)	(-0.961)	(-0.885)	(0.996)	(0.248)	(-0.126)
$\beta_{1,5}$	-0.8325***	0.0082	-0.2769	0.0064	0.2113	0.0201
	(-4.352)	(0.949)	(-0.503)	(0.062)	(0.638)	(0.359)
$\beta_{1,22}$	-1.9422***	0.0498**	0.2687	0.1658	-2.0990	0.0029
	(-3.815)	(2.168)	(0.147)	(0.487)	(-1.244)	(0.010)
$c_{1,1}$	-0.2261	-0.0441	7.1448***	0.0605	1.5533	0.4683
	(-0.102)	(-0.442)	(4.152)	(0.189)	(0.370)	(0.660)
$c_{1,5}$	32.0216***	0.4188*	0.4607	0.6278	-5.0643	-0.4883
	(6.646)	(1.927)	(0.078)	(0.569)	(-0.666)	(-0.380)
$c_{1,22}$	111.4225***	-1.9719**	-2.6138	-0.5955	51.920	-2.1173
	(5.222)	(-2.049)	(-0.281)	(-0.344)	(1.329)	(-0.321)
α_2	0.0009	0.0000	0.0003*	0.0000	0.0014*	0.0002*
	(0.768)	(0.394)	(1.928)	(0.665)	(1.663)	(1.716)
$\beta_{2,1}$	0.1873	0.0125	-0.2028**	-0.0276	0.2006*	0.0785***
	(0.904)	(1.334)	(-2.082)	(-1.521)	(1.714)	(3.970)
$\beta_{2,5}$	-0.2756	-0.0006	0.6444***	0.0282	0.3041	-0.0842**
	(-0.574)	(-0.029)	(3.213)	(0.756)	(1.416)	(-2.320)
$\beta_{2,22}$	0.6607	0.0155	-0.4362	0.1696**	0.0929	0.0035
	(1.104)	(0.574)	(-1.037)	(2.160)	(0.282)	(0.063)
$c_{2,1}$	0.7103	0.0093	1.5248***	0.0956	1.7271***	0.4618***
	(0.204)	(0.059)	(2.979)	(1.001)	(3.335)	(5.274)
$c_{2,5}$	2.6251	0.5191	0.9183	0.4429**	-1.1159	0.2626
	(0.367)	(1.608)	(0.8572)	(2.222)	(-0.855)	(1.190)
$c_{2,22}$	-2.8213	0.0088	0.2984	-0.4853*	-3.3161	-0.1865
	(-0.320)	(0.022)	(0.199)	(-1.736)	(-1.149)	(-0.382)
LR	60.460***	3.619	12.755***	3.336	2.112	10.212**

Part B: 30 min data results						
	2009		2010		2012	
	RVF	RVS	RVF	RVS	RVF	RVS
α_1	-0.0297***	0.0004	0.0000	0.0001	0.0034***	0.0011
	(-8.057)	(1.539)	(0.017)	(1.434)	(2.915)	(1.197)
$\beta_{1,1}$	-0.2716***	-0.0002	-0.0183	-0.0274	-0.3903	0.0084
	(-3.415)	(-0.042)	(-0.076)	(-1.009)	(-1.547)	(0.041)
$\beta_{1,5}$	-0.4551*	-0.0359	0.5744	-0.0024	-0.2856	0.1406
	(-1.845)	(-2.198)	(0.848)	(-0.031)	(-0.230)	(0.139)
$\beta_{1,22}$	-1.4137***	0.0646***	1.5442	0.4545**	7.4379*	2.0186
	(-4.708)	(3.255)	(0.895)	(2.348)	(1.955)	(0.651)
$c_{1,1}$	6.2285***	-0.1448	-1.0169	0.1176	4.0789***	0.4746
	(3.147)	(-1.107)	(-0.506)	(0.521)	(4.531)	(0.647)
$c_{1,5}$	14.5439***	0.7639***	0.6278	-1.1147*	-0.2637	-1.0509
	(3.854)	(3.061)	(0.122)	(-1.930)	(-0.055)	(-0.270)
$c_{1,22}$	42.6040***	-0.5969*	-3.0230	-0.8315	-39.3354**	-10.7468
	(7.924)	(-1.679)	(-0.552)	(-1.353)	(-2.355)	(-0.789)
α_2	0.0008	0.0000	0.0001	0.0000	0.0004**	0.0002*
	(1.140)	(0.240)	(0.879)	(1.595)	(2.562)	(1.960)
$\beta_{2,1}$	0.1384	0.0256**	-0.0202	-0.0039	0.9816***	0.3434***
	(0.723)	(2.020)	(-0.218)	(-0.376)	(10.591)	(4.546)
$\beta_{2,5}$	-0.2613	-0.0273	0.2192	0.0561**	-0.3826**	-0.3629***
	(-0.556)	(-0.877)	(1.074)	(2.449)	(-2.442)	(-2.841)
$\beta_{2,22}$	0.2673	0.0730	-0.0116	0.0037	0.2325	0.0783
	(0.318)	(1.315)	(-0.032)	(0.093)	(1.050)	(0.434)

Table 5B.5 (Continued)

	2009		2010		2012	
	RVF	RVS	RVF	RVS	RVF	RVS
$c_{2,1}$	0.4264	0.0099	1.8959**	0.2073**	-0.1995	0.1342
	(0.2177)	(0.077)	(2.286)	(2.229)	(-1.423)	(1.175)
$c_{2,5}$	3.4966	0.5538**	-2.0380	0.2778*	0.5254	0.6265***
	(0.858)	(2.055)	(-1.423)	(1.729)	(1.547)	(2.262)
$c_{2,22}$	-2.4646	-0.0372	2.4034	-0.0257	-1.1109	-0.3906
	(-0.516)	(-0.118)	(1.220)	(-0.116)	(-1.630)	(-0.703)
LR	59.794***	4.877	3.590	5.557	24.134***	2.621

Note: The table shows the estimation results of the heterogeneous autoregressive (HAR) model with dummy variables for volatility spillovers using alternative time frequencies. The results using 10 min data are shown in Part A and the results using 30 min data are displayed in Part B. The model is specified as:

$$RVF_t = (\alpha_1 + \beta_{1,1}RVF_{t-1} + \beta_{1,5}RVF_{(t-1|t-5)} + \beta_{1,22}RVF_{(t-1|t-22)} + c_{1,1}RVS_{t-1} + c_{1,5}RVS_{(t-1|t-5)} + c_{1,22}RVS_{(t-1|t-22)})D_t$$
$$+(\alpha_2 + \beta_{2,1}RVF_{t-1} + \beta_{2,5}RVF_{(t-1|t-5)} + \beta_{2,22}RVF_{(t-1|t-22)} + c_{2,1}RVS_{t-1} + c_{2,5}RVS_{(t-1|t-5)} + c_{2,22}RVS_{(t-1|t-22)})(1-D_t) + \varepsilon_t$$

$$RVS_t = (\alpha_1 + \beta_{1,1}RVF_{t-1} + \beta_{1,5}RVF_{(t-1|t-5)} + \beta_{1,22}RVF_{(t-1|t-22)} + c_{1,1}RVS_{t-1} + c_{1,5}RVS_{(t-1|t-5)} + c_{1,22}RVS_{(t-1|t-22)})D_t$$
$$+(\alpha_2 + \beta_{2,1}RVF_{t-1} + \beta_{2,5}RVF_{(t-1|t-5)} + \beta_{2,22}RVF_{(t-1|t-22)} + c_{2,1}RVS_{t-1} + c_{2,5}RVS_{(t-1|t-5)} + c_{2,22}RVS_{(t-1|t-22)})(1-D_t) + \varepsilon_t$$

RVF_t is the daily realised volatility for futures returns while RVS_t is the daily realised volatility for spot returns at time *t*. $RVF_{(t-1|t-k)} = \frac{1}{k}\sum_{j=1}^{k} RVF_{t-j}$; $RVS_{(t-1|t-k)} = \frac{1}{k}\sum_{j=1}^{k} RVS_{t-j}$. The sample period runs from February to November each year (longest available), because of the limited observations available each year. D_t is the dummy variable set to be 1 during the period before 30 April and 0 afterwards. The results for 2009, 2010 and 2011 are shown in Panel A, Panel B and Panel C, respectively. The values of the t-statistics for each parameter are presented in parentheses. LR is the likelihood ratio test for the equality of the volatility spillover parameters before and after 30 April each year. Specifically, it is the joint test of $c_{1,1}= c_{2,1}$, $c_{1,5}= c_{2,5}$, $c_{1,22}= c_{2,22}$ for futures realised volatility spillovers; and the joint test of $\beta_{1,1}= \beta_{2,1}$, $\beta_{1,5}= \beta_{2,5}$, $\beta_{1,22}= \beta_{2,22}$ for spot realised volatility spillovers. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Appendix 5C: Estimation results of the TAR model using moving average thresholds

In Section 5.1, Table 5.3 presents the estimation results of the TAR model by using Chan's (1993) approach to determine the threshold values. Chan's (1993) procedure can only provide a single threshold value for the whole sample period; however, it may be more appropriate to allow the threshold to be time-varying in some cases. Therefore, this chapter uses an alternative method to decide the threshold values, i.e. a simple 10-day moving average of the futures mispricing Z_t. The results of the TAR model using moving average thresholds for h=10, 15 and 30 minute intervals are displayed in Table 5C.1 to Table 5C. The results are qualitatively similar to those generated by using Chan's (1993) procedure. By using 10 min data, it is shown that the speed of adjustment shifts after the submission deadline for both the upper and lower regimes in 2009 and 2011, but not in 2010. The results for the 15 min data demonstrate similar findings as those for the 10 min data, but the shift of adjustment speed in 2011 only occurs in the upper regime. In the case of the results obtained by using 30 min data, the mean-revering speed is different before and after the submission deadline only in the lower regime for 2009 and 2011. Overall, the results produced by using the TAR model using moving average thresholds support the argument that allowance submission can affect the mean-reverting speed of the spot and futures relationship.

Table 5C.1: Estimation results of TAR model with dummies using 10 min data (moving average thresholds)

	α	δ	ρ_1	ρ_2	ρ_3	ρ_4	ρ_1=ρ_2	ρ_3=ρ_4
Panel A: Year 2009								
2009 02-07	0.0014***	0.0022***	-0.2892***	-0.1416***	-0.2529***	-0.1833***	19.595***	1.743
	(3.423)	(4.086)	(-13.358)	(-4.588)	(-10.819)	(-3.684)		
2009 02-08	0.0011***	0.0026***	-0.2905***	-0.1323***	-0.2542***	-0.1742***	27.746***	2.932*
	(3.440)	(5.464)	(-14.482)	(-4.828)	(-11.712)	(-3.992)		
2009 02-10	0.0007***	0.0029***	-0.2936***	-0.1481***	-0.2567***	-0.1451***	32.976***	10.163***
	(3.459)	(7.500)	(-16.326)	(-6.600)	(-13.105)	(-4.656)		
Panel B: Year 2010								
2010 02-07	0.0015***	-0.0004*	-0.1649***	-0.1739***	-0.1723***	-0.2204***	0.207	1.997
	(9.960)	(-1.820)	(-10.512)	(-12.433)	(-7.360)	(-8.513)		
2010 02-08	0.0011***	-0.0000	-0.1610***	-0.1581***	-0.1687***	-0.2265***	0.024	3.482*
	(9.779)	(-0.2323)	(-10.528)	(-12.650)	(-7.370)	(-10.295)		
2010 02-10	0.0080***	0.0003**	-0.1620***	-0.1445***	-0.1698***	-0.2098***	1.038	2.076
	(9.693)	(2.013)	(-11.397)	(-13.775)	(-7.944)	(-11.228)		
Panel C: Year 2011								
2011 02-07	0.0011***	0.0023***	-0.0805***	-0.1422***	-0.1232***	-0.1046***	10.893***	0.455
	(5.540)	(4.921)	(-7.426)	(-8.529)	(-8.167)	(-4.311)		
2011 02-08	0.0010***	0.0028***	-0.0897***	-0.1398***	-0.1346***	-0.1084***	8.825***	1.136
	(6.446)	(6.295)	(-8.648)	(-9.567)	(-9.307)	(-5.179)		
2011 02-10	0.0009***	0.0033***	-0.0992***	-0.1424***	-0.1464***	-0.1098***	8.827***	2.968*
	(7.942)	(8.213)	(-10.424)	(-11.736)	(-11.017)	(-6.319)		

Note: The table shows the estimation results of the threshold autoregressive (TAR) model with dummy variables using 10 min data. The model is specified as:

$$\Delta Z_t = \alpha + \delta D_t + \rho_1 Z_{t-1} I_t D_t + \rho_2 Z_{t-1} I_t (1-D_t) + \rho_3 Z_{t-1}(1-I_t) D_t + \rho_4 Z_{t-1}(1-I_t)(1-D_t) + \sum_{i=1}^{k} \lambda_i \Delta Z_{t-i} + \varepsilon_t$$

where D_t is a dummy variable set to be 1 during the period before 30 April and 0 otherwise. I_t is also a dummy variable taking the value of 1 if Z_{t-1} is greater than or equal to the threshold, and 0 otherwise. The thresholds are determined by using a 10-day moving average. 2009 02-07 indicates the sample period covering February 2009 to July 2009; and by analogy for the rest of the sample periods. The results for 2009, 2010 and 2011 are shown in Panel A, Panel B and Panel C, respectively. $\alpha+\delta$ and α are the intercept terms during the period before and after 30 April, respectively. The values of the t-statistics for each parameter are presented in parentheses. $\rho_1 = \rho_2$ and $\rho_3 = \rho_4$ are the Wald-tests for equality. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 5C.2: Estimation results of TAR model with dummies using 15 min data (moving average thresholds)

	α	δ	ρ_1	ρ_2	ρ_3	ρ_4	$\rho_1=\rho_2$	$\rho_3=\rho_4$
Panel A: Year 2009								
2009 02-07	0.0017***	0.0023***	-0.3191***	-0.1783***	-0.2818***	-0.1929***	12.679***	1.791
	(3.450)	(3.504)	(-11.559)	(-4.872)	(-9.750)	(-3.086)		
2009 02-08	0.0013***	0.0027***	-0.3194***	-0.1671***	-0.2820***	-0.1842***	18.209***	2.782*
	(3.497)	(4.743)	(-12.490)	(-5.134)	(-10.504)	(-3.374)		
2009 02-10	0.0008***	0.0031***	-0.3140***	-0.1728***	-0.2776***	-0.1950***	21.478***	3.666*
	(3.316)	(6.475)	(-13.682)	(-6.409)	(-11.417)	(-5.105)		
Panel B: Year 2010								
2010 02-07	0.0012***	-0.0005*	-0.1139***	-0.1376***	-0.2113***	-0.2190***	0.958	0.035
	(6.557)	(-1.950)	(-5.748)	(-8.121)	(-7.391)	(-7.113)		
2010 02-08	0.0009***	-0.0002	-0.1120***	-0.1217***	-0.2098***	-0.2394***	0.180	0.625
	(6.1324)	(-0.808)	(-5.825)	(-7.949)	(-7.535)	(-9.144)		
2010 02-10	0.0006***	0.0001	-0.1120***	-0.1152***	-0.2099***	-0.2288***	0.023	0.317
	(5.928)	(0.446)	(-6.253)	(-8.767)	(-8.047)	(-10.157)		
Panel C: Year 2011								
2011 02-07	0.0012***	0.0046***	-0.1314***	-0.1463***	-0.2135***	-0.1163***	0.356	6.546**
	(4.257)	(7.472)	(-9.376)	(-6.583)	(-11.116)	(-3.404)		
2011 02-08	0.0011***	0.0053***	-0.1468***	-0.1531***	-0.2367***	-0.1220***	0.079	11.550***
	(5.211)	(9.175)	(-10.854)	(-7.938)	(-12.785)	(-4.133)		
2011 02-10	0.0010***	0.0060***	-0.1609***	-0.1601***	-0.2577***	-0.1268***	0.002	20.668
	(6.580)	(11.534)	(-12.919)	(-10.022)	(-15.148)	(-5.211)		

Note: The table shows the estimation results of the threshold autoregressive (TAR) model with dummy variables using 15 min data. The model is specified as:

$$\Delta Z_t = \alpha + \delta D_t + \rho_1 Z_{t-1} I_t D_t + \rho_2 Z_{t-1} I_t (1-D_t) + \rho_3 Z_{t-1}(1-I_t) D_t + \rho_4 Z_{t-1}(1-I_t)(1-D_t) + \sum_{i=1}^{k} \lambda_i \Delta Z_{t-i} + \varepsilon_t$$

where D_t is a dummy variable set to be 1 during the period before 30 April and 0 otherwise. I_t is also a dummy variable taking the value of 1 if Z_{t-1} is greater than or equal to the threshold, and 0 otherwise. The thresholds are determined by using a 10-day moving average. 2009 02-07 indicates the sample period covering February 2009 to July 2009; and by analogy for the rest of the sample periods. The results for 2009, 2010 and 2011 are shown in Panel A, Panel B and Panel C, respectively. $\alpha+\delta$ and α are the intercept terms during the period before and after 30 April, respectively. The values of the t-statistics for each parameter are presented in parentheses. $\rho_1=\rho_2$ and $\rho_3=\rho_4$ are the Wald-tests for equality. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Table 5C.3: Estimation results of TAR model with dummies using 30 min data (moving average thresholds)

	α	δ	ρ_1	ρ_2	ρ_3	ρ_4	$\rho_1=\rho_2$	$\rho_3=\rho_4$
Panel A: Year 2009								
2009 02-07	0.0020***	0.0024**	-0.3460***	-0.2211***	-0.3037***	-0.2017**	4.762**	1.070
	(2.777)	(2.470)	(-8.539)	(-4.036)	(-7.009)	(-2.168)		
2009 02-08	0.0016***	0.0028***	-0.3440***	-0.2070***	-0.3020***	-0.1874**	7.087***	1.752
	(2.814)	(3.424)	(-9.175)	(-4.268)	(-7.509)	(-2.327)		
2009 02-10	0.0010**	0.0033***	-0.3373***	-0.1954***	-0.2955***	-0.2124***	10.578***	1.724
	(2.560)	(4.829)	(-10.046)	(-4.875)	(-8.128)	(-3.788)		
Panel B: Year 2010								
2010 02-07	0.0008***	0.0006	-0.1315***	-0.1198***	-0.1115**	-0.0704**	0.145	0.517
	(2.708)	(1.358)	(-5.890)	(-5.215)	(-2.449)	(-1.995)		
2010 02-08	0.0006**	0.0008*	-0.1289***	-0.1087***	-0.1098**	-0.1398***	0.486	0.302
	(2.470)	(1.924)	(-5.855)	(-5.295)	(-2.434)	(-4.398)		
2010 02-10	0.0004**	0.0009***	-0.1277***	-0.1053***	-0.1090***	-0.1265***	0.749	0.127
	(2.306)	(2.703)	(-6.257)	(-5.970)	(-2.594)	(-4.795)		
Panel C: Year 2011								
2011 02-07	0.0011***	0.0023***	-0.0805***	-0.1422***	-0.1232***	-0.1046***	10.893***	0.455
	(5.540)	(4.921)	(-7.426)	(-8.529)	(-8.167)	(-4.311)		
2011 02-08	0.0010***	0.0028***	-0.0897***	-0.1398***	-0.1346***	-0.1084***	8.825***	1.136
	(6.446)	(6.2952)	(-8.648)	(-9.567)	(-9.307)	(-5.179)		
2011 02-10	0.0009***	0.0033***	-0.0992***	-0.1424***	-0.1464***	-0.1098***	8.827***	2.968
	(7.942)	(8.213)	(-10.424)	(-11.736)	(-11.017)	(-6.319)		

Note: The table shows the estimation results of the threshold autoregressive (TAR) model with dummy variables using 30 min data. The model is specified as:

$$\Delta Z_t = \alpha + \delta D_t + \rho_1 Z_{t-1} I_t D_t + \rho_2 Z_{t-1} I_t (1-D_t) + \rho_3 Z_{t-1}(1-I_t) D_t + \rho_4 Z_{t-1}(1-I_t)(1-D_t) + \sum_{i=1}^{k} \lambda_i \Delta Z_{t-i} + \varepsilon_t$$

where D_t is a dummy variable set to be 1 during the period before 30 April and 0 otherwise. I_t is also a dummy variable taking the value of 1 if Z_{t-1} is greater than or equal to the threshold, and 0 otherwise. The thresholds are determined by using a 10-day moving average. 2009 02-07 indicates the sample period covering February 2009 to July 2009; and by analogy for the rest of the sample periods. The results for 2009, 2010 and 2011 are shown in Panel A, Panel B and Panel C, respectively. $\alpha+\delta$ and α are the intercept terms during the period before and after 30 April, respectively. The values of the t-statistics for each parameter are presented in parentheses. $\rho_1 = \rho_2$ and $\rho_3 = \rho_4$ are the Wald-tests for equality. ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively.

Chapter 6

Conclusion

6.1. Summary of the findings and the implications

Using the data from the second commitment period of the EU ETS, this thesis investigates the time series properties and trading behaviour in the European carbon emission markets. Specifically, this research examines the performance of Markov regime switching and alternative hedging strategies, the effects of arbitrage opportunities on feedback trading, and the impact of the allowance submission deadline on the relationship between carbon spot and futures markets. In this section, the author summarises the main findings of this thesis and discusses the implications of the findings.

The first empirical chapter, Chapter 3, models the relationship between carbon spot and futures markets by incorporating regime switching, disequilibrium adjustment into the return process with state dependent and clustering in the volatility process, and compares the performance of regime switching hedging strategies with alternative approaches. Specifically, the author proposes a Markov regime switching model (MRS) with a long run relationship (LR) and DCC-GARCH errors, to connect the idea of long run disequilibrium adjustment measured by a lagged basis with that of uncertainty estimated by DCC-GARCH, across high/low variance states (referred to as the MRS-LR-DCC model). The empirical results show that the class of Markov regime switching hedging strategies significantly outperform constant OLS, VECM and GARCH hedging approaches for all the hedging performance measures considered, including minimising hedged portfolio variance, maximising hedgers' utility, and reducing the VaR exposure of the hedged portfolio, for both in-sample and out-of-sample analysis. Within the class of Markov regime switching hedging strategies, the MRS-LR-DCC model achieves the highest variance reduction, and the improvements offered by the MRS-LR-DCC approach over other hedging strategies are statistically significant at conventional levels, as indicated by the results of White's (2000) reality check. In addition, the results suggest that the MRS-LR model constantly outstrips the MRS model for all measures and for both in-sample and out-of-sample analysis. This implies that incorporating the long run relationship measured by a lagged basis into the hedging model can provide incremental value for hedging. Besides the symmetric hedging performance measures mentioned above, this chapter also considers the downside risk measures and differences in hedging performance between long and short hedging positions. The results of the downside risk analysis show that the constant and GARCH hedging approaches still underperform the class of Markov regime switching strategies and the MRS-LR-DCC model performs best in most cases, for both long and short hedging positions, which is generally in line with the results achieved by using symmetric measures. This suggests that no matter what position market participants hold, they can benefit from using regime switching hedging strategies. Overall, the results of this chapter demonstrate the importance of using state dependent hedge ratios to hedge the financial risk in carbon emission markets. Risk managers using Markov regime switching approaches to hedge their exposure to carbon emission allowances can achieve greater variance reduction and better hedging performance.

In Chapter 4, this thesis develops and estimates several feedback trading models in which the feedback investors' demand function not only depends on the last period's asset returns, but also on the potential arbitrage opportunities within the spot and futures markets. It is an extension of Sentana and Wadhwani's (1992) feedback trading model by considering the impact of arbitrage opportunities on the demand of feedback traders, in both an additive way and a multiplicative way. The results firstly show that there is no evidence of feedback trading in European carbon emission markets, where institutional investors dominate due to the EU ETS regulations, implying that institutional investors are not necessarily all feedback traders. The finding is inconsistent with the common belief that institutional investors significantly contribute to feedback trading activities. However, significant feedback trading is found in a few other energy markets. In addition, the results of the augmented feedback trading models suggest that arbitrage opportunities can affect demand from feedback traders in several energy markets, in both an additive and a multiplicative way. This supports the view that arbitrage opportunities have an influence on feedback trading. Furthermore, this thesis finds that the response of feedback traders to the last period's return or arbitrage opportunities varies significantly across bull and bear market conditions. This indicates that the impact of arbitrage opportunities on feedback trading is also dependent on bull/bear market regimes. Finally, all the findings above are robust to different measures of arbitrage opportunities, including the spot-futures basis and the convenience yield. To summarise, the findings of this chapter support the argument that feedback traders in some markets also consider the potential arbitrage opportunities when making investment decisions. The findings are important in understanding investors' trading behaviour and trading strategies in the carbon emission and energy markets and also contribute to the debate about whether institutional investors are feedback traders or not.

Chapter 5 studies the impact of the allowance submission deadline under the EU ETS on the time series characteristics of the relationship between carbon spot and futures markets by using high frequency data. In particular, this chapter examines whether the mean-reverting process of the relationship between carbon spot and futures prices, and the price discovery and volatility spillover process in the carbon spot and futures markets are different before and after the submission deadline each year. The results show that spot and futures prices are cointegrated with each other for the periods before and after the submission deadline, which suggests that the previous mixed results regarding the cointegration relationship between carbon spot and futures prices are not caused by the allowance submission deadline. However, the chapter finds that there is a shift in the equilibrium level, adjustment speed and the no-arbitrage bands after the submission deadline, which implies that the mean-reverting process changes after the allowance submission deadline. Moreover, the results indicate that the impact of allowance submission on the price discovery process in carbon emission markets is not significant, as there is a bidirectional causal relationship between carbon spot and futures returns for the periods before and after the submission deadline. Furthermore, the chapter finds that the volatility spillover process changes due to the submission of carbon allowances, especially from the spot market to the futures markets. Finally, the findings in the chapter are robust to different intraday time frequencies. The effects described above are more significant in 2009 and 2011 than in 2010. The weak impact of the submission deadline on the spot and futures relationship in 2010 is due to the fact that industrial production and GHG emission in the EU slow down significantly in 2009 because of the global financial crisis and the European sovereign debt crisis. The findings of the chapter indicate that, when modelling the relationship between carbon spot and futures markets (e.g. for arbitrage purposes), the difference in the mean-reverting process and volatility spillover before and after the submission deadline should be taken into account.

Overall, the thesis finds that carbon emission markets yield different time series characteristics and trading behaviours from other financial markets. The findings of this thesis are of interest to risk managers, environmental investors and arbitragers participating in the carbon emission market and could help policy makers to improve the mechanisms of the EU ETS in the next commitment period.

6.2. Limitations and further research

Last but not least, a few limitations of the thesis need to be addressed. Firstly, this thesis uses the second commitment period data of the EU ETS from 2008 to 2012. Although European carbon emission markets were created in 2005, this research does not combine the Phase I and Phase II data of the EU ETS together because of the different mechanisms used in each commitment period. In order to obtain enough observations to estimate the Markov regime switching models, Chapter 3 uses the spot and futures price data on a daily basis. However, most studies on the performance of regime switching hedging strategies use weekly data and a sample period of longer than 15 years (e.g. Alizadeh and Nomikos, 2004; Lee and Yoder, 2007a, b; Alizadeh et al., 2008; Lee, 2010). This shows that most research assumes that risk managers rebalance their portfolios on a weekly basis while this thesis assumes that they rebalance their portfolios every day, which is unrealistic in practise. This frequent rebalancing would incur significant transaction and monitoring costs, which would have negative effects on the actual performance of the Markov regime switching hedging strategies.

Another limitation of the thesis is the proxy used for arbitrage opportunities. In Chapter 4, this research adopts two measures for arbitrage opportunities: the lagged values of the spot-futures basis; and the convenience yield. Both measures show the degree that spot and futures prices deviate from each other and thus can act as signals for the presence of arbitrage opportunities. However, strictly speaking, arbitrage activities are triggered when the profit generated by arbitrage is greater than the round trip transaction costs. There are no arbitrage activities when the deviation is within no-arbitrage bands. Therefore, when the basis and convenience yield move within certain thresholds determined by the transaction costs, they are not perfect measures for arbitrage opportunities as these small deviations cannot trigger arbitrage activities. With advances in understanding the characteristics of arbitrage activities, there is no doubt that a better proxy can be found to measure the arbitrage opportunities.

The third limitation of the thesis is related to the thin trading problem in carbon emission markets suggested by Montagnoli and De Vries (2010). The trading volume of carbon emission markets has increased dramatically in the EU ETS Phase II; however, when observing the tick-by-tick data, in some cases, there are only one or two transactions within a 10-minute interval, especially in the spot market. The thin trading problem will induce price jumps and temporary large mispricing of futures contracts which cannot immediately be corrected through arbitrage activities, and which makes it difficult to convert irregular transaction data into equidistant price data. In order to address this problem, Chapter 5 only considers the transactions that took place between 09:00 to 16:00 GMT, and constructs the price data at 10-minute, 15-minute and 30-minute intervals, but not 5-minute intervals. Nonetheless, it also can be observed from Figure 5.1 that there are several large values in the time series of the carbon futures mispricing with 15-minute time intervals. With the development of the carbon emission markets, the author believes that the thickness of carbon emission markets will not be a problem for empirical research in the next commitment period.

Apart from these limitations, this thesis raises several questions for future research. Firstly, this thesis shows the impact of the allowance submission deadline on the mean-reverting process of carbon futures mispricing and the volatility spillover between the spot and futures markets. However, the impact of the submission deadline on hedging has not been examined. The pricing efficiency of futures contracts and the basis risk are important in determining the performance of futures hedging (Figlewski, 1984). Therefore, the hedging performance in carbon emission markets may be affected by the allowance submission deadline. The first suggestion for future research is to examine whether the impact is significant or not.

Secondly, this thesis analyses hedging, feedback trading and arbitrage activities in carbon emission markets. Nevertheless, the profitability of technical trading rules in carbon emission markets, including momentum and contrarian strategies, has not been investigated. Sullivan et al. (1999) evaluate the performance of 7,846 technical trading rules in the U.S. stock market and address the data snooping issue. Qi and Wu (2006) and Marshall et al. (2008) conduct similar research in foreign exchange and commodity markets, respectively. Given the high volatility and low level of market efficiency in carbon emission markets, technical trading rules are expected to generate significant abnormal returns. In addition, the allowance submission deadline may also have an influence on the performance of technical trading strategies. For the reasons described above, the second direction for future research would involve studying the profitability of quantitative timing trading strategies and the impact of the allowance submission deadline on the performance of these strategies.

Thirdly, the thesis focuses on the European carbon emissions markets and only considers a single type of carbon financial instrument, i.e. the EUA. Further research could therefore examine the characteristics of carbon emission markets in other parts of the world, and could include other types of carbon financial instruments, for example the Certified Emission Reduction (CER) from the CDM programmes and the Emission Reduction Unit (ERU) from the JI projects.

Finally, the third commitment period (2013-2020) of the EU ETS has already been launched in 2013. A number of important regulatory changes have been made from Phase II to Phase III. For example, a larger proportion of carbon allowances are now distributed through auction than through free allocation; more restrictions are imposed on using carbon emission allowances outside of the EU as a substitute for EUAs, etc. With increasing data availability, another suggestion for future research would be to investigate the new features of carbon emission markets in EU ETS Phase III.

References

Adams, J.B., Montesi, C.J., 1995. Major issues related to hedge accounting. Financial Accounting Standards Board.

Aguirre, M.A., Saidi, R., 1999. Feedback trading in exchange-rate markets: Evidence from within and across economic blocks. Journal of Economics & Finance, 23, 1-14.

Alberola, E., Chevallier, J., Chèze, B., 2008. Price drivers and structural breaks in European carbon prices 2005–2007. Energy Policy 36, 787-797.

Alizadeh, A., Nomikos, N., 2004. A Markov regime switching approach for hedging stock indices. Journal of Futures Markets 24, 649-674.

Alizadeh, A.H., Nomikos, N.K., Pouliasis, P.K., 2008. A Markov regime switching approach for hedging energy commodities. Journal of Banking & Finance 32, 1970-1983.

Andersen, T.G., 1996. Return volatility and trading volume: An information flow interpretation of stochastic volatility. The Journal of Finance 51, 169-204.

Andersen, T.G., Bollerslev, T., 1998. Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. International Economic Review, 885-905.

Andersen, T.G., Bollerslev, T., Diebold, F.X., 2007. Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility. Review of Economics and Statistics 89, 701-720.

Andersen, T.G., Bollerslev, T., Diebold, F.X., Labys, P., 2001. The distribution of realized exchange rate volatility. Journal of the American Statistical Association 96, 42-55.

Andersen, T.G., Bollerslev, T., Diebold, F.X., Labys, P., 2003. Modeling and forecasting realized volatility. Econometrica 71, 579-625.

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

Antoniou, A., 2011. Positive feedback trading: Evidence from futures markets. Global Business & Economics Review, 13, 13-25.

Areal, N.M., Taylor, S.J., 2002. The realized volatility of FTSE-100 futures prices. Journal of Futures Markets 22, 627-648.

Balke, N.S., Fomby, T.B., 1997. Threshold cointegration. International Economic Review 38, 627-645.

Benz, E., Trück, S., 2009. Modelling the price dynamics of CO2 emission allowances. Energy Economics 31, 4-15.

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.

Biais, B., 1993. Price formation and equilibrium liquidity in fragmented and centralized markets. Journal of Finance 48, 157-185.

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

Bohl, M.T., Reitz, S., 2006. Do positive feedback traders act in Germany's Neuer market? Quarterly Journal of Business & Economics, 45, 3-14.

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

Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics 31, 307-327.

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 management. Journal of Futures Markets 29, 197-217.

Borak, S., Härdle, W., Trück, S., Weron, R., 2006. Convenience yields for CO2 emission allowance futures contracts. Working paper, Economic Risk Berlin N 6.

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

Bubák, V., Kočenda, E., Žikeš, F., 2011. Volatility transmission in emerging European foreign exchange markets. Journal of Banking & Finance 35, 2829-2841.

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

Button, J., 2008. Carbon: commodity or currency-The case for an international carbon market based on the currency model. Harvard Environmental Law Review 32, 571-596.

Cai, J., 1994. A Markov model of switching-regime ARCH. Journal of Business & Economic Statistics 12, 309-316.

Calel, R., 2013. Carbon markets: A historical overview. Wiley Interdisciplinary Climate Change 4, 107–119.

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.

Chan, K.-S., 1993. Consistency and limiting distribution of the least squares estimator of a threshold autoregressive model. Annals of Statistics 21, 520-533.

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

Charles, A., Darné, O., Fouilloux, J., 2013. Market efficiency in the European carbon markets. Energy Policy 60, 785-792.

Chartrath, A., Christie-David., R., Dhanda, K.K., Koch, T.W., 2002. Index futures leadership, basis behaviour, and trader selectivity. Journal of Futures Markets, 22, 649-677.

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

Chau, F., Holmes, P., Paudyal, K., 2008. The impact of universal stock futures on feedback trading and volatility dynamics. Journal of Business Finance & Accounting, 35, 227-249.

Chen, W.P., Chou, R.K., Chung, H., 2009. Decimalization, ETFs and futures pricing efficiency. Journal of Futures Markets 29, 157-178.

Chen, X., Ghysels, E., 2011. News—good or bad—and its impact on volatility predictions over multiple horizons. Review of Financial Studies 24, 46-81.

Chevallier, J., 2009. Modelling the convenience yield in carbon prices using daily and realized measures. International Review of Applied Financial Issues & Economics 1, 56-73.

Chevallier, J., 2010. A note on cointegrating and vector autoregressive relationship between CO2 allowances spot and futures prices. Energy Bulletin 30, 1564-1584.

Chevallier, J., 2011a. A model of carbon price interactions with macroeconomic and energy dynamics. Energy Economics 33, 1295-1312.

Chevallier, J., 2011b. Evaluating the carbon-macroeconomy relationship: Evidence from threshold vector error-correction and Markov-switching VAR models. Economic Modelling 28, 2634-2656.

Chevallier, J., 2011c. Detecting instability in the volatility of carbon prices. Energy Economics 33, 99-110.

Chevallier, J., Sevi, B., 2011. On the realized volatility of the ECX CO2 emissions 2008 futures contract: Distribution, dynamics and forecasting. Annals of Finance 7, 1-29.

Chevallier, J., 2012. Cointegration between carbon spot and futures prices: From linear to nonlinear modelling. Energy Bulletin 32, 160-181.

Choudhry, T., 1997. Short-run deviations and volatility in spot and futures stock returns: Evidence from Australia, Hong Kong, and Japan. Journal of Futures Markets 17, 689-705.

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

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

Coase, R.H., 1937. The nature of the firm. Economica 4, 386-405.

Coase, R.H., 1960. The problem of social cost. Journal of Law & Economics 3, 1-44.

Cotter, J., Hanly, J., 2006. Reevaluating hedging performance. Journal of Futures Markets 26, 677-702.

Corsi, F., 2009. A simple approximate long-memory model of realized volatility. Journal of Financial Econometrics 7, 174-196.

Creti, A., Jouvet, P. A., Mignon, V., 2012. Carbon price drivers: Phase I versus Phase II equilibrium? Energy Economics 34, 327-334.

Culter, 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., Markellos, R.N., 2008. Are the European carbon markets efficient? Review of futures markets 17, 103-128.

Daskalakis, G., Psychoyios, D., Markellos, R.N., 2009. Modelling CO2 emission allowance prices and derivatives: Evidence from the European trading scheme. Journal of Banking & 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.

Dean, W.G., Faff, R.W., 2008. Evidence of feedback trading with Markov switching regimes. Review of Quantitative Finance & Accounting, 30, 133-151.

Dean, W.G., Faff, R.W., 2011. Feedback trading and the behavioural ICAPM: Multivariate evidence across international equity and bond markets. Applied Financial Economics, 21, 1665-1678.

Demirer, R., Lien, D., 2003. Downside risk for short and long hedgers. International Review of Economics & Finance 12, 25-44.

Ding, Z., Granger, C.W., Engle, R.F., 1993. A long memory property of stock market returns and a new model. Journal of Empirical Finance 1, 83-106.

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., 1982. Autoregressive Conditional Heteroskedasticity with Estimates of the variance of UK Inflation. Econometrica 50, 987–1008.

Engle, R.F., 2002. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business & Economic Statistics 20, 339-350.

Engle, R.F., Granger, C.W., 1987. Co-integration and error correction: representation, estimation, and testing. Econometrica: Journal of the Econometric Society 55, 251-276.

Engle, R.F., Kroner, K.F., 1995. Multivariate simultaneous generalized ARCH. Econometric Theory 11, 122-150.

Engle, R.F., Ng, V.K., Measuring and testing the impact 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 & Policies 8, 467-499.

Fan, J.H., Roca, E., Akimov, A., 2013. Estimation and performance evaluation of optimal hedge ratios in the carbon market of the European Union Emissions Trading Scheme. Australian Journal of Management, forthcoming.

Figlewski, S., 1984. Hedging performance and basis risk in stock index futures. Journal of Finance 39, 657-669.

Fong, W.M., See, K.H., 2002. A Markov switching model of the conditional volatility of crude oil futures prices. Energy Economics 24, 71-95.

Frunza, M.-C., Guegan, D., 2010. Derivative pricing and hedging on Carbon markets. CES working papers.

Fuertes, A.M., Miffre, J., Rallis, G., 2010. Tactical allocation in commodity futures markets: Combining momentum and term structure signals. Journal of Banking & Finance, 34, 2530-2548.

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

Granger, C.W., 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica: Journal of the Econometric Society, 424-438.

Gray, S.F., 1996. Modeling the conditional distribution of interest rates as a regime-switching process. Journal of Financial Economics 42, 27-62.

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.

Godbey, J.M., Hilliard, J.E. 2007. Adjusting stacked-hedge ratios for stochastic convenience yield: a minimum variance approach. Quantitative Finance, 7, 289-300.

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

Haas, M., Mittnik, S., Paolella, M.S., 2004. Mixed normal conditional heteroskedasticity. Journal of Financial Econometrics 2, 211-250.

Hamilton, J., 1989. A new approach to the economic analysis of nonstationary time series and the business cycle. Econometrica 57, 357-384.

Hamilton, J.D., 1990. Analysis of time series subject to changes in regime. Journal of Econometrics 45, 39-70.

Hamilton, J.D., 1994. Time series analysis. Cambridge University Press: Cambridge.

Hamilton, J.D., Susmel, R., 1994. Autoregressive conditional heteroskedasticity and changes in regime. Journal of Econometrics 64, 307-333.

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

Ho, T., Stoll, H.R., 1981. Optimal dealer pricing under transactions and return uncertainty. Journal of Financial Economics 9, 47-73.

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

Ibikunle, G., 2012. Financial market microstructure of the EU emissions futures. PhD thesis, University of East Anglia.

Jansen, E.S., Teräsvirta, T., 1996. Testing parameter constancy and super exogeneity in econometric equations. Oxford Bulletin of Economics & Statistics 58, 735-763.

Jarque, C.M., Bera, A.K., 1980. Efficient tests for normality, homoscedasticity and serial independence of regression residuals. Economics Letters 6, 255-259.

Johansen, S., 1988. Statistical analysis of cointegration vectors. Journal of Economics Dynamics & Control 12, 231-254.

Joyeux, R., Milunovich, G., 2010. Testing market efficiency in the EU carbon futures market Applied Financial Economics 20, 803-809.

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.

Koch, N., 2011. Co-Movements between carbon, energy and financial markets: A multivariate GARCH approach. Working paper.

Kogan, L., Livdan, D., Yaron, A., 2009. Oil futures prices in a production economy with investment constraints. Journal of Finance, 64, 1345-1375.

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

Koutmos, G., 1997. Feedback trading and the autocorrelation pattern of stock returns: further empirical evidence. Journal of International Money & Finance, 16, 625-636.

Koutmos, G., Saidi, R., 2001. Positive feedback trading in emerging capital markets. Applied Financial Economics, 11, 291-297.

Kroner, K.F., Sultan, J., 1993. Time-varying distributions and dynamic hedging with foreign currency futures. Journal of Financial & Quantitative Analysis 28, 535-551.

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

Lai, Y.S., Sheu, H.J., 2010. The incremental value of a futures hedge using realized volatility. Journal of Futures Markets 30, 874-896.

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

Laopodis, N.T., 2008. Noise trading and autocorrelation interactions in the foreign exchange market: Evidence from developed and emerging economies. Journal of Economics & Finance, 32, 271-293.

Lee, H.-T., 2009a. A copula-based regime-switching GARCH model for optimal futures hedging. Journal of Futures Markets, 29, 946-972.

Lee, H.-T., 2009b. Optimal futures hedging under jump switching dynamics. Journal of Empirical Finance, 16, 446-456.

Lee, H.-T., 2010. Regime switching correlation hedging. Journal of Banking & Finance 34, 2728-2741.

Lee, H.-T., Yoder, J.K., 2007a. A bivariate markov regime switching garch approach to estimate time varying minimum variance hedge ratios. Applied Economics 39, 1253-1265.

Lee, H.T., Yoder, J., 2007b. Optimal hedging with a regime-switching time-varying correlation GARCH model. Journal of Futures Markets 27, 495-516.

Lee, H.-T., Yoder, J.K., Mittelhammer, R.C., McCluskey, J.J., 2006. A random coefficient autoregressive Markov regime switching model for dynamic futures hedging. Journal of Futures Markets, 26, 103-129.

Lee, T.-H., 1994. Spread and volatility in spot and forward exchange rates. Journal of International Money & Finance 13, 375-383.

Levy, E., 1997. Asian options. In: Clewlow L, Strickland, C. (eds.) Exotic options: The state of the art. International Thomson Business Press, London.

Lien, D., 1996. The effect of the cointegration relationship on futures hedging: a note. Journal of Futures Markets 16, 773-780.

Lien, D., 2008. A further note on the optimality of the OLS hedge strategy. Journal of Futures Markets 28, 308-311.

Lien, D., 2012. A note on the performance of regime switching hedge strategy. Journal of Futures Markets 32, 389-396.

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

Lin, S.-K., Chen, S.-N., Li, C.-Y., 2012. Pricing Derivatives with modeling CO2 emission allowance using a regime switching jump diffusion model: Evidence from the European Trading Scheme. EFMA conference paper.

Ljung, G.M., Box, G.E., 1978. On a measure of lack of fit in time series models. Biometrika 65, 297-303.

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 & 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.

McMillan, D.G., Ülkü, N., 2009. Persistent mispricing in a recently opened emerging index futures market: arbitrageurs invited. Journal of Futures Markets 29, 218-243.

Miclaus, P.G., Lupu, R., Dumitrescu, S.A., Bobirca, A., 2008. Testing the efficiency of the European carbon futures market using event-study methodology. International Journal of Energy & Environment 2, 121-128.

Miffre, J., Rallis, G., 2007. Momentum strategies in commodity futures markets. Journal of Banking & 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.

Millios, 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.

Mizrach, B., Otsubo, Y., 2013. The market microstructure of the European Climate Exchange. Available at SSRN 1621340.

Monoyios, M., Sarno, L., 2002. Mean reversion in stock index futures markets: A nonlinear analysis. Journal of Futures Markets 22, 285-314.

Montagnoli, A., De Vries, F. P., 2010. Carbon trading thickness and market efficiency. Energy Economics 32, 1331-1336.

Müller, U.A., Dacorogna, M.M., Davé, R.D., Olsen, R.B., Pictet, O.V., von Weizsäcker, J.E., 1997. Volatilities of different time resolutions—analyzing the dynamics of market components. Journal of Empirical Finance 4, 213-239.

National Research Council, 2011. America's climate choices. National Academies Press, Washington, D.C.

Newell, R.G., Pizer, W.A., Raimi, D., 2012. Carbon markets: Past, present, and future. National Bureau of Economic Research Working Papers No. 18504.

Newell, R.G., Pizer, W.A., Raimi, D., 2013. Carbon markets 15 years after Kyoto: Lessons learned, new challenges. Journal of Economic Perspectives 27, 123-146.

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

Phillips, P.C., Perron, P., 1988. Testing for a unit root in time series regression. Biometrika 75, 335-346.

Paolella, M., Taschini, L., 2006. An econometric analysis of emission trading allowances. Working paper, Swiss Finance Institute, 06-26.

Paolella, M., Taschini, L., 2008. An econometric analysis of emission allowance prices. Journal of Banking & Finance 32, 2022-2032.

Pinho, C., Madaleno, M., 2010. Hedging with CO2 allowances: the ECX market. Working paper, Universidade de Aveiro.

Pirrong, C., 2005. Momentum in futures markets. EFA 2005 Moscow Meetings Paper.

Point Carbon, 2010. Carbon 2010: Return of the sovereign. Report on the carbon market, 2010.

Politis, D.N., Romano, J.P., 1994. The stationary bootstrap. Journal of the American Statistical Association 89, 1303-1313.

Qi, M., Wu, Y., 2006. Technical trading-rule profitability, data snooping, and reality check: Evidence from the foreign exchange market. Journal of Money, Credit & Banking 38, 2135-2158.

Rittler, D., 2012. Price discovery and volatility spillovers in the European Union emissions trading scheme: A high-frequency analysis. Journal of Banking & Finance 36, 774-785.

Roll R., Schwartz, E., Subrahmanyam, A., 2007. Liquidity and the law of one price: The case of the futures-cash basis. Journal of Finance, 62, 2201-2234.

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

Salvador, E., Arago, V., 2013. Measuring Hedging Effectiveness of Index Futures Contracts: Do Dynamic Models Outperform Static Models? A Regime-switching Approach. Journal of Futures Markets, forthcoming.

Schuppli, M., Bohl, M.T., 2010. Do foreign institutional investors destabilize China’s A-share markets? Journal of International Financial Markets, Institutional & Money, 20, 36-50.

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

Sephton, P., 1998. GARCH and Markov hedging at the Winnipeg commodity exchange. Canadian Journal of Agricultural Economics, 46, 117-126.

Shen, Q., Szakmary, A.C., Sharma, S.C., 2007. An examination of momentum strategies in commodity futures markets. Journal of Futures Markets, 27, 227-256.

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

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

Stern, N., 2007. The economics of climate change : The Stern review. Cambridege University Press: Cambridge.

Sullivan, R., Timmermann, A., White, H., 1999. Data-snooping, technical trading rule performance, and the bootstrap. Journal of Finance 54, 1647-1691.

Tong, H., 1978. On a threshold model. Sijthoff & Noordhoff.

Tong, H., 1990. Non-Linear time series: A dynamical system approach. Oxford University Press, Oxford.

Tse, Y.K., Tsui, A.K.C., 2002. A multivariate generalized autoregressive conditional heteroscedasticity model with time-varying correlations. Journal of Business & Economic Statistics 20, 351-362.

Uhrig-Homburg, M., Wagner, M., 2009. Futures price dynamics of CO2 emission allowances: An empirical analysis of the trial period. Journal of Derivatives 17, 73-88.

UNFCCC, 1997. ‘Proposed elements of a protocol to the United Nations framework convention on climate change.’ In: Proceedings of the Conference in Brazil in Response to the Berlin Mandate. Chapter No. 1: Brazil., Brazil.

Viswanathan, S., 2010. Developing an efficient carbon emssions allowance market. Duke University report.

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

Watanabe, T., 2002. Margin requirements, positive feedback trading, and stock return autocorrelations: the case of Japan. Applied Financial Economics, 12, 395-403.

White, H., 2000. A reality check for data snooping. Econometrica 68, 1097-1126.

Working, H., 1948. Theory of the inverse carrying charge in futures markets. Journal of Farm Economics, 30, 1-28.

World Bank, 2008. State and trends of carbon market 2008. World Bank Carbon Finance Unit Publications and Reports, 2008.

World Bank, 2010. State and trends of carbon market 2010. World Bank Carbon Finance Unit Publications and Reports, 2010.

World Bank, 2012. State and trends of carbon markets 2012. World Bank Carbon Finance Unit Publications and Reports, 2012.

Zhong, M., Darrat, A.F., Otero, R., 2004. Price discovery and volatility spillovers in index futures markets: Some evidence from Mexico. Journal of Banking & Finance 28, 3037-3054.