Sentiment Effects in Professionally Traded Markets: Evidence from Oil and Emissions Futures

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September 2017

A thesis submitted to Dublin City University Business School in partial fulfillment of the requirements for the degree of Doctor of Philosophy

Declaration

I hereby certify that this material, which I now submit for assessment on the programme of study leading to the award of Doctor of Philosophy is entirely my own work, and that I have exercised reasonable care to ensure that the work is original, and does not to the best of my knowledge breach any law of copyright, and has not been taken from the work of others save and to the extent that such work has been cited and acknowledged within the text of my work.

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ID No.: 58211432

Date:

An expert is a person who has made all the mistakes that can be made in a very narrow field.

Niels Bohr, 1885 - 1962

Acknowledgments

I would like to thank my supervisory team of Mark Cummins, Michael Dowling, Alan F. Smeaton, Adam Bermingham and Brian O'Kelly. Their inspiration and encouragement has kept me focused throughout the process of this Ph.D.

Financial support from the Daniel O'Hare Scholarship, DCU Business School and the Irish Accounting and Finance Association is gratefully acknowledged. I also wish to thank the Irish Centre for Cloud Computing and Commerce (IC^4) and the Business Innovation Platform Social Media Data Initiative for providing the Twitter data, and the Intercontinental Exchange (ICE) for tick data for the final part of my research presented in this thesis.

I would like to thank my colleagues, friends and family. I was helped greatly by hard working and friendly colleagues Anushree Priyadarshini, Artemisa Jaramillo Galan, Bettina Wuerdinger, Fabian Gogolin, Sahar Validi, Yulia Plaksina, Sheelagh Murtagh, Sergej Svorobej, Fearghal Kearney, Liang Xiaoning, Wu Szu Hsin, Julie Brueckner, Huong Tran, Tang Minhong, Li Na, Liu Xinyang and Mitra Kami Delivand. Many members of staff from DCUBS, the School of Mathematical Sciences and across DCU were a real help giving me lots of encouragement including Teresa Hogan, Ciarán Mac An Bhaird, Shaen Corbet, Binesh Nair, Graham Hunt, Hiroyuki Kawakatsu, Liam Gallagher, Ronan Powell, Valerio Poti, Gerry Conyngham, Sandra McMahon, Pierangelo Rosati, Theo Lynn, Ursula Baxter, Margaret Galuszynska, Clare Balfe, Muriel Keegan, Eabhnat Ni Fhloinn, Eugene O'Riordan, Olaf Menkens, Jurgen Burzlaff, Ban Ong, Emmanuel Buffet, Angela Murphy, Karen O'Shea, Joe Jones, Susan Jones, Philip McKinley and Willie O'Sullivan.

Finally I wish to thank my family, Gerald, Barbara, Danielle, Nadine, Oran, Kian and Anna, and Lady, a loyal and fierce friend.

Contents

Abbreviations

AAAI	Association for the Advancement of Artificial Intelligence
ADF	Augmented Dickey Fuller
AFP	Agence France Presse
AMEX	American Stock Exchange
AP	Associated Press
API2	Average of the Argus and the IHS McCloskey NW Europe Steam Coal Marker
AR	Average Abnormal Return
ARA	Amsterdam Rotterdam Antwerp
BDI	Baltic Dry Index
BST	British Summer Time
CAR	Cumulative Average Abnormal Return
CFTC	Commodity Futures Trading Commission
CO_2	Carbon Dioxide
COP	Conference of the Parties
Corr	Correlation
Count All	Count of the Number of All Tweets (regardless of sentiment)
Count Neg	Count of the Number of Negative Tweets
Count Pos	Count of the Number of Positive Tweets
ECOMFIN	Energy and Commodity Finance
EMH	Efficient Market Hypothesis
EP	European Parliament
EU ETS	European Union Emissions Trading Scheme
EUA	European Union Emission Allowance
EWGCFM	Euro Working Group for Commodities and Financial Modelling
FIGARCH	Fractionally Integrated Generalized Autoregressive Conditional Heteroscedastic
FTSE	Financial Times Stock Exchange
FWER	Familywise Error Rate
GARCH	Generalized Autoregressive Conditional Heteroskedastic
GHG	Greenhouse Gas
GMT	Greenwich Mean Time
IAFA	Irish Accounting and Finance Association

ICE	Intercontinental Exchange
IEEE	Institute of Electrical and Electronics Engineers
IPCC	Intergovernmental Panel on Climate Change
IPO	Initial Public Offering
ISNE	Irish Society for New Economists
KPSS	Kwiatkowski Phillips Schmidt Shin
MEP	Member of the European Parliament
MHT	Multiple Hypothesis Testing
MSCI	Morgan Stanley Capital International
NAP	National Allocation Plan
NASDAQ	National Association of Securities Dealers Automated Quotations
NBP	National Balance Point
NKY	Nikkei Index
NTT	Nippon Telegraph and Telephone Telecommunications Company
NYSE	New York Stock Exchange
NYU	New York University
OLS	Ordinary Least Squares
OPEC	Organization of Petroleum Exporting Countries
OVX	Oil Volatility Index
PC	Personal Computer
PCA	Principal Component Analysis
RSP	Resolution on Topical Subject
sCER	Secondary Market in Certificates of Emission Reduction
SP500	Standard and Poor's 500
Stoxx 50	Euro Stoxx 50 Index
SSRN	Social Science Research Network
Sum Neg	Sum of Sentiment Impact Scores of Negative Tweets
Sum Pos	Sum of Sentiment Impact Scores of Positive Tweets
T-GARCH	Threshold Generalized Autoregressive Conditional Heteroskedastic
UNFCCC	United Nations Framework Convention on Climate Change
USDEUR	The value of one US Dollar expressed in Euro
USDHKD	The value of one US Dollar expressed in Hong Kong Dollars

USDJPY	The value of one US Dollar expressed in Japanese Yen
V2X	Euro Stoxx 50 Volatility Index
VAR	Vector Auto Regressive
VECM	Vector Error Correction Model
VFTSE	Volatility of the Financial Times Stock Exchange
VIX	Chicago Board Options Exchange Volatility Index
WTI	West Texas Intermediate

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Sentiment Effects in Professionally Traded Markets: Evidence from Oil and Emissions Futures

Peter Deeney

Abstract

This thesis shows that sentiment has influence in professionally traded oil and emissions markets. The sentiment index of Baker and Wurgler (2006) is adapted for the oil markets and is used to show that sentiment has a positive effect on WTI and Brent crude oil prices. Having established the value of this index in the oil markets it is extended to include the wider energy markets and used to show that sentiment also has an effect in the EU emissions trading scheme (EU ETS). It is found that there is some evidence that decisions of the European Parliament (EP) are associated with a drop in emission allowance (EUA) prices particularly when these decisions occur at times of low sentiment, low news exposure and when they come from non-party political sources. It is found that an increase in volatility of EUA returns is associated with EP decisions made at these times.

In order to investigate further the effect of sentiment in the EU ETS, sentiment measured from tweets concerning the emissions market is shown to predict price level and volatility using intra-day data. Bi-directional Granger causality is found between changes in emissions market sentiment and EUA returns, this is especially true for negative sentiment. There is only very weak evidence of an association between climate change sentiment and the EUA returns showing that the EU ETS is not very high in the consciousness of people posting tweets about climate change. Finally, there is some evidence that energy commodity prices and stock market returns can explain, but not predict, EUA prices. This suggests that the EU ETS is efficient with regard to this fundamental information but that in general the Efficient Market Hypothesis does not provide a complete description of the market dynamics.

This thesis therefore shows not only that the Efficient Market Hypothesis does not provide a complete description of market dynamics but that sentiment does not rely on uninformed traders to have a real and substantial effect in the emissions and oil markets.

Chapter 1

Introduction

1.1 Introduction

The central contribution of this thesis is that sentiment is found to explain returns and volatility in the professionally traded energy futures markets, specifically the WTI and Brent crude oil, and the EU emissions allowance markets. Baker and Wurgler (2006) find that sentiment is an important influence on stock prices in the equity markets, particularly for stocks which are hard to value. The influence of sentiment in the equity markets has been explained because there are many uninformed traders and there is some difficulty obtaining information about each individual asset. This influence persists because there are limits to arbitrage such as market frictions, the cost of capital and often there are difficulties in short selling due to a lack of available shares. The energy markets are different from the equity markets. These markets are professionally traded, have more transparency, it is easier to take short positions and borrowing is possible on the corporate bond market. Given these factors the effect of sentiment on prices may be unexpected. However, there is still uncertainty about future events and some important information is not publicly available such as estimates of oil, coal and gas reserves. In addition there are limits to the positions traders may take. These lesser conditions are sufficient to permit sentiment to have an effect in the oil and emissions markets. This thesis shows that the decisions of oil and emissions traders are, to a limited extent, explained and even predicted by sentiment.

The Affect Infusion Model of Forgas (1995) tells us that the influence of emotions on judgements is more pronounced for judgements requiring open constructive thinking, than for judgements made by following previously well-established patterns. This is applicable to the energy market because open and constructive thinking is required from traders as they deal with new developments such as Brexit, unexpected outcomes from OPEC meetings or political violence. Hence, the arguments in Forgas (1995) suggest that sentiment has an effect on decisions made by energy traders.

In this investigation we find that the conditions in the energy market, namely limitations on information availability and limitations on position sizes, and in the case of the emissions market, inattention, are sufficient for sentiment to have a lasting and substantial effect on prices and volatility. This is an important contribution to behavioural finance which has, in the case of equity markets, depended heavily on the presence and activity of uninformed traders to explain market inefficiencies, however there is a growing literature establishing the activity of behavioural biases in professional traders.

1.2 Motivation and Context

A behavioural finance approach has been used to explain the differences between observed price dynamics and the theoretical price dynamics expected from the Efficient Market Hypothesis (EMH). We see from Coval and Shumway (2005), Coates and Herbert (2008), O'Connell and Teo (2009), Coates (2012), Palao and Pardo (2012), Cummins et al. (2015) and, Dowling et al. (2016) that even in professionally traded markets there are behavioural biases. In this thesis we propose that sentiment, which has been seen to have an effect in the equities markets, may be observed in the energy futures markets, specifically the WTI and Brent crude oil markets, and the EU emissions allowance market. The sentiment of a community about a subject is the collection of positive, negative and neutral opinions held by that community concerning the subject. In Chapters 2 and 3 sentiment is measured using financial proxies, in Chapter 4 it is measured from tweets. Information from Twitter contains sentiment because the people who posted the tweets express their opinion in these posts. This has been recognized widely in the sentiment analysis literature, see Thelwall et al. (2010), Bollen et al. (2011), Corea and Cervellati (2015), Siapera et al. (2015) and Yang et al. (2015) among others.

There are several reasons to explain why sentiment would have an effect in asset pricing: the presence of uninformed traders, see Shleifer and Summers (1990), Brown (1999), de Long et al. (1990), Shleifer and Vishny (1997), Barberis and Thaler (2003), Tetlock (2007), Verma and Verma (2008) and Kaufmann (2011); lack of attention, see Barber and Odean (2008); and a lack of reliable fundamental information or information asymmetry, see Baker and Wurgler (2006).

There are also explanations put forward to explain why the effects of sentiment would not be removed quickly by arbitrage: short selling constraints, see Baker and Stein (2004), and Baker and Wurgler (2006); market frictions, see Barberis and Thaler (2003); and the cost and risk of arbitrage, see Shleifer and Vishny (1997) and, Barberis and Thaler (2003).

These are certainly good explanations for the action of sentiment on thinly traded stocks in the equity markets where it may not be possible to short some stocks, but these problems are not present to the same extent in the commodity futures markets where, there are few if any uninformed traders, liquidity can be extremely high leading to a high degree of market attention and low market frictions. (In spite of this we find evidence of market inattention in the emissions market.) In addition there is considerable information available concerning the oil and emissions markets. Access to the corporate bond market means that energy companies are able to raise money relatively cheaply, and so the cost of holding on to an arbitrage position should not be sufficient to explain the continued effect of sentiment. There are however limitations to taking short positions imposed by asset managers in terms of position sizes and margin calls, rather than by the availability of shares. These limits do have effects in the market, see Acharya et al. (2013). Thus we propose that even with professional trading, greater information availability, and in the case of the oil markets massive liquidity, there is an effect due to sentiment and this effect is not removed quickly by arbitrage as would be suggested by the Efficient Markets Hypothesis (EMH).

The EU carbon market is populated largely by professional traders working for large electricity generators, steel producers, cement producers, airlines and other large industries, see Mizrach and Otsubo (2014), Griffin et al. (2015) and Palao and Pardo (2017). While the market in EUAs is much less liquid than the oil market there were still 446,506 EUA prompt December futures transactions during the year from 17th December 2012 to 16th December 2013 analysed in Chapter 4. In classical financial theory the EU ETS would be a rational market where prices reflect fundamental information very quickly according to the EMH. Instead we find that market sentiment can explain prices and volatility.

Sentiment is measured in two ways in this thesis, first as the sentiment of the market measured from suitable proxies selected from the market data and second, as the sentiment of tweets about climate change and the emissions market. The volume of trades, volatility, the level of speculative activity and the put-call ratio are all considered to be activities associated with the sentiment of market participants and are used as proxies for market sentiment. The second method of measuring sentiment is to examine the text of tweets concerning the emissions market using the sentiment analysis provided by DataSift[1], a leading supplier of news and data analytics. Twitter sentiment is not the same as market sentiment since not all those who post tweets are traders, therefore it provides a very useful alternative source for measuring sentiment. Using Twitter gives the advantage that it measures sentiment from a different perspective than from a proxy based index. In this way we verify that sentiment influences the markets.

The contexts of this study are the oil market and the EU emissions trading scheme (EU ETS), both of which are very important and interesting contexts for such a study. Oil is the world's primary energy source for transportation, a major source of energy for heating and electricity generation, a raw material for many chemical industries and the most traded of all commodities. The oil markets are the subject of Chapter 2.

The EU ETS is the principal area of interest for this thesis being the subject of

[1]Datasift has provided the tweets and analysis of these tweets for several published studies as outlined in Section 4.2.3.

Chapters 3 and 4. The EU ETS is a particularly interesting subject for the influence of sentiment because prices are determined not just by the wider energy market but also by regulatory issues. The EU ETS is important for many reasons. The EU ETS is the EU's principal method to reduce the emission of greenhouse gases[2]. There has been much discussion and action regarding the need to reduce the quantity of greenhouse gases (GHG) in the atmosphere in order to reduce climate change. The EU ETS puts a price on GHG emissions so that firms may benefit financially from reducing their GHG emissions. The price of the emission allowances (EUAs) depends on supply and demand. The supply is agreed in advance by the EU states and the EU ETS; however there is the possibility of regulatory changes. The demand depends on the amount of GHG emitted by the regulated installations across the EU, Iceland, Lichtenstein and Norway, this too can be subject to regulatory changes such as the recent inclusion of aviation. In addition to its importance in reducing GHG emissions, there is a considerable quantity of trade in the EUA market. For example during the final year of the December 2015 futures contract there was €25.8bn traded, during the same period the December 2016 contract had €6.6bn traded and the 2017 contract had €2.5bn traded. The 2016 cap for emissions is 2.084 trillion tonnes, which at the present price of €5.81 per tonne[3] is €12.108 trillion. The cost of EUAs has been part of the EU economy since 2005. A third reason why the EU ETS is important is that it is the largest emissions trading scheme in the world. Research into this scheme is paving the way for many other schemes, in particular the Chinese national emissions scheme which is due to begin in 2017.

The oil market was chosen as a testing ground to verify that a sentiment index based on Baker and Wurgler (2006) would be of use in energy commodity markets. This was necessary due to the novelty of investigating sentiment in the relatively new asset class of emission allowances. Thus Chapter 2 establishes the method of creating a sentiment index which is used in Chapter 3. In Chapter 3 it was necessary to address the effect of regulatory changes in the emissions market because the price changes caused

[2]http://ec.europa.eu/clima/policies/ets/index_en.htm [Accessed on 11th May 2016]

[3]Price at the close of business on 14th October from Intercontinental Exchange for the Dec 2016 futures contract.

by regulatory decisions are quite large. Thus in Chapter 3 we look at the effect of European Parliament decisions on EUA prices with different sentiment, news exposure and party-political / non party-political sourcing for the decisions. After establishing that sentiment was effective in the energy commodity markets (Chapter 2) and in particular in the EU emissions market (Chapter 3), the final, largest and most novel aspect of the thesis, the use of tweets, is presented in Chapter 4. In this chapter we measure sentiment from a very different source, namely tweets, and show it to influence both the EUA returns and their volatility. Thus we have presented very strong evidence that sentiment measured in two quite distinct ways, has an influence in both the oil and emissions markets both of which are professionally traded.

It is evident that this research is topical and relevant. Chen, He and Yu (2015) concerns the use of the OVX [4] for prediction of oil futures level and volatility; Lee and Ko (2016) examines predictability in stock markets; Yin and Yang (2016) looks at the prediction of oil prices and Maslyuk-Escobedo et al. (2016) examines sentiment and jumps in oil prices. These four papers cite Chapter 2 which was published Deeney, Cummins, Dowling and Bermingham (2015). Zhu et al. (2015) examines changes in the EUA market and has cited Deeney et al. (2016a) which was published from Chapter 3. The research in this thesis deals with important and current topics and makes a real contribution to the literature.

1.3 Contribution

This thesis contributes to the literature by demonstrating the influence of sentiment in professionally traded markets, namely in the oil markets and in the EU Emissions Trading Scheme (EU ETS). Sentiment is shown to have a significant effect on prices and volatility in these markets. We see from Baker and Wurgler (2006) that lack of reliable information, and from Shleifer and Vishny (1997) and, Acharya et al. (2013) that the limits imposed on traders by portfolio managers, are among the explanations which

[4] The CBOE Crude Oil ETF Volatility Index (OVX) measures the market's expectation of 30-day volatility of crude oil prices by applying the VIX® methodology to United States Oil Fund, LP options spanning a wide range of strike prices.

account for the initial action and the continued effect of sentiment. In addition we find in Chapter 3 that market inattention is a factor facilitating the effect of sentiment in the EU ETS. This makes a contribution to the literature because these markets are almost exclusively traded by professionals, see Mizrach and Otsubo (2014), Griffin et al. (2015) and Palao and Pardo (2017), and in these markets arbitrage is less restricted than in the equity markets. In addition to this contribution, this is the first study of the effect of sentiment in the emissions markets and the first study of the effect of energy and equity market influence on emissions at intra-day frequency as well as being one of only a few studies of sentiment in the energy commodity markets[5]. It is also one of very few studies to use a multiple hypothesis testing (MHT) framework to take account of the multiple comparisons problem. The multiple comparisons problem occurs when many hypothesis tests are conducted simultaneously. Some false rejections of null hypotheses are likely to occur in these situations merely as the result of chance and not because of an underlying effect. This is discussed in more detail in Sections 2.4.2, 3.4.1 and 4.5.4. The individual contribution of each of the three central chapters is now discussed.

1.4 Chapter Outline

Chapters 2, 3 and 4 look at the effect of sentiment in the oil market, the interaction of sentiment with the regulatory decisions of the EU ETS and the effect of Twitter sentiment on EUA prices and volatility. Chapter 2 shows that the method of Baker and Wurgler (2006), which was used successfully to construct a sentiment index for the equity markets, may be adapted to the oil markets. Chapter 3 shows that sentiment has an effect in the emissions market in terms of the reception of European Parliament decisions and Chapter 4 demonstrates that sentiment measured from tweets does influence EUA price and volatility.

1.4.1 Chapter 2, Sentiment in Oil Markets

This chapter establishes that oil market sentiment may be measured by adapting the

[5]Maslyuk et al. (2013) uses the cumulative sentiment index from Thomson Reuters News Analytics to examine price discontinuities in energy spot and futures and Borovkova (2011) uses the same source to examine the shape of the forward curve for oil futures prices, and Lechthaler and Leinert (2012) uses this source for oil markets.

method of Baker and Wurgler (2006) and shows that the resulting sentiment measure is associated with contemporaneous price movements in Brent and WTI crude oils. Baker and Wurgler (2006) select the following proxies for sentiment from the financial data, these proxies are considered indicative of market sentiment, they are: the NYSE turnover, the closed end fund premium, the number and average first day returns of IPOs, the share of equity issues in total equity and debt issues, and the dividend premium. To extract a common sentiment signal these proxies are used in a principal component analysis. For the oil market we measure sentiment using the following proxies: the volume and volatility of prompt month oil futures, the put-call ratio of options on these futures contracts, the ratio of non-commercial futures and options to oil supply and a local volatility index. The volume of oil trades is analogous to the NYSE turnover, volatility is recognized as an indicator of fear, see Whaley (2000), the put-call ratio is also recognized as an indicator of market fear, see Bathia and Bredin (2013), and the ratio of non-commercial trades to oil demand is a measure of speculation see Coleman (2012), (Table 2.1). These monthly proxies are combined using principal component analysis. The findings are that the expected fundamental drivers of oil price such as oil inventory level, OPEC spare capacity and world economic activity indicators are indeed significantly associated with oil prices. When the sentiment indices for WTI and Brent are added to these models they are found to improve them both statistically and economically. The key contribution of this chapter is that oil market sentiment is seen to influence both WTI and Brent oil prices, despite the oil market being largely professional with reasonably easy shorting availability and extremely high liquidity.

Chapter 2 Key Findings:

- Models comprising stock markets, currencies, world economy activity indicators, US oil inventory, world oil supply, OPEC surplus and the proportion of oil supplied by OPEC form useful fundamental models for WTI and Brent oil prices. These models are improved when a sentiment index is added. The sentiment index for WTI and Brent uses volume of trades, historic volatility, put-call ratio, ratio of speculative trades to oil supply and the stock market implied volatility.

- The improvement obtained by adding the sentiment indices is statistically significant.
- The size of the coefficient of the sentiment index is larger than any of the other coefficients in a standardized model, indicating that it is as least as important as any of the fundamental variables.

1.4.2 Chapter 3, Influences from the European Parliament on EU Emissions Prices

Having established a method for measuring sentiment in the oil market by adapting the Baker and Wurgler (2006) index in Chapter 2, this method of measuring sentiment is applied to the EU ETS. The price of EUAs is highly dependent on regulatory changes as well as the energy market. This chapter looks at the way in which decisions made by the European Parliament (EP) change EUA prices. As the EU ETS only exists due to regulations it is expected that even the suspicion of changes in these regulations would have an influence on EUA prices. We examine the effects of EP decisions across different levels of sentiment and market awareness as well across different sources for the legislation. This investigation uses the method established by the first chapter to produce a sentiment index for the interlinked emissions and energy markets. The key contribution of this chapter is the finding that sentiment, among other influences, does have an influence in the market's reaction to decisions made by the European Parliament.

Chapter 3 Key Findings:

- Regulatory decisions of the European Parliament play a crucial role in the price development of EUAs. There is weak evidence that European Parliament decisions generally lower the EUA price and very strong evidence that these decisions increase the volatility of EUA returns.
- The level of awareness or interest before decisions, the level of energy market sentiment and the source of the legislation are considered as cross-sectional effects

because these factors are likely to influence the behaviour of the European Parliament. Members of the European Parliament (MEPs) are conscious of their voters' interests and so the level of media exposure and energy market sentiment would be likely to be influential. The source of the legislation is considered because MEPs are likely to act differently to proposals from inside or outside their political groups, and furthermore, the political groups may publicize their intentions more effectively than non-political sources of legislation.

- There is a more pronounced drop in EUA prices and an increase in volatility after decisions of the European Parliament when the level of sentiment is below its median.
- When a decision does not originate from one of the European Parliament's political groups there is a larger effect on the market.
- If the level of market attention is lower than the median, the change to the EUA price and volatility after a decision of the European Parliament is greater.
- There is need for clearer forward guidance to be given by the European Parliament to the market, so that decisions do not surprise the market and add to volatility.

1.4.3 Chapter 4, Twitter Sentiment and the EU Carbon Market

Since it is found that energy market sentiment, as well as political origin and media exposure affects the receptivity of the EUA market to regulatory changes, we now examine the direct effect of sentiment, and do so at intra-day frequency. This chapter looks at the ways in which we might extract meaningful information from the sentiment measured from tweets which express people's opinions concerning climate change and the EU emissions market. The use of Twitter allows sentiment to be measured at intra-day frequency which is used with intra-day financial data to examine the effect of sentiment on EUA returns and volatility. An important advantage in using Twitter rather than other social media platforms such as blogs or commercial media, is that the messages which are to be analysed are short, less than or equal to 140 characters. This brevity makes it unlikely that subject drift would occur. Furthermore there is ample literature already showing that Twitter is a useful source of sentiment information.

Tweets are used extensively in the literature to evaluate the sentiment of large numbers of people concerning various subjects including financial markets. In order to get a comprehensive sample of tweets we search for tweets containing particular search terms, such as “climate change”, “emissions trading” etc. (see Table 4.1). Having selected an initial list of 44 search terms these are tested in a scoping exercise to check for subject accuracy. Using these results we reduce the list to 17 search terms which span the topics of climate change and the emissions market. A further reduction produces a list of 5 search terms specifically for the emissions market. These are then used to find tweets posted from Europe in English during the final year of the 2013 EUA futures contract, which was from 17th December 2012 to 16th December 2013. These tweets are gathered and analysed by DataSift. This year is selected as it includes the backloading decision of the European Parliament on 16th April 2013 which was highly influential for EUA prices as seen in Chapter 3.

To test the accuracy of the Tweet sample it is necessary to read the text of hundreds of the tweets. This will indicate whether relevant tweets have been captured. Since we are restricting our analysis to English tweets from within the EU, it is not surprising that we find that the most frequent time zones for carbon market tweets are London (38%) , Amsterdam (25%) and Brussels (14%).

Vector Auto Regression (VAR) and Granger causality analysis were used to test for an association between the sentiment from the emissions market tweets and EUA returns, and between sentiment from the climate change tweets and EUA returns. The results are that there is bi-directional Granger causality between changes in emissions market sentiment and EUA returns, and that strong (weak) emissions market sentiment is associated higher (lower) levels of EUA volatility. There is only very weak evidence of an association between changes in climate change sentiment and EUA returns. There is a similar pattern of strong evidence of an association between stronger (weaker) climate change sentiment and higher (lower) EUA volatility. Finally there was some evidence that the EU ETS responds quickly to energy market information, in that there was some evidence of contemporaneous association between EUA returns and gas, oil and FTSE returns, but no evidence for a one hour predictive model.

Chapter 4 Key Findings:

- There is bi-directional Granger causality between changes in the sentiment of tweets concerning the emissions market and EUA returns.
- No reliable evidence was found that tweets concerning climate change had an association with EUA prices.
- There was very strong evidence of an association between strong (weak) sentiment from both the emissions market and climate change tweets, and high (low) volatility of EUA returns.
- There was some evidence that the energy market can explain but not predict EUA prices, this indicates that the carbon market assimilates information from the energy market very quickly.

1.5 Research dissemination

Chapter 2, *Sentiment in Oil Markets,* has developed after initial versions were presented in 2013 at the Irish Accounting and Finance Association Conference (Deeney et al.; 2013a), the Irish Society for New Economists Conference Deeney et al. (2013b), the Infiniti International Finance Conference (Deeney et al.; 2013c) and the 53rd meeting of the Euro Working Group for Commodities and Financial Modelling *(Deeney et al.; 2013d).* Chen, He and Yu (2015), Maslyuk-Escobedo et al. (2016), Lee and Ko (2016), Yin and Yang (2016), Batten et al. (2017), Hung (2017) and Byrne et al. (2017) have already cited the paper produced from this chapter which was published in the International Review of Financial Analysis as Deeney, Cummins, Dowling and Bermingham (2015).

Chapter 3, *Influences from the European Parliament on EU emissions prices*, has been cited in Zhu et al. (2017), Chang et al. (2017) and Lou et al. (2017), and published as Deeney, Cummins, Dowling and Smeaton (2016a) in the journal Energy Policy. It was presented in 2014 at the Irish Accounting and Finance Association Conference (Deeney et al.; 2014a), the Irish Society for New Economists Conference (Deeney et al.; 2014b), the Academy of International Business Doctoral Colloquium (Deeney et al.; 2014c) and the 55th meeting of the Euro Working Group for Commodities and Financial Modelling (Deeney et al.; 2014d).

An early version of Chapter 4 has been presented in 2015 at the Irish Accounting and Finance Association Conference (Deeney, Cummins, Dowling and Smeaton; 2015a) and the Energy Finance Conference in London (Deeney, Cummins, Dowling and Smeaton; 2015b). A more developed version has been presented at the Energy and Commodity Finance (ECOMFIN) Conference (Deeney et al.; 2016b) the Infiniti International Finance Conference (Deeney et al.; 2016c) and the Irish Accounting and Finance Association Conference (Deeney et al.; 2016d). These were held in May and June 2016.

Chapter 2

Sentiment in the Oil Markets

2.1 Introduction

Sentiment is shown to influence both West Texas Intermediate (WTI) and Brent futures prices during the period 2002 - 2013. This is demonstrated while controlling for stock indices, exchange rates, financial costs, inventory and supply levels as well as OPEC activity. Sentiment indices are developed for WTI and Brent crude oils using a suite of financial proxies similar to those used in equity research where the influence of sentiment has already been established. Given the novel nature of this study, a multiple hypothesis testing technique is used to ensure that these conclusions are statistically robust.

This research is motivated by evidence that sentiment influences the behaviour of the stock markets. We show that sentiment influences prices in the professionally-traded oil markets by measuring sentiment using indices constructed from a suite of appropriate financial oil market proxies. These indices for West Texas Intermediate (WTI) and Brent crude oils significantly improve a fundamental model of oil prices for each oil during the period January 2002 - December 2013 using monthly data. We choose the prompt month futures markets as these are much less subject to short term shocks which are present in spot markets. Examples of such shocks are unexpected short periods of cold weather and temporary shipping delays. Thus we are likely to avoid the immediate effect of the "cash" market (Pindyck; 2001) and actually be more influenced by the "storage" market, since futures are effectively a financial oil storage mechanism. This has the effect of smoothing out some of the volatility of the spot market and thus makes the choice of futures more useful for the examination of sentiment. Financialization of the commodity markets since 2005 has provided a mechanism by which sentiment can have an increased influence on commodity prices by introducing a large highly liquid market in commodity derivatives which drives spot prices, see Silverio and Szklo (2012) and Bhardwaj et al. (2015). There is a question as to whether financialization has caused spikes in commodity prices. There is support [1] for this hypothesis as well as, possibly greater, evidence against [2] it. The futures markets are of interest not only to traders wanting to purchase or sell oil, but to investors wishing to hedge oil risks and to speculators. Wu and McCallum (2005), among others, agree that the futures prices contain very useful information for the future spot market. For the purposes of this investigation we focus on futures as they are highly liquid assets and since they look forward, are more susceptible to sentiment and less susceptible to short term shocks.

Sentiment is not only a phenomenon observed by professional traders but sentiment influences professional traders. O'Connell and Teo (2009) demonstrate trader overconfidence; Coates and Herbert (2008) show a link between testosterone levels and trading outcomes; Froot et al. (2011) show that current trading decisions are subject to sensitivity to past portfolio losses, while a study by Fenton-O'Creevy et al. (2011) of 118 UK-based professional traders in equity, bond, and derivatives markets finds that traders allow emotions to influence their trading decision-making in a manner that deviates from purely rational decision-making, see Dowling et al. (2016).

Sentiment is known to exist in the equity markets. The work of Baker and Wurgler (2006) shows that sentiment is most influential on firms which are difficult to value. This confirms the work of Barberis et al. (1998) which shows that decisions made regarding investment are at times biased and subject to systematic errors. Schmeling (2009) reports that sentiment has a significant influence on stock market returns across many industrialized countries and has a greater effect on countries which have less market

[1] Masters (2008), Masters (2009), Robles et al. (2009), de Schutter (2010), Herman et al. (2011) and, Cheng and Xiong (2014) give support for the Master's Hypothesis that financialization was responsible for commodity price spikes.

[2] Irwin et al. (2009), Pirrong (2010), Wright (2011) and Dwyer et al. (2012) do not find evidence that financialization was responsible for commodity price spikes, in particular the following focus on the oil markets and fail to find evidence that financialization drives prices Buyuksahin and Harris (2011), Irwin and Sanders (2012), Fattouh et al. (2013), Aulerich et al. (2013) and, Brunetti et al. (2016)

integrity and more herd-like behaviour from investors. These effects are not removed by arbitrage due to the limits to arbitrage encountered in the equity markets as described by Barberis and Thaler (2003).

Wang (2001) shows that sentiment is active in the agricultural commodity markets. Borovkova (2011) demonstrates the influence of sentiment in the oil markets by showing that the shape of the forward curve is influenced by very strong or very weak sentiment as measured by the Thomson Reuters NewsScope product.[3] Dowling et al. (2016) show evidence for the existence of psychological price barriers in the crude oil markets, as does Palao and Pardo (2012) in the EU emissions market. Both Borovkova (2011) and Dowling et al. (2016) explain that sentiment is influential in the oil markets, but these papers do not consider the whole range of sentiment but look at very high or very low periods of sentiment. We show that sentiment can be quantified as a continuous variable and can be used to explain price movements. In this investigation we use sentiment in oil price models for WTI and Brent and treat it as an additional variable to the chosen fundamental variables. In doing so we add to the literature showing that sentiment does not just have an influence in extreme or in specific circumstances but has a widespread measurable effect.

We propose that there is sentiment in the oil markets because of the need for speculation and because of information asymmetry between oil producers and the other market participants. Hedging pressure theory proposes that long and short hedging activity in the oil markets is not balanced and therefore there is a need for speculators, see Hirshleifer (1990). This theoretical insight is supported by empirical evidence from de Roon et al. (2000) who examined 20 futures markets and used data on traders' positions to find evidence to support hedging pressure theory. This analysis took account of market risk which, according to Cheng and Xiong (2014), would be expected to influence the behaviour of hedgers. Further support for hedging pressure is found in the empirical work of Bessembinder (1992) who finds that the net holdings of hedgers influences the returns in foreign exchange and agricultural commodities. In general we find that oil producers are vulnerable to unexpected changes in the price of oil and need

[3]Thomson Reuters Newscope measures the sentiment of the text in news reports using a proprietary sentiment engine.

short hedging positions. However, oil consumers are less vulnerable as they have many other costs in addition to oil prices and so have less need for long hedging positions. This is in keeping with hedging pressure theory from Keynes (1930) and Hicks (1975). Thus we have a situation where speculators provide insurance to producers by taking the excess long positions not taken by consumers, but only producers have access to all the information regarding oil reserves and supply issues.

Kaufmann (2011), Coleman (2012), Fan and Xu (2011) and Cifarelli and Paladino (2010) all show that speculation is an important driver of oil prices. In the equity markets there are limits to arbitrage in particular there is often a lack of available shares to take short positions. While this is not such an issue in the futures markets, there are limits such as the size of the positions traders are permitted to take and the size of the margin calls which traders will incur while they wait for their profits to materialize. Acharya et al. (2013) make it clear that the limits imposed by margin calls can make arbitrage partially ineffective in the oil markets. Therefore arbitrage is limited in its ability to remove the effect of sentiment.

Following the methods applied by Baker and Wurgler (2006), Lemmon and Portniaguina (2006) and Baker et al. (2012) in their analysis of the equity markets, we build a similar oil sentiment index and compare the performance of a fundamental model before and after this sentiment index has been included. Prompt month futures of WTI and Brent crude oils are used from January 2002 to December 2013 at monthly frequency. The expiry of these futures contracts is approximately two weeks after the dates used in our data, thus any increased volatility due to the Samuelson hypothesis is avoided.

Baker and Wurgler (2006) used the following sentiment proxies in an equity context: volume of trades, market volatility, closed end fund discount, IPO number and opening returns, and the put-call ratio. None of these was, on their own, a simple measure of sentiment; each had an idiosyncratic component but a principal component analysis (PCA) was applied to extract the common signal. In this investigation we use: the volume of the oil futures traded, the historic volatility of the oil price, the put-call ratio of oil options, the ratio of speculative trades to oil demand and the implied volatility of a local stock market index, namely the S&P 500 for WTI and the Euro Stoxx 50 for Brent. None of these is a pure measure of sentiment but, we use a PCA process to extract the common signal similar to Baker and Wurgler (2006).

The selected proxies for WTI or Brent crude oil are entered into a principal component analysis, the first principal component of which is defined as the sentiment index for each oil. It is established that low correlations exist between changes in the sentiment indices and changes in a range of key fundamental economic variables, showing that the effectiveness of these indices is not a consequence of fundamental information. As these sentiment indices are extracted from proxies for sentiment, similar to proxies used in equities research, it is reasonably argued that these indices are measuring oil market sentiment.

To test the influence of the sentiment indices for WTI and Brent crude oil, each index is added to a benchmark oil price model consisting of non-sentiment variables. The effect of sentiment on oil prices is then evaluated statistically while explicitly controlling for key fundamental variables that are known to drive oil prices. Hamilton (2009b) adds that there are many fundamental influences and an increasing effect of a scarcity premium, though his prediction in Hamilton (2014) was inaccurate it, states that oil prices are driven by: the emerging economies; oil production and geopolitical disturbances. These influences are part of the complex pattern of oil price discovery, we therefore choose the following key fundamental drivers:

1. broad economic performance as measured by stock index movements, we use the S&P 500, Euro Stoxx 50, Hang Seng and Nikkei which represent the US, the Eurozone, China and Japan the world's four largest consumers of oil, following Li and Lin (2011);

2. the US dollar exchange rates for the stock indices used previously in (1), namely the Euro, Japanese Yen and Hong Kong dollar following Reboredo (2012), Beckmann and Czudaj (2013) and Brahmasrene et al. (2014) who indicate a direct connection between foreign exchange rates and oil prices;

3. the Baltic Dry Index (BDI), the cost of shipping dry goods by sea, following Kilian

(2009) and Coleman (2012);

4. the cost of corporate debt, where we use Moody's Aaa as a benchmark corporate bond rate, following Coleman (2012);

5. the US oil inventory and the World oil supply, and

6. OPEC's spare capacity and proportion of world production following Kaufmann (2004), Hamilton (2009b), Lin and Tamvakis (2010) and Coleman (2012).

To informally measure the improvement to the fundamental model we calculate the R^2 and F-test results; the likelihood ratio test is used to formally test whether the improvement to the models after the inclusion of the sentiment indices is significant or not. As we perform 120 simultaneous hypothesis tests, it is necessary to address the multiple comparison problem. That is, when many hypothesis tests are being carried out simultaneously there is a probability that some null hypotheses may be rejected falsely. This is addressed with a generalized version of the multiple hypothesis testing procedure of Holm (1979).

The remainder of this chapter is set out as follows. Section 2.2 explains the selection of the proxies and the method by which principal component analyses are used to form the oil sentiment indices for WTI and Brent. Section 2.3 shows the methods used for building the fuel price benchmark models against which the sentiment indices are tested. Section 2.4 presents the empirical results for WTI and Brent crude oils and demonstrates the robustness of our finding that sentiment influences oil prices, while using a multiple hypothesis testing (MHT) framework. Section 2.5 concludes.

2.2 Creating an Oil Sentiment Index

In this section the method of constructing an oil sentiment index is described. The construction involves combining proxies for sentiment using PCA, as used by Baker and Stein (2004), Baker and Wurgler (2006), Lemmon and Portniaguina (2006), and Mian and Sankaraguruswamy (2012) who examine sentiment in the equities markets.

The proxies used for the oil markets are selected so as to be similar to those which have been used building sentiment indices in equity research.

2.2.1 Selecting the Oil Sentiment Proxies

Equities research uses a wide variety of proxies for sentiment. None of these proxies are a perfect measure of sentiment but they are combined using principal component analysis (PCA) to produce useful sentiment indices. In the same way proxies for sentiment are chosen from the oil market data and are combined using PCA to form two sentiment indices, one for WTI crude oil and one for Brent crude oil.

Baker and Wurgler (2006) use the following proxies: NYSE turnover, closed end fund discount, number and average first day return of IPOs, share of equity issues in total equity and debt issues, and dividend premium. These are combined in the PCA process to produce a sentiment index. Baker and Wurgler (2006) explain that while each proxy will contain an idiosyncratic as well as a sentiment component, the PCA isolates the common sentiment component. We chose appropriate oil market proxies based on sentiment research in equities which measure market activity, oil price volatility, market fear, speculation and general stock market volatility. These choices are supported from within the literature as set out below and in Table 2.1. The proxies selected to build the oil sentiment indices are specific to each crude oil as follows:

1. the trading volume of the prompt-month futures contract;
2. the 30-day historical volatility of the prompt-month futures price;
3. the put-call ratio for options on oil futures;
4. an oil speculation indicator, namely the ratio of non-commercial futures and options positions to oil demand, and
5. a geographically appropriate implied volatility index (VIX for WTI and the volatility of the Euro Stoxx 50 for Brent).

Volume of trades are used as a proxy for investor sentiment by Scheinkman and Xiong (2003), Baker and Stein (2004), Baker and Wurgler (2007) and Canbaş and

Measure	Equity Proxy	Oil Proxy	Literature
Market Activity	Volume of trades in the stock market	Volume of trades of oil futures	Scheinkman and Xiong (2003), Baker and Stein (2004), Baker and Wurgler (2006), Canbaş and Kandır (2009)
Asset Volatility	Volatility of historic market return	Volatility of historic futures returns	Whaley (2000)
Market Fear	Put-call ratio for equity options	Put-call ratio for oil options	Bathia and Bredin (2013)
Speculation	IPO volume and initial returns	Ratio of non commercial trading volume to oil demand	Coleman (2012), Bunn and Chen (2013), Kolodziej and Kaufmann (2013)
Market Volatility	An implied volatility index	An implied volatility index	Simon and Wiggins III (2001), Whaley (2000, 2009)

Table 2.1: Comparison of Proxies for Sentiment in the Equity Markets and the Oil Markets

Kandır (2009). While it is clear that the volume of trades is a direct measure of market activity, the literature shows that it is also an indicator of market sentiment.

Volatility is considered to be a measure of market fear by Whaley (2000), hence the choice of a volatility measure as a sentiment proxy for each oil. The oil-based implied volatility measure (OVX) was not available for the 12 years required. Hence the 30-day historical volatility of the oil futures price is used. This is calculated as the standard deviation of the log price returns for the previous 30 trading days for prompt month futures contracts. Thirty-day volatility, which uses approximately the previous month-and-a-half of price data, was chosen as it is a reasonable compromise between the measurement of the volatility being accurate and being current. The volatility figures are obtained from Bloomberg LP and are the second proxy.

The put-call ratio is used as a measure of market fear in equity research, for example by Bathia and Bredin (2013). The put-call ratio for oil futures options is the third proxy. The data used is the aggregated open interest futures from Bloomberg LP.

Speculation is measured by Coleman (2012) and Bunn and Chen (2013) using the churn ratio, which was the ratio of the number of forwards or futures contracts to physical delivery, this indicated the level of speculation in the oil and electricity markets respectively. A more specific measure is also used, namely the number of non-commercial futures positions from the US Commodity Futures Trading Commission (CFTC); this measure is used by Kolodziej and Kaufmann (2013). The CFTC defines a commercial position on a commodity as one held by someone who produces, processes or sells the commodity, this includes using futures to hedge actual exposure to commodity prices. In this investigation, we combine these two methods and use the ratio of non-commercial WTI futures to world oil supply from the US Dept of Energy as a speculation indicator for WTI. A similar indicator for Brent is constructed from the corresponding data from the CFTC for Brent non-commercial futures positions where available, and is the fourth proxy. A difficulty with the data is that Brent non-commercial data is unavailable before April 2008; to overcome this the WTI data is used in its place from January 2002 to March 2008, this is a reasonable approximation as the price of Brent and WTI were very closely aligned before 2011.

The VIX is used as a proxy of sentiment by Simon and Wiggins III (2001). Volatility indices are considered to be measures of investor fear or anxiety, see Whaley (2000) and Whaley (2009). The VIX is the weighted average of implied volatilities of first and second month options on the Chicago Board of Trade. We use this measure as a proxy when analysing WTI. The volatility of the Euro Stoxx 50 index (V2X) is used for Brent. The Euro Stoxx 50 index is comprised of 50 of the largest stocks in the Eurozone and represents more than 50% of all the Eurozone equities by capitalization. Equity index volatility is the fifth and final proxy and is chosen as a proxy for overall sentiment in the economy.

2.2.2 Building a Sentiment Index by Principal Component Analysis

This investigation uses PCA to produce a linear combination of the proxies. The first principal component is the linear combination of the proxies which captures the maximum variance compared with other linear combinations subject to normalization. Baker and Wurgler (2007) offer two comments regarding the robustness of this method: first that it reduces reliance on individual proxies, even though measured individually some are very significant; and second, that an index constructed from individual proxies would behave almost identically to that formed by PCA.

A first stage index is constructed following Baker and Wurgler (2006) to decide whether to use each proxy's current value or its first time-lagged value. This is to take into consideration the possibility that some of the proxies may be stronger leading indicators than others. The first stage index is the first principal component of all the current and first lags of the proxies. For each proxy the correlation of the current value with the first stage index and the correlation of the proxy's first lag with the first stage index are calculated. The larger value decides whether the current or first lag is chosen to build the sentiment indices. The selected proxies are then used in a second PCA stage, the first principal component of which is defined to be the sentiment index for the crude oil in question.

The results of the PCA based oil sentiment construction processes are summarized in Table 2.2. Thus for WTI and Brent the sentiment indices are calculated as follows,

$$WTISentiment_t = 0.36\,TradingVolume_{t-1} - 0.44\,WTIVolatility_t - 0.53\,PutCallRatio_{t-1}$$

$$+0.59\,Spec\,WTI_t - 0.22\,VIX_{t-1} \tag{2.1}$$

$$BrentSentiment_t = 0.19\,TradingVolume_{t-1} - 0.63\,BrentVolatility_t + 0.06\,PutCallRatio_{t-1}$$

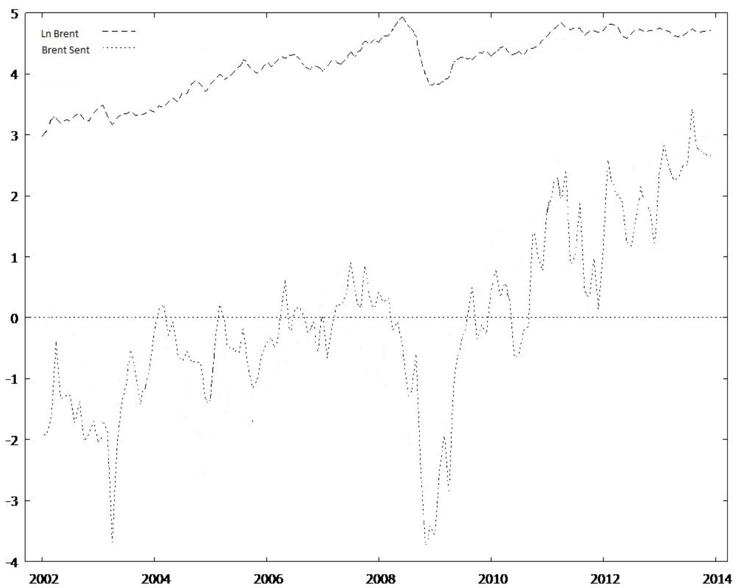
$$+0.46\,Spec\,Brent_t - 0.60\,Volatility\,of\,Stoxx_{t-1} \tag{2.2}$$

where $WTI\,Volatility_t$ or $Brent\,Volatility_t$ is the 30-day historical volatility of WTI or Brent and $Spec\,WTI_t$ or $Spec\,Brent_t$ is the speculation indicator for each oil. The PCA process calculates the ratio of the components which maximizes variance subject to the sum of the squared loadings being one.

Wang (2001) showed that sentiment from speculators and hedgers did contain useful information regarding the movements of agricultural commodity prices but that sentiment from small traders was not useful, this is similar to the finding in Chapter 4 of a difference between climate change sentiment and emissions market sentiment. It is conjectured here that sentiment in the professionally-traded oil markets is useful in explaining oil prices. When Baker and Wurgler (2006), Lemmon and Portniaguina (2006) and Chung et al. (2012) examine the stock markets they use an orthogonalization procedure to remove from the equity sentiment proxies anything which could be attributed to the economic cycle. This procedure effectively produces an index which depends heavily on the choice of economic cycle variables. In order to capture the sentiment in the oil markets, this orthogonalization step is not carried out. This choice keeps the sentiment indices and the choice of fundamental variables independent of each other. This approach is argued to be reasonable due to there being insignificant or low correlation between the oil sentiment indices and the fundamental variables (Table 2.3). This finding also refutes a criticism that the sentiment indices are effective because they capture fundamental information.

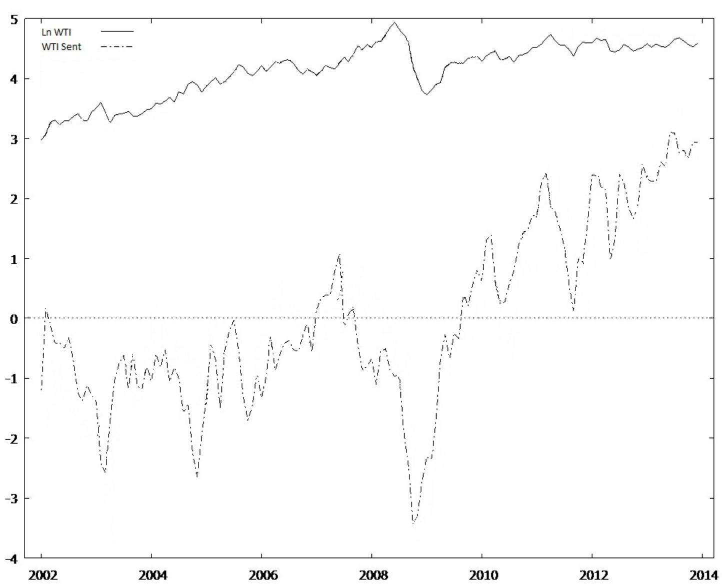
2.2.3 The Sentiment Indices for WTI and Brent

Figures 2.1 and 2.2 plot the WTI and Brent sentiment indices as well as the log of the WTI and Brent price series. It is seen that the Brent sentiment index is quite similar to that of WTI with both showing a general upward trend over the period. In addition both have a severe dip during the period of rapid oil price change in 2008.



The figure shows the natural log of the price of Brent (dashed line) in US$ at the top of the plot. On the same numerical scale we have the oil sentiment indices for Brent (dot line) lower on the same plot. The sentiment scale is described in section 2.2.3.

Figure 2.1: Log of Brent price and its Sentiment Index



The figure shows the natural log of the price of WTI (solid line) in US$ at the top of the plot. On the same numerical scale we have the oil sentiment index for WTI (dash and dot line) lower on the same plot. The sentiment scale is described in section 2.2.3.

Figure 2.2: Log of WTI price and its Sentiment Index

Table 2.3 shows that there is low or insignificant correlation between the first dif-

	WTI		Brent	
Proxy	**Current or First Lag**	**Loading**	**Current (t) or Lag (t-1)**	**Loading**
Trading Volume	First Lag	0.36	First Lag	0.19
30-Day Volatility	Current	-0.44	Current	-0.63
Put Call Ratio	First Lag	-0.53	First Lag	0.06
Speculation Indicator	Current	0.59	Current	0.46
VIX , V2X	First Lag	-0.22	First Lag	-0.60
Variance Explained	33%		27%	

The table shows the loadings from the principal component analysis of the WTI and Brent sentiment proxies. The choice of current (t) or first lag (t-1) is made using the method of Baker and Wurgler (2006). The linear combination of these proxies with their loadings is the first principal component for each set of sentiment proxies. This first principal component is the sentiment index for each crude oil. The percentage of variance explained by this first component is listed. V2X is the volatility index based on the Euro Stoxx 50.

Table 2.2: PCA loadings for WTI and Brent Oil Sentiment indices.

ferences of the two sentiment indices and the first differences of the key fundamental variables that we will consider in the fundamental oil price models, which will be defined later in Eqn.2.3 and Eqn.2.4 in Section 2.3. This demonstrates that the indices are not simply capturing information from these fundamental variables but are bringing new information to the model. As this information is extracted from proxies modelled on channels of sentiment in equity markets, it is reasonably argued that the oil sentiment indices are measuring oil market sentiment.

2.3 Testing Framework

To test whether changes in the oil sentiment indices explain price movements in prompt-month futures contracts for WTI and Brent, a benchmark model for these crude oils is proposed and tested using a multivariate regression. The benchmark model is specifically chosen to capture fundamental rather than sentiment influences on oil prices. The oil sentiment indices are added to the benchmark model for each crude oil and the extended models are tested again. Changes in model performance are measured using the informal R^2 measure and variance ratio tests, along with formal likelihood ratio tests. A common model for both oils is used so that a fair comparison may be made of the effect of the sentiment index on WTI and Brent crude oils.

The standard tests for stationarity (Augmented Dickey Fuller and Kwiatkowski

Proxy	ΔWTI Sentiment Index	ΔBrent Sentiment Index
$\triangle SP500$	0.37	0.10
$\Delta Euro\ Stoxx$	0.36	-0.05
$\Delta Nikkei$	0.31	0.10
$\Delta Hang\ Seng$	0.27	0.21
$\Delta USDEUR$	-0.20	-0.24
$\Delta USDJPY$	0.14	0.01
$\Delta USDHKD$	-0.05	0.03
ΔBDI	-0.01	0.14
$\Delta Moody$	-0.10	-0.03
$\Delta US\ Oil\ Inventory$	0.05	0.00
$\Delta World\ Oil\ Supply$	-0.06	-0.09
$\Delta OPEC\ Surplus$	0.14	0.13
$\Delta OPEC\ Proportion$	-0.18	0.09

The table shows the correlations between the first differences of the fundamental variables, and the first differences of the sentiment indices for WTI and Brent crude oils. These fundamental variables are used in the benchmark models of oil price. The results are generally very low correlation with 18 of the 26 correlations below the 5% significance level of 0.1642. The sentiment index for WTI is weakly correlated with the stock indices which is expected as the US is a larger oil producer than Europe.

Table 2.3: Correlation Table: Sentiment Indices and Fundamental Benchmark Variables

Phillips Schmidt Shin) were carried out. There was strong evidence against the ADF null of non-stationarity and no evidence against the KPSS null of stationarity, see Table 2.4.

2.3.1 Benchmark Model Specification

Benchmark models for WTI and Brent are proposed at monthly frequency using the following fundamental variables:

1. Equity indices: S&P 500, Euro Stoxx, Nikkei and Hang Seng
2. The US$ exchange rate for the Euro, the Japanese Yen and the Hong Kong dollar
3. Baltic Dry Index
4. Corporate bond rates, where we specifically consider Moody's Aaa corporate bond rate
5. US oil inventory and World oil supply
6. OPEC's proportion of world production and OPEC's spare capacity.

We choose a selection of equity indices, from the USA (world's largest oil consumer), the Eurozone (2nd), China (3rd) and Japan (4th) which together accounted for 50%

Variable	ADF	ADF + Trend	KPSS	KPSS + Trend
$\triangle WTI$	2.7 x 10^{-12}	3.7 x 10^{-11}	> 0.1	> 0.1
$\triangle Brent$	4.6 x 10^{-11}	6.4 x 10^{-10}	> 0.1	> 0.1
$\triangle SP500$	4.9 x 10^{-12}	7.0 x 10^{-11}	> 0.1	> 0.1
$\Delta Euro\ Stoxx$	7.7 x 10^{-4}	5.7 x 10^{-3}	> 0.1	> 0.1
$\Delta Nikkei$	1.6 x 10^{-12}	1.9 x 10^{-11}	> 0.1	> 0.1
$\Delta Hang\ Seng$	2.6 x 10^{-14}	3.6 x 10^{-13}	> 0.1	> 0.1
$\Delta USDEUR$	1.8 x 10^{-16}	2.0 x 10^{-15}	> 0.1	> 0.1
$\Delta USDJPY$	1.3 x 10^{-14}	1.7 x 10^{-13}	> 0.1	> 0.1
$\Delta USDHKD$	9.9 x 10^{-12}	2.1 x 10^{-11}	> 0.1	> 0.1
ΔBDI	1.0 x 10^{-8}	8.1 x 10^{-8}	> 0.1	> 0.1
$\Delta Moody$	2.4 x 10^{-16}	2.9 x 10^{-16}	> 0.1	> 0.1
$\Delta US\ Oil\ Inventory$	3.4 x 10^{-21}	1.5 x 10^{-23}	> 0.1	> 0.1
$\Delta World\ Oil\ Supply$	2.1 x 10^{-2}	1.0 x 10^{-1}	> 0.1	> 0.1
$\Delta OPEC\ Surplus$	4.0 x 10^{-9}	4.1 x 10^{-8}	> 0.1	> 0.1
$\Delta OPEC\ Proportion$	2.8 x 10^{-19}	2.7 x 10^{-20}	> 0.1	> 0.1

The table presents the p-values of the stationarity tests for the variables. The Augmented Dickey Fuller (ADF) test has a null of non-stationarity. The Kwiatkowski Phillips Schmidt Shin (KPSS) test has a null of stationarity. The results show strong evidence to accept that the variables are stationary. Models with the addition of a constant, and with the addition of a constant and a trend are used for robustness.

Table 2.4: Stationarity Test Results

of world oil consumption in 2012 [4]. These regions are represented in our testing by S&P 500, EuroStoxx 50, Hang Seng and the Nikkei stock indices. There is abundant literature addressing the interactions of oil prices and stock prices. Jones and Kaul (1996) have reported negative co-movements of stock prices in response to oil price shocks between 1947 and 1991, although Fan and Xu (2011) find that from 2004 to 2009 the S&P 500 did not provide a significant explanation of oil prices. Zhang and Li (2016) looked at oil prices from 1990 to 2012 and have found close correlations between oil prices and equity indices particularly after 2008, with the signs of the correlation always positive, which is also the case here. There has been some debate concerning the influence of Asian demand on oil prices, see Li and Lin 2011, Beirne et al. 2013 and Alquist and Gervais 2013 which supports the inclusion of Hong Kong and Japanese stock indices. It is clear that there is a complex relationship between oil price and equity prices and hence stock markets must be part of the fundamental model. The variables $S\&P\,500_t$, $Stoxx\,50_t$, NKY_t, $Hang\ Seng_t$ are the S&P 500, Euro Stoxx 50, Nikkei and Hang Seng stock indices.

[4] US Energy Information Administration, the situation has changed by 2015 when the top consumers in sequence were USA, China, Eurozone, India and Japan.

Beckmann and Czudaj (2013) have found that nominal dollar depreciation causes nominal oil price increase. Brahmasrene et al. (2014) find that US exchange rates Granger cause oil prices in the short run, although Reboredo (2012) finds that oil price and exchange rate interaction is weak. These findings and the selection of stock indices lead to the choice of the US Dollar against the Euro, Yen and Hong Kong dollar as the exchange rates for the benchmark model. The variables $USDEUR_t$, $USDJPY_t$ and $USDHKD_t$ are the values of \$1US expressed in Euro, Yen or Hong Kong dollars.

The Baltic Dry Index (BDI) which tracks the cost of shipping goods across the oceans is used as an indicator of global industrial production following Mitchell et al. (2005), Frale et al. (2008), Kilian (2009), Fan and Xu (2011) and Coleman (2012). This literature shows that the BDI is a useful indicator for income and economic growth as it immediately records the demand for the transport of finished goods. A criticism of using the BDI is that it is influenced by fuel costs, and so is an endogenous variable. This problem is addressed by Kilian (2009) who states that the variation in BDI rates is much larger than the variation in bunker fuel costs, and so the influence of the endogeneity is not important, that is, the BDI rates are primarily set by economic activity, rather than the price of bunker fuel. BDI_t is the Baltic Dry index of shipping costs.

Moody's Aaa corporate bond rate is used because Coleman (2012) suggests that since extraction of oil is a capital-intensive business, the cost of capital should be reflected in the price of oil, and that since oil companies are highly rated Coleman (2012) uses the Aaa rate. $Corp\,Bond_t$ is Moody's Aaa corporate bond rate.

Following the basic law of supply and demand, the US oil inventory at Cushing, Oklahoma and world oil supply from the US Dept of Energy are also included. $US\,Oil\,Inventory_t$ is the US oil inventory, $World\,Oil\,Supply_t$ is the world oil supply.

The proportion of world oil that is produced by OPEC has been found to influence oil prices by Kaufmann (2004), Hamilton (2009b), Lin and Tamvakis (2010) and Coleman (2012). This would occur due to market power. Also included is the difference between OPEC's estimated capacity and production as this represents the decision of OPEC

Variable	Mean	Std Dev	Skew	Ex Kurt
Δ WTI	0.011	0.091	-0.797	2.030
Δ Brent	0.012	0.086	-0.939	3.148
Δ S&P 500	0.003	0.045	-0.941	1.947
Δ Stoxx 50	-0.001	0.057	-0.764	1.301
Δ Nikkei	0.003	0.058	-0.910	2.514
Δ Hang Seng	0.005	0.062	-0.781	2.066
Δ USD Euro	-0.003	0.031	0.437	1.308
Δ USD Yen	-0.002	0.027	0.338	0.369
Δ USD Hong Kong dollar	0.000	0.001	-0.904	5.614
Δ BDI	0.006	0.249	-1.453	6.624
Δ Bond Rate	-0.002	0.037	-0.726	4.909
Δ US Oil Inventory	0.001	0.030	-0.220	-0.122
Δ World Oil Supply	0.001	0.007	-0.084	1.258
Δ OPEC Spare Capacity	-0.008	0.170	-1.668	12.383
Δ OPEC Proportion	0.000	0.013	-0.337	2.640

The table shows descriptive statistics for log returns data used in the benchmark models. The data is from January 2002 to December 2013 (N = 144 months). The price of the prompt month WTI and Brent crude oil futures contracts are in US$ per barrel. Corporate Bond rate is Moody's Aaa rate. Std Dev, is standard deviation, Skew, is skewness and Ex Kurt, is excess kurtosis.

Table 2.5: Descriptive Statistics

producers to restrict supply. $OPEC\,Spare\,Capacity_t$ and $OPEC\,Prop_t$ are the OPEC spare capacity and OPEC proportion of world production.

Based on the above arguments, the benchmark model for WTI and Brent crude oil is set out in Eqn. 2.3. Before running the regressions, all the data are log transformed, first-differenced, standardized and checked for stationarity using Augmented Dickey Fuller (ADF) and Kwiatkowski Phillips Schmidt Shin (KPSS) tests which show the log returns of the fundamental variables and sentiment indices to be stationary, see Table 2.4. Descriptive statistics are given in Table 2.5. The benchmark model is given in Eqn. 2.3:

$$\Delta Oil_t = \alpha + \beta_1 \Delta S\&P\,500_t + \beta_2 \Delta Stoxx\,50_t + \beta_3 \Delta NKY_t + \beta_4 \Delta Hang\,Seng_t,$$

$$+\beta_5 \Delta USDEUR_t + \beta_6 \Delta USDJPY_t + \beta_7 \Delta USDHKD_t + +\beta_8 \Delta BDI_t$$

$$+\beta_9 \Delta Corp\,Bond_t + \beta_{10} \Delta US\,Oil\,Inventory_t + \beta_{11} \Delta World\,Oil\,Supply_t$$

$$+\beta_{12}\Delta OPEC\ Spare\,Capacity_t + \beta_{13}\Delta OPEC\ Prop_t + \varepsilon_t \tag{2.3}$$

where all variables are expressed in log returns, so for example ΔOil_t is the log returns of the WTI or Brent prompt month crude oil price.

With the addition of the sentiment index this model becomes:

$$\Delta Oil_t = \alpha + \beta_1 \Delta S\&P\ 500_t + \beta_2 \Delta Stoxx\ 50_t + \beta_3 \Delta NKY_t + \beta_4 \Delta Hang\ Seng_t,$$

$$+\beta_5 \Delta USDEUR_t + \beta_6 \Delta USDJPY_t + \beta_7 \Delta USDHKD_t + +\beta_8 \Delta BDI_t$$

$$+\beta_9 \Delta Corp\ Bond_t + \beta_{10} \Delta US\ Oil\ Inventory_t + \beta_{11} \Delta World\ Oil\ Supply_t$$

$$+\beta_{12}\Delta OPEC\ Spare\,Capacity_t + \beta_{13}\Delta OPEC\ Prop_t + \beta_{14}\Delta Oil\ Sentiment_t + \varepsilon_t \tag{2.4}$$

where $\Delta Oil\,Sentiment_t$ is first difference of the oil sentiment index for WTI or Brent at time t measured in months. As is usual practice, standardized variables are used so that comparisons between the variables may be made and so that calculations may not be liable to floating point errors, see Aboura and Chevallier (2013), thus the α terms are zero.

2.4 Results

There is a clear improvement to the benchmark models for WTI and Brent on the inclusion of the oil sentiment indices as is seen in Table 2.6. This indicates that these indices, and hence oil market sentiment, has a significant influence on WTI and Brent oil prices.

2.4.1 Performance of the Oil Sentiment Indices

The sentiment indices for WTI and Brent make a statistically significant and economically important improvement to the fundamental models for oil price changes during the 12 years from January 2002 to December 2013. The results are presented in Table 2.6 and show that the R^2 statistic increases in the WTI and Brent benchmark models from 41.2% and 36.1% to 56.6% and 53.9% respectively; in addition the variance ratio test is much more significant. More formally, there is a strongly significant result from the likelihood ratio test of the improvement to the fundamental model, after the inclusion of the sentiment indices for WTI and Brent.

Looking at the results in Table 2.6 it is notable that the coefficients of the S&P 500, Euro Stoxx 50 and the Nikkei are all insignificant at MHT levels, except for Stoxx for WTI when sentiment is included. There is a range of findings in the literature. Our result is in contrast with with Jones and Kaul (1996) who find a negative reaction from stock markets to oil prices. Sukcharoen et al. (2014) find that the connection between oil markets and equity markets in countries which trade oil heavily (USA and Canada) to be weak but non-existent for other countries. The result we find here is in line with the that of Fan and Xu (2011) that the S&P500 was not significantly connected with oil prices for roughly the same period of time. Following the results of Alquist and Gervais (2013) and Beirne et al. (2013), we find that there is evidence at conventional levels that the Hang Seng significantly explains WTI and Brent prices; this will be revisited in Section 2.4.2.

The exchange rates used are expressed as the price of US$1 in various local currencies, namely the Euro, Yen and Hong Kong dollar. Only the Euro and the Japanese Yen are found to be significant, though the Yen is much less significant than the Euro. The cost of one US dollar in Japanese Yen has a positive coefficient meaning that a weakening Yen is on average accompanied by higher oil prices measured in US dollars. The links between exchange rates and oil prices are not entirely straightforward, see Beckmann and Czudaj 2013, and Reboredo 2012, but it is clear that an appreciation in oil price is accompanied by appreciation of the currency of the exporter, and since

Japan produces a much smaller amount of oil than the US, 140,000 barrels per day from Japan in contrast to 11,110,000 from the US[5], the positive coefficient is in line with expectations. The coefficient of the cost of US$1 in Euro is negative, indicating that a weakening Euro against the US dollar is, on average, accompanied by negative oil price returns and so a fall in the price of oil measured in US dollars, this is in line with Chen and Chen (2007), Akram (2009) and Aloui et al. (2013). This indicates that as the Euro weakens Europeans will actually have to buy fewer of the more expensive dollars to pay for oil. This may be because a depreciation of the local currency causes lower demand for oil, as explained by the term denomination channel, see Beckmann and Czudaj (2013). The greater size of Eurozone relative to Japan and the fact that the Eurozone (which does not include UK or Norway) produces 500,000 barrels of oil per day, may explain why the Euro exchange rate coefficient is negative while the Yen's coefficient is positive.

It is interesting that there is very weak evidence that the Baltic Dry Index (BDI) is associated with oil price changes; it is only just significant at the 10% level. This is unexpected as the BDI has been used as a proxy for worldwide industrial activity by Mitchell et al. (2005), Frale et al. (2008), Kilian (2009), Fan and Xu (2011), and Coleman (2012). The cost of borrowing as measured by Moody's Aaa corporate bond rate has the expected positive coefficient as found by Coleman (2012) indicating that as borrowing becomes more expensive so does oil. As would be expected by the law of supply and demand, the US oil inventory has a highly significant negative coefficient for WTI prices and a less significant negative coefficient for Brent prices see Hamilton (2009b,a, 2014). There is no evidence that world oil supply is significant; which is unexpected. OPEC spare capacity is a measure of the difference between OPEC capacity to deliver oil and the actual quantity delivered, it is thus a measure of how much oil OPEC is holding back from the market. This variable has a positive coefficient as expected. Finally the proportion of world oil production which is from OPEC has a significant positive coefficient indicating that OPEC has considerable market power as is expected

[5]The 2012 data is from the US Energy Information Administration and was accessed on 29th October 2014 from http://www.eia.gov/countries/

from the work of Kaufmann (2004) and, Lin and Tamvakis (2010).

Jan 2002 - Dec 2013		$\Delta\, WTI$		$\Delta\, Brent$
N = 143 Months	**Bench**	**Bench + Sentiment**	**Bench**	**Bench + Sentiment**
$\Delta S\&P500$	0.110	0.215	0.086	0.098
	(0.51)	(0.14)	(0.62)	(0.52)
$\Delta Stoxx\,50$	-0.249	-0.340**	-0.215	-0.186
	(0.11)	(0.012)	(0.18)	(0.18)
ΔNKY	0.049	-0.076	0.060	-0.041
	(0.65)	(0.41)	(0.59)	(0.67)
$\Delta Hang\ Seng$	0.247**	0.232**	0.247**	0.225**
	(0.030)	(0.018)	(0.037)	(0.028)
$\Delta USDEUR$	**-0.353*** **	**-0.309*** **	**-0.339*** **	**-0.275*** **
	(0.0001)	(0.0001)	(0.0004)	(0.0009)
$\Delta USDJPY$	0.197**	**0.213*** **	0.152*	0.112
	(0.023)	(0.004)	(0.090)	(0.15)
$\Delta USDHKD$	0.074	0.010	0.118	0.042
	(0.32)	(0.88)	(0.13)	(0.53)
ΔBDI	0.107	0.078	0.110	0.113*
	(0.16)	(0.23)	(0.16)	(0.097)
$\Delta MoodyCAAA$	**0.213*** **	0.125**	0.173**	0.154**
	(0.0034)	(0.049)	(0.022)	(0.018)
$\Delta US\ Oil\ Inventory$	-0.186**	**-0.164*** **	-0.137*	-0.084**
	(0.011)	(0.0096)	(0.073)	(0.020)
$\Delta World\ Oil\ Supply$	0.085	0.066	0.046	-0.014
	(0.27)	(0.32)	(0.57)	(0.84)
$\Delta OPEC\ Spare\ Capacity$	**0.219*** **	0.118*	0.203**	0.069
	(0.0076)	(0.10)	(0.017)	(0.36)
$\Delta OPEC\ Proportion$	0.167**	0.143**	0.165**	**0.175** **
	(0.030)	(0.030)	(0.039)	(0.011)
$\Delta Oil\ Sentiment$		**0.443*** **		**0.459*** **
		(0.0000)		(0.0000)
Log Likelihood	164.43	142.64	170.36	148.50
p-value of the Likelihood Ratio Test		**4.1 x 10^{-11}**		**3.8 x 10^{-11}**
Variance Ratio (F) Test	**4.6 x 10^{-10}**	**2.7 x 10^{-17}**	**4.9 x 10^{-8}**	**3.5 x 10^{-15}**
$\mathbf{R^2}$	41.2%	56.6%	36.1%	52.9%

The table shows OLS regression results for the WTI and Brent benchmark models before and after the inclusion of the sentiment index described by Eqns. (2.3) and (2.4). The data has been first differenced and standardized. The likelihood ratio test formally compares model performance of the sentiment model (Bench + Sentiment) relative to the benchmark (Bench) model. *, ** and *** indicate significance at the 10%, 5% and 1% levels; p-values appear in brackets below each coefficient. Bold print indicates coefficients which were significant under the Generalised Holm Multiple Hypothesis Testing framework see Section 2.4.2.

Table 2.6: OLS Regression Results for WTI and Brent 2002 - 2013

2.4.2 Review of Results and Discussion

Recognizing the novel nature of our research into oil market sentiment, we deliberately take a prudent approach. There is a *multiple comparisons problem* that exists in this testing framework; it is a source of bias that we explicitly address by applying recently developed *generalized* multiple hypothesis testing (MHT) techniques. The multiple comparisons problem occurs when a large number of hypothesis tests are performed simultaneously, leading to a non-negligible likelihood that some statistically significant results may be identified by pure random chance alone, rather than as a result of any underlying statistical relationships. In our testing framework, the model specifications set out a total of 120 individual hypothesis tests comprising of individual coefficient tests, F tests, the ADF and KPSS tests and likelihood ratio tests. Hence, the multiple comparisons problem is an important issue to consider and address in order to build robust conclusions. For a more technical treatment of MHT issues, see Holm (1979), Romano et al. (2010), Cummins (2013a), Cummins (2013b) and Appendix A.

To give the greatest power to identify true discoveries, we set a probability of $\alpha = 0.1$ as the upper bound probability that there are $k = 6$ or more false rejections of null hypotheses amongst the 120 tests; we choose 6 as this is approximately 5% of the total number of hypotheses tested. Using these criteria we can be much more assured that the conclusions we draw are statistically reliable and robust. In this particular study, the generalized Holm procedure in Romano et al. (2010) leads us to reject 48 null hypotheses while at the conventional significance of 5%, 63 hypotheses would have been rejected. This MHT framework is more conservative than conventional significance levels, where in the latter case one ignores the multiple comparisons problem. In so doing wrong economic conclusions could be drawn from the extra 15 rejected null hypotheses. With this motivation in place, we revisit the results set out in the previous section (2.4.1) and seek to address the multiple comparisons problem that was not explicitly considered. This is an important statistical correction missing from prior sentiment investigations.

In Table 2.6 results which are considered significant under the MHT process are indicated in bold. Most notably, there is no change to the conclusion that the sentiment indices for WTI and Brent oil significantly account for oil prices. This is an important finding and allows us to argue with statistical confidence that sentiment affects professionally traded oil markets. (Mizrach and Otsubo (2014) and Griffin et al. (2015) state that energy markets are professionally traded.) It is also found that the US$ Euro exchange rate significantly explains the movement of oil prices. At the more demanding levels of significance required by the MHT procedure, the anomalous result found previously that changes in the Stoxx 50 explained WTI price movements is not found to be significant. Furthermore the Hang Seng and the BDI are not found to be significant. The US Euro, US$ Yen exchange rate, the Moody corporate bond rate, the US oil inventory, OPEC spare capacity and OPEC proportion are found to be significant. Due to the MHT approach we may be very confident of these findings.

There are of course other influences on oil prices apart from our benchmark model and sentiment. Cheng and Xiong (2014) find that risk sharing and information discovery has had an effect on oil prices. Specifically, Cheng and Xiong (2014) find that the increase in liquidity brings not only improved price discovery but opens the commodity markets to shocks from other markets. This was found also by Bhardwaj et al. (2016) where the interaction between commodities and equities is seen to be temporarily higher at the time of the financial crisis in 2007. This finding is in line with Silverio and Szklo (2012) who find the effect of the financial crisis on the linkage between futures and spot prices of oil lasted only a short while. Part of the reason for this change in correlation is that the higher price for oil during the start of the crisis was mistakenly interpreted by markets as an increase in economic activity (Cheng and Xiong; 2014). The consequence for this investigation, is that we need to be careful interpreting our results, but this has been done through the use of the MHT techniques where much more reliable inferences are drawn then by using conventional techniques.

2.5 Conclusion

We find that sentiment is an important consideration when explaining WTI and Brent prices using monthly data from Jan 2002 to Dec 2013. This was done following the methods of Baker and Wurgler (2006) by building sentiment indices for both WTI and Brent using similar proxies to those used in equities research. The two indices were constructed using principal component analysis of the following sentiment proxies: volume of futures contracts, the volatility of the oil price, oil speculation indicators, the put-call ratio for options on oil futures and stock index volatility. The inclusion of these sentiment indices significantly improved the performance of fundamental models for oil prices as measured by the likelihood ratio test and also brought about a large increase in the R^2 statistic. The findings are supported by a multiple hypothesis testing framework which gives a very high degree of confidence that we are not merely observing a chance result due to the multiple comparison problem.

Sentiment has already been seen to affect equity markets, our findings expand the discovery of sentiment effects in the oil markets. This not only leaves open the possibility that sentiment indices can be constructed for energy markets other than oil, gas and coal being the obvious next steps, but also acts as a call for further research on the mechanism by which sentiment influences oil pricing. We take immediate advantage of this success in applying it to another professionally traded energy commodity market, the EU Emissions Trading Scheme (EU ETS) the largest emissions market in the world.

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Chapter 3

Influences from the European Parliament on EU Emissions Prices

3.1 Introduction

The decisions of the European Parliament (EP) are shown to influence both EU emission allowance (EUA) prices and volatility. This is not a universal influence though, only the decisions which are either (i) parliament-led, as opposed to topical decisions originating from the political groups, (ii) made during times of low market sentiment or (iii) made during times of low market awareness, reduce the price and increase the volatility of EUA futures. Daily EUA prompt December futures prices from 2007 to 2014 are used in the study, with decisions analysed using an event study approach for price impact, and a GARCH specification for volatility impact. Our findings suggest the need for policymakers to improve communication of long-term strategies for the EUA market in order to reduce the evident ongoing uncertainty experienced by traders around decisions made by the EP. The sentiment findings indicate a need to consider market dynamics in terms of decision timing so that market turbulence is not an unintended by-product of an EP decision.

In April 2013 the European Parliament was expected to pass a European Commission legislative proposal to fix the recognized oversupply issue in the EU Emissions Trading

Scheme (EU ETS), see Koch et al. (2014). The Commission's proposal [1] involved postponing until 2019-2020 the release of 900 million EU emissions allowances (EUAs) - each allowance granting permission to a regulated installation to emit one tonne of CO_2 equivalent - that were originally due to be released into the market in 2013-15. The hope of the Commission was that this would support the declining price of allowances already trading in the emissions market and thus act as an incentive towards the reduction of emissions across the EU. On 16th April 2013, (known here as the backloading day), the European Parliament narrowly voted against the proposal. There was an immediate impact on EUA prices, which dropped by over a third. The futures price of an EUA permitting the emission of one tonne of CO_2, which had cost €4.76 at close of business on 15th April, fell to €3.09 at the close of business on 16th April. This was by far the largest daily change in EUA futures prices during the period under investigation.

This is one example where legislation passed by the European Parliament (EP), which holds legislative authority over the EU ETS, impacted on EUA prices. Prior research supports a wider argument that EUA prices are influenced by regulatory actions see Daskalakis and Markellos (2009) and Koch et al. (2014). There has been work done by Mansanet-Bataller and Pardo (2009), Conrad et al. (2012), Hitzemann et al. (2015) and Chen et al. (2017) to show that announcements concerning National Allocation Plans (NAPs)and verified emissions and economic data announcements have an effect on EUA returns. We add to this literature by showing that decisions of the European Parliament (EP), which do not follow the same regular announcement pattern as the NAPs, similarly affect EUA returns. We use a GARCH analysis to examine EUA returns volatility before and after the times of European Parliament decisions. European Parliament decision dates are known in advance but are not regularly spaced. The approach taken and the results show a similarity with Chen et al. (2017) who examined the behaviour of EUA prices before and after regularly scheduled events. Missing from prior studies though is a systematic investigation of the overall impact of emissions market specific, and related legislation and resolutions passed by the EP, thus leav-

[1] European Commission Press Release accessed on 9th June 2015 at http://europa.eu/rapid/press-release_MEMO-13-343_en.htm

ing a number of open questions. Do the legislative efforts of the EP move the EUA market? Are particular types of legislation and resolutions more influential? Are there conditional effects under which legislation and resolutions have a greater market impact? These are important questions. It is clear from Blyth et al. (2007), Fuss et al. (2008) and Yang et al. (2008) that there is considerable regulatory risk in the EU ETS. The resulting uncertainty in the price of carbon, has major implications for investment decisions in the power sector. Indeed the uncertainty regarding the implementation of measures to combat climate change makes possible the contradictory opinions regarding the existence of a carbon bubble (Griffin et al.; 2015) and a projected higher demand for fossil fuels[2].

Our study addresses these issues by tracking 29 relevant decisions made by the EP from 2nd October 2007 to 5th February 2014, and examining how the origin of each decision, the level of market sentiment and the level of market attention, all have an influence on the price behaviour of Phase II and Phase III EUA futures. There is some evidence to show that the decisions made by the EP act, on average, to reduce emission allowance prices and very strong evidence that EP decisions are associated with increases in volatility. This is quite striking given that the success of the trading scheme requires prices of emission allowances to be at a sufficiently high level so as to act as a disincentive to traditional high emission energy production and energy-intensive business practices. We contrast "party-political" decisions brought to the EP by the seven political groups of MEPs[3], with "non-party-political" decisions brought from other sources. The other sources are the committees of the European Parliament, the European Commission and the European Council; these are official bureaucratic organizations rather the seven political groups of MEPs that respond to voters' concerns. The classification of the source of each decision is recorded by the EP itself.

[2]The Telegraph, The Guardian and Carbon Tracker accessed on 6th June 2015 display differing perspectives on the prospect of a carbon bubble. http://www.telegraph.co.uk/finance/newsbysector/energy/oilandGas/11615079/Shell-CEO-carbon-bubble-campaigners-ignores-reality.html

http://www.theguardian.com/environment/2013/apr/19/carbon-bubble-financial-crash-crisis

http://www.carbontracker.org/resources/

[3]The groups of MEPs for the present 8th European Parliament are, the European People's Party (EPP), the Progressive Alliance of Socialists and Democrats (S&D) containing the Party of European Socialists (PES), the Alliance of Liberals and Democrats for Europe (ALDE), the European Conservatives and Reformists, the European United Left – Nordic Green Left, the Greens / European Free Alliance (Greens-EFA) or the Europe of Freedom and Direct Democracy. Accessed on 6th June 2015 at http://www.europarl.europa.eu/aboutparliament/en/20150201PVL00010/Organisation

An example of a non-party-political decision would be that brought forward by the EP Committee on Transport and Tourism on 11^{th}March 2008 concerning the inclusion of airlines in the EU ETS. An example of a party-political decision would be that brought before the parliament by five of the political groups[4] on 5^{th} June 2008 concerning US emissions and climate change policy. When we analyse resolutions categorized as "non-party-political" and those termed "party-political", we find that it is the non-party-political initiatives which are the particular drivers of these negative returns. We also find there is heightened volatility around key legislative decision dates when we incorporate this information in an appropriately designed GARCH volatility model, indicating that market uncertainty is a feature of prices around these dates. It may be the case that some form of *forward guidance* such as is used by central banks, would be beneficial in communicating, in advance, the nature of complex legislative decisions to the market. This action might reduce volatility in the market, as has been found to be the case by Campbell et al. (2012) and, Kool and Thornton (2012) who analyse the macroeconomic effects of Federal Reserve forward guidance. The main challenge though with this policy solution is that the EP is subject to many competing influences, and does not have the independence and targeted focus of a central bank.

A possible explanation for the strong effect of EP decisions on EUA prices during times of low media exposure can be found in the Investor Attention Hypothesis from Barber and Odean (2008), Hirshleifer et al. (2009), Da et al. (2011) and Vozlyublennaia (2014). In an equity context this proposes that since attention is a limited resource, investors will make decisions about firms to which their attention has first been drawn, and that until their attention is drawn to a stock, its price will only slowly reflect new information due to lack of trading interest. We draw on this line of argument and adopt the theory for emissions markets. The amount of attention given to emissions trading is normally small, as it is only a very small part of the energy market. To illustrate this point, from 2010 to 2014 the value of the trades of the most liquid EUA futures contracts (prompt December) was 0.88% of the value of trades of the most

[4]The groups were EPP, PES, ALDE, Greens-EFA and the UEN.The Union for Europe of the Nations (UEN) was an active political group in the European Parliament from 1999 to 2009.

liquid futures contracts of Brent oil (prompt month); in 2012 the value of the trades in EUAs was \$73 billion while the total value of the world's oil production that year was \$3.27 trillion[5]. When attention is focused on emissions by the media or by the actions of MEPs, the market in turn pays attention and anticipates the decisions made by the European Parliament. When the European Parliament makes decisions about the emissions market when there is low media coverage or when the decision arises from non-party-political sources within the EU namely, the European Parliament committees, the European Commission or the European Council, then market inattention will lead to a lagged corrective price adjustment and an increase in volatility.

We also test for differences in behaviour when sentiment is relatively high compared with times when it is low. This is in line with the negativity effect mentioned by Soroka (2006), Chevalier and Mayzlin (2006), Akhtar et al. (2013) and Sprenger, Sandner, Tumasjan and Welpe (2014) who point out that markets generally react more strongly to negative news than to positive news. We find that EP decisions made when sentiment is low, have a negative impact on returns and are associated with an increase in volatility. The impact on returns is determined by an event study which shows that on days on which the EP makes a decision there are, on average, significant negative returns, and these negative returns become cumulatively greater in the following week. An explanation for the cumulative reduction in prices is that this may be similar to the post earnings announcement drift of Bernard and Thomas (1989) and Hirshleifer et al. (2009). After an earnings announcement it is common to find that the price of the stock continues moving in the same direction due to a lack of investor attention. This effect is more pronounced when news affecting the price of the stock is difficult to interpret, see Song and Schwarz (2010). We find that there is a similar continued movement of EUA prices after the announcement of an EP regulatory decision. We posit that this is due to similar investor inattention in the emissions markets. The implications of many of these decisions are more difficult to interpret than straightforward messages like earnings announcements and so the effect is extended. This offers an explanation

[5] Data from Bloomberg, EU ETS Factsheet at
http://ec.europa.eu/clima/publications/docs/factsheet_ets_en.pdf,
and the Energy Information Administration EIA at http://www.eia.gov/ all accessed on 9th June 2015

for the continued slow movement of prices after an EP announcement.

This study is similar in intent to a recent investigation by Lin and Tamvakis (2010) which examined the impact of OPEC output decisions on crude oil prices. Based on an argument, in part, that OPEC had the ability to adjust the volume of oil produced, and was thus a major actor in the market, a systematic investigation was carried out of each OPEC meeting where a quota decision was made. In the case of the EUA market the major player, the EP, has even greater power as it can alter the structure of the market's operation, affect supply through adjusting allowances available in the market, and even boost demand through an ability to determine which installations and industries must partake in the scheme. This suggests a need to formally investigate the influence of EP decisions on the prices at which EUAs trade in the market.

In a further contribution, extending work done independently by Koch et al. (2014), we examine the potential conditional determinants of market reaction to EP legislation. In particular we develop innovative measures of market sentiment and market attention, which are known in other markets to influence reaction to new information. This is a different approach from Koch et al. (2014) who use the monthly Economic Sentiment Index (from Eurostat) as a proxy for economic outlook. An emissions market sentiment index is constructed by adapting the principal component analysis approach of Baker and Wurgler (2006) in equity markets, and particularly based on the oil sentiment index proposed in Deeney, Cummins, Dowling and Bermingham (2015) and presented in Chapter 2. The components of this index draw on volatility and speculative measures from the EUA market, while also drawing pertinent information from the wider energy markets, and the financial markets. As a further contribution we apply a multiple hypothesis testing framework to counter the multiple comparisons problem. This problem arises when many hypothesis tests are carried out simultaneously; it is possible that some null hypotheses would be rejected erroneously, see Appendix A. This precaution is useful here as EUAs are a relatively new asset class and we wish to proceed with some caution as we examine explicit sentiment for the first time in the EU emissions market.

Sentiment has been found to be a significant influence in equities markets e.g. Baker and Wurgler (2006) and Schmeling (2009), and more recently in the energy and commodity markets, see Silverio and Szklo (2012) and Deeney, Cummins, Dowling and Bermingham (2015). Sentiment has been found to be particularly effective at predicting the prices of stocks with greater inherent uncertainty; these have been characterized by Baker and Wurgler (2006) as being young, small, unprofitable, non-dividend-paying, with high volatility, capable of extreme growth or becoming distressed. It can be argued that the European emissions market contains some of these same characteristics, albeit from different sources. For example, there is the already discussed dependency on uncertain political events; a history of extreme movements, see Koch et al. (2014); and strong crossover influences and volatilities from other energy markets, see Bredin and Muckley (2011), Chevallier (2011a) and Mansanet-Bataller et al. (2011). The sentiment state of market participants at the time that new information arrives is also known to be important. Mian and Sankaraguruswamy (2012) show that sentiment mediates how investors react to news, with high sentiment periods related to a positive reaction to news and the opposite for low sentiment periods. Investors tend to choose good news to focus on in high sentiment times and bad news to focus on in times of low sentiment. We thus expect that whether the market is in a time of high or low sentiment will mediate the reaction of prices to new legislation.

Fang and Peress (2009) show that news exposure has an influence on the returns of stocks in the US market. We thus construct a market attention variable based on news stories about the EUA market and emissions trading. We propose this variable as measuring market attention. We argue that market attention both informs market participants, see Tetlock (2007), and is informed by market participants, see Oberlechner and Hocking (2004), and therefore acts as a guide to the level of market interest in upcoming news events. Following from this, we find that low market attention of issues relevant to the EU ETS in advance of a legislative decision, is associated with greater "price shock", and we find there is a significant cumulative negative price reaction in the days after a low market attention decision.

The results show deficiencies in the EMH. The EMH states that the carbon market should update the prices for EUAs as soon as new information becomes available. In 2013 there were approximately half a million trades on prompt December futures, this is a mean of 2,000 trades per day, so the reaction of the market to news should be visible within minutes. Our empirical results show that the effect on the market of decisions by the European Parliament depends to a large extent on the origin of these decisions and, on the level of media attention and market sentiment at the time of the decisions. When we exclude the outlier of the backloading day we find that for low news and non-party-political decisions it takes a day for the market to react, indeed it is even slower for low sentiment, see Table 3.7. We find that there is market inattention, this contradicts the EMH.

The data and methodology are detailed in Section 3.2, followed by the testing schemes in Section 3.3, the findings and analysis in Section 3.4, and we conclude with further discussion of the implications for policy makers and market participants in Section 3.5. Our policy implications centre on the general importance of understanding the reaction of market participants to legislative decisions and the need to improve communication with market participants as to the long-term policy goals for the EUA market. This calls for more effective signposting of the intermediate steps that will be adopted to achieve these goals. There also needs to be greater understanding of the factors affecting the market at a given point in time, as shown particularly by the sentiment and media coverage findings. This conditional understanding is argued to be of potential benefit to policy makers across a variety of regulated markets and in particular to the nascent Chinese national emissions market.

3.2 Data and Methodology

Prior research suggests that EUA prices are influenced by regulatory actions, see Daskalakis and Markellos (2009) and Koch et al. (2014). We add to prior studies by a systematic investigation of the overall impact of emissions market specific and related legislation passed by the EP. We contribute to the existing literature on the EU

ETS by testing whether policy decisions of the EP influence the price and volatility of EUAs. We provide a distinction by means of examining whether there is a differential effect to the impact of EP policy decisions depending on: (i) the origin of EP policy decisions, i.e. whether non-party-political or party-political; (ii) the level of market sentiment (high or low); and (iii) the level of market attention (high or low) which we measure in terms of emissions market news exposure.

The origin of EP policy decisions influences the impact of those decisions on the price and volatility of emission allowance prices. The EP itself classifies the origin of each decision. We divide these into "non-party-political" resolutions brought by a combination of the parliament's own committees, the European Council and the European Commission, and "party-political" resolutions brought by a combination of the political groups in the parliament. A full explanation is given in Section 3.2.2. This allows us to understand which sources of legislation and which parts of the European political system have the greatest impact on emissions markets. The investigation based on market sentiment provides policy makers with insights into the timing of policy decisions and to what extent the prevailing market dynamics have an impact. For this analysis, we develop a unique EUA market sentiment index based on financial proxy information relating to the emissions market and the wider energy and financial markets. A decision is considered to be high sentiment if it takes place on a day on which the market sentiment index is higher than the median sentiment for all the decision dates under consideration. Construction of the market sentiment index follows the method of Baker and Wurgler (2006) and Deeney, Cummins, Dowling and Bermingham (2015) - a detailed explanation is given in Section 3.2.3 which follows the methods presented in Section 2.2. Finally, the analysis based on emissions market attention provides insights into the the timing of policy decisions and to what extent the level of market attention to climate change and emissions affects impacts. The analysis allows us to consider how the level of public awareness of these issues influences the tendency of MEPs to vote in a way which the market expects. This has implications for policy makers who simultaneously must plan to avoid damage to the environment, give clear signals to the

Statistic	Log Return EUA
N	1,625
Mean	-0.000815
Max	0.24525
Min	-0.43208
Median	0.00000
Standard Deviation	0.03294
Skewness	-0.90640
Excess Kurtosis	23.305

The table presents descriptive statistics for daily log returns of the prompt December EUA futures contracts from 3rd October 2007 to 5th February 2014. and I futures are used, hence data during 2007 refers to Dec 2008 futures.

Table 3.1: Descriptive Statistics of EUA Futures Returns

market, and must attempt to carry out the wishes of their electorate. A policy decision is considered to take place in a period of high news if the news exposure at the time of the decision is higher than the median for all the decision dates under consideration. The news exposure measure is based on Fang and Peress (2009) and is detailed in Section 3.2.4.

3.2.1 EUA Prices

We use the prices of prompt December futures in our anlaysis; these are the futures contracts with an expiry of the next December. The December contracts are traded in much higher volumes than EUAs on the spot market. December futures are the most liquid of the futures contracts available, see Zhu et al. (2015). Futures contracts for Phase II (2008 - 2012) and Phase III (2013 - 2020) allowances are examined using daily data beginning on 2nd October 2007 and ending on 5th February 2014. Phase I allowances (2005 - 2007) are not examined as they were not permitted to be used after Phase I finished in 2007, whereas allowances could be banked and used from Phase II into Phase III. The data before 1st January 2008 refers to the December 2008 futures contracts. Table 3.1 presents descriptive statistics for the log returns of the prompt December EUA futures contract over the sample period and Figure 3.1 shows the time series. A discussion of the outlier on 16th April 2013 follows at the end of Section 3.2.2.

3.2.2 EP Policy Decision Selection and Classification

The overall objective of our study is to test what impact policy decisions of the EP

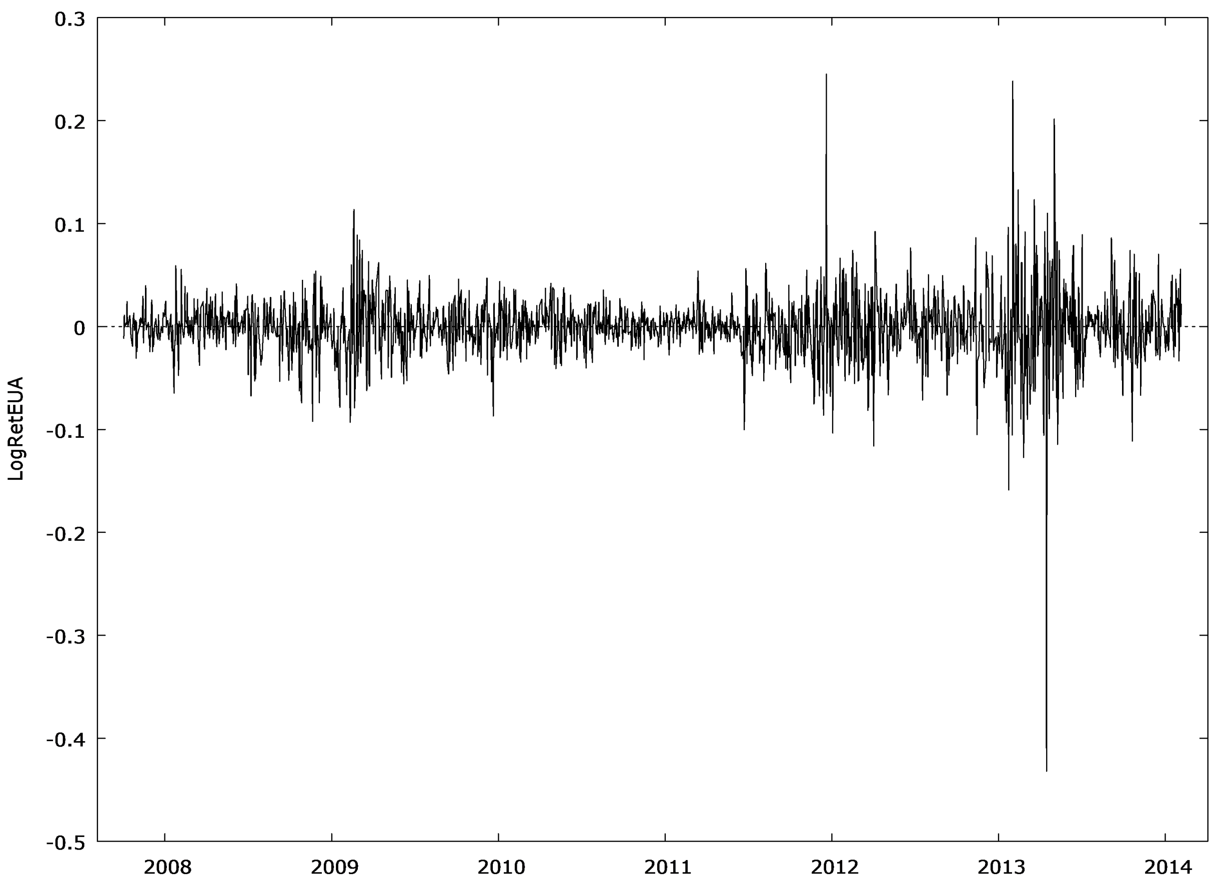

Figure 3.1: Log Returns of EU Emission Allowance Prices 2007 - 2014

have on the level of EUA prices and their volatility. Therefore, identifying the dates of EP policy decisions relating to the EU ETS is fundamental to our objective. During the course of legislation making its way through the EP, there are many stages before the date of the actual decision, including debates in the council, votes by relevant committees, and debates in the parliament. We select the "Decision by Parliament" date for each policy decision as given in the European Parliament Legislative Observatory.[6] This source provides a list of key stages of a resolution as it makes its way through the EP and gives the origin of each resolution.

The EP itself classifies resolutions brought to it. Thus we may objectively distinguish resolutions originating from the political groups of the MEPs (which we term "party-political"), from resolutions brought by the EP's committees, the European Council, or the European Commission (termed by us as "non-party-political"). To find all the relevant decisions, we search for the terms: "EU ETS", "emissions trading" and "carbon trading" in the European Parliament Legislative Observatory. We do not use the term "climate change" as this was found to be too broad and would have found EP policy decisions which concern climate change mitigation, adaptation and other matters only loosely related to the EU ETS. A list of the dates and classifications of the EP decisions, obtained from our search, is given in Tables 3.2 and 3.3, along with brief explanations of their connection with and potential influence on the EU ETS. Thirty seven policy decisions were identified over our sample period of 2nd October 2007 to 5th February 2014. In order to ensure a reasonable period for the calculation of the parameters needed in the event study described in Section 3.3.1, we choose 20 days for the length of the estimation window and five days on either side of the decision day as the event window. This is shorter than similar studies such as Lin and Tamvakis (2010) who examined regularly spaced OPEC meetings, but we must compromise between having a reasonable number of events and adequate lengths for each of the estimation and event windows. Having chosen a 20 day estimation window and five days on either side of the decision as the event window we are compelled to omit 8 of the 37 identified events. This is because we cannot have an event occurring in the estimation window

[6] Accessed on 20th November 2014 at http://www.europarl.europa.eu/oeil/home/home.do.

of another event as the estimation window is used to calculate the parameters for the expected behaviour without any event taking place. This means that two events must be fewer than 5 trading days apart or more than 25 days, therefore we chose 29 of the 37 events. The result of the selection process is that there are 10 events classified as party-political, 14 classified as high sentiment and 14 classified as high news exposure, see Table 3.5. A list of the EP decisions and the totals for each category are found in Tables 3.2 and 3.3.

The 16th April 2013 requires special consideration for the reasons outlined in the introduction. On this date there was a very close vote of the EP rejecting backloading.[7] As noted earlier, backloading was the proposal to delay the release of 900 million EUAs until 2019-2020, which were originally due to be released into the market in 2013-2015. On this date the price of EUAs fell from €4.76 to €3.09 on the futures market, a collapse of approximately 35%. This was the largest percentage drop in a single day observed in the EUA futures market by a large margin. The second largest movement on a single day, a drop of 24%, was on 26th April 2006 when the publication of the verified emissions data showed a glut of EUAs. The size of the drop on 16th April 2013 can be seen in the EUA log returns series provided in Figure 3.1. The EP backloading rejection date may therefore be deemed an extreme event, this is further discussed in more detail in Section 4.4.1. While this anecdotally illustrates the ability of an EP decision to move EUA prices, it presents the problem that inclusion of this one day's data may drive the conclusions on its own. For robustness, we therefore conduct our statistical analysis with and without the inclusion of 16th April 2013 - which we will herein refer to as the backloading rejection date - for both the event study and the GARCH analyses.

[7] On the same day there was also a resolution to delay the imposition of penalties arising from the failure of aircraft operators to abide by an earlier directive on emissions, but this would not have had the same importance as the rejection of backloading as it affects penalties applied in one sector of the market and whereas backloading is looking to address on a system-wide basis the recognized oversupply of allowances in the market.

Date	Origin	Sentiment	News	Relevance of Decision
11/10/2007	Non-Party Political	High	High	Support for EU ETS to include air transport
11/03/2008	Non-Party Political	High	Low	Air transport to be included in EU ETS
24/04/2008	Party Political	High	High	Increasing the ambit of the EU ETS and support for the polluter pays principle
05/06/2008	Party Political	High	High	Expresses hope that US will trade emissions with EU ETS
08/07/2008	Non-Party Political	High	High	Air transport to be included in EU ETS
09/07/2008	Non-Party Political	High	High	Support for low carbon energy efficient technologies
04/09/2008	Non-Party Political	High	Low	Policy to curb CO_2 emissions
21/10/2008	Non-Party Political	High	High	Commitment to Global climate change Alliance and plans for spending EU ETS income.
17/12/2008	Non-Party Political	High	High	Resolution to extend EU ETS to include maritime, shipping and aviation
03/02/2009	Non-Party Political	High	Low	Second strategic energy review aiming to reduce GHG by 80% by 2050
11/03/2009	Party Political	High	High	Resolution on an EU strategy for a comprehensive climate change agreement in Copenhagen and the adequate provision of financing for climate change policy
23/04/2009	Party Political	High	High	Proposal of a Global Forest Carbon Mechanism and commitments to spend EU ETS income
22/10/2009	Party Political	Low	High	Resolution on the upcoming EU-US Summit calling for stronger cooperation in energy efficiency and bio-fuels.
25/11/2009	Party Political	Low	High	Resolution on the EU strategy for the Copenhagen Conference on climate change (COP 15)

The table shows the European Parliament (EP) decisions under consideration from 2007 to 2009. Decisions are either less than 5 trading days or more than 25 days apart. The classifications are assigned by the EP itself and indicate the following types of decisions: resolution on topical subjects (RSP) refers to resolutions brought forward by one of the Party Political groups of MEPs within the European Parliament, we categorize these as "Party Political" and categorize others as "Non-Party Political". Two decisions were taken on 24th April 2008 and since one was "Party Political" this date has been categorized as Party Political. Decisions for 2010 - 2013 are in Tab.3.3.

Table 3.2: List of Selected Dates of European Parliament Decisions 2007 - 2009

Date	Origin	Sentiment	News	Decision
11/03/2010	Party Political	Low	High	Commitment to meet GHG targets and the use of the European Investment Bank to support low carbon targets
06/05/2010	Non-Party Political	Low	Low	Adapting to climate change: towards a European framework for action. Possible changes of electricity generation using renewable and fossil fuels.
17/06/2010	Party Political	Low	Low	Resolution on the EU-US disagreement on air transport in EU ETS
25/11/2010	Non-Party Political	Low	High	Inclusion of maritime transport in the EU ETS
08/03/2011	Non-Party Political	Low	Low	Financial Transaction Tax and strengthening of EU ETS
05/07/2011	Non-Party Political	Low	Low	Options to move beyond 20% GHG emission reductions and assessing the risk of carbon leakage
14/09/2011	Non-Party Political	Low	Low	Wholesale energy market integrity and transparency
17/11/2011	Party Political	Low	Low	Resolution on the EU-US disagreement on air transport inclusion in EU ETS
15/03/2012	Non-Party Political	Low	Low	Road map for moving to a competitive low carbon economy in 2050
19/04/2012	Non-Party Political	Low	Low	Proposal to tax electricity generation using GHG output as one component
22/11/2012	Party Political	Low	Low	Resolution on the climate change Conference in Doha, Qatar
12/03/2013	Non-Party Political	Low	Low	Greenhouse Gas emissions, climate change: mechanism for monitoring and reporting
16/04/2013	Non-Party Political	Low	Low	* (Backloading rejected) Scheme for greenhouse Gas emission allowance trading: temporary derogation from the EU ETS
23/10/2013	Party Political	Low	Low	Resolution on the climate change conference in Warsaw, Poland (COP 19)
10/12/2013	Non-Party Political	Low	Low	Greenhouse Gas emission allowance trading: timing of auctions

The table shows the European Parliament (EP) decisions from 2010 to 2013. For an explanation of the EP classification of decisions see Table 3.2. The decision * on 16th April 2013, the backloading rejection day, caused the largest drop in EUA prices during the period of the investigation. The EP narrowly rejected a plan to delay the release of EUAs known as backloading. All statistical tests were repeated omitting this date so as to ensure the robust nature of our conclusions.

Table 3.3: List of Selected Dates of European Parliament Decisions 2010 - 2014

3.2.3 Measurement of Market Sentiment

Having selected and classified the dates for analysis we turn to the second question in our analysis. We ask whether the impact of policy decisions depends in any way on the level of market sentiment at the time of the decision. Towards answering this question, we develop a unique emissions market sentiment index following a similar index constructed for the oil markets in Deeney, Cummins, Dowling and Bermingham (2015) and discussed in Section 2.2. For our purposes, we use financial proxy information relating to the emissions, energy and the financial markets.

A decision of the EP is characterized as being high sentiment if it occurs on a day when the market sentiment index is above the median for the set of decisions under consideration, that is, the set of decisions under consideration will be either all 29 decisions or 28 when the backloading day is omitted or a subset of these days. A daily market sentiment index is constructed for the emissions market using principal component analysis (PCA) of appropriately chosen financial proxies, in line with Baker and Wurgler (2006), Lemmon and Portniaguina (2006), and Deeney, Cummins, Dowling and Bermingham (2015). This approach has most popularly been applied to the equities markets, where there are abundant data available and levels of market liquidity are for the most part high. By contrast, in the emissions market liquidity is lower, with the volume of options traded being particularly low, see Byun and Cho (2013). This makes the use of emissions market specific financial information less reliable on a stand-alone basis than we would desire, see Byun and Cho (2013). To overcome this weakness, we construct an index which includes additional financial information from the wider energy markets not just the emissions market. This aligns with Bredin and Muckley (2011), Chevallier (2011a), and Mansanet-Bataller et al. (2011), who find the emissions market to be intrinsically linked with the energy markets. We choose the coal and gas markets because they have an established connection to the prices of EUAs, as shown by Alberola et al. (2008) and Chevallier (2011a). For coal prices, we use the API2 grade for Amsterdam-Rotterdam-Antwerp (ARA) prompt month futures contract, following Chevallier (2011a). For gas prices, we use the UK's National Balance Point (NBP) prompt month futures price, following Creti et al. (2012) and Aatola et al. (2013). For oil prices, we use the benchmark Brent prompt month futures contract, providing us with a key oil market indicator and proxy measure of economic activity, see Zhu et al. (2015). To capture a measure of "market fear" in the European economy, we use the implied volatility index associated with the FTSE index, termed VFTSE. This follows Whaley (2000) who associates index volatility and market fear. As a robustness check the sentiment index calculations were repeated using the Euro Stoxx 50's volatility index instead of the VFTSE. The classification of the 29 days was identical.

The specific financial proxies used in the construction of the market sentiment index comprise volume, open interest and volatility measures and are as follows:

1. the volume of trades of the prompt December EUA futures contract;
2. the aggregate total of all EUA futures contracts of all expiry dates excluding the prompt December contract;
3. the 20-day volatility of the prompt December EUA futures contract;
4. the 20-day volatility of the prompt month Brent crude oil futures contract;
5. the 20-day volatility of the prompt month NBP natural Gas futures contract;
6. the 20-day volatility of the prompt month ARA Coal futures contract;
7. the open interest of Brent crude oil futures contracts;
8. the open interest of NBP natural Gas futures contracts and
9. the implied volatility of the FTSE index, i.e. VFTSE.

For our first two proxies we use the volume of EUA futures contracts. Scheinkman and Xiong (2003), Baker and Stein (2004), Baker and Wurgler (2007) and Canbaş and Kandır (2009) use the volume of trades as a proxy for investor sentiment across equity markets. The volume of trades is a natural measure of market activity, and as shown by this literature, it is also an indicator of market sentiment.

The volatility of futures prices is also a recognized indicator of market sentiment, see Whaley (2000), as it indicates rapid changes in price. For our analysis we calculate twenty-day historical volatility for emissions, oil, gas and coal futures prices; a period of 20 trading days corresponds approximately to one calendar month. The twenty-day time frame is chosen as a reasonable balance between a sufficiently long period for the accurate calculation of volatility and a short enough period for the volatility information to be current, this choice follows the monthly time scale used by Baker and Wurgler (2006) in their seminal paper on sentiment indices and will match our later choice for the estimation window length for the event study.

The level of open interest of futures contracts is an indicator of the level of speculation and market activity in the oil and gas markets. It is the quantity of futures contracts which are not closed, liquidated or delivered. Open interest data for coal and EUA futures was not available for the period under examination and so we include information from the oil and natural gas markets.

The volatility of a large stock index has commonly been used as a measure of market fear in the literature. Whaley (2000), Simon and Wiggins III (2001) and Whaley (2009) have used the VIX implied volatility index as a proxy of market sentiment, specifically, fear. The VFTSE is used here as a European equivalent to the US-centered VIX. The VFTSE is calculated from the implied volatility of FTSE 100 index options covering out-of-the-money strike prices for the near and next term maturities. An alternative choice would be the volatility of the Euro Stoxx 50 but the VFTSE is chosen as the FTSE 100 has a greater weighting of large energy firms, including BG Group, BP, Petrofac, Royal Dutch Shell, Tullow Oil and Wood Group, with a total market capitalization of Stg £286 billion (€389 billion) compared with the Euro Stoxx 50, including ENI, Repsol and Total, which have a total market capitalization of €194 billion[8]. This is shown to be a robust choice because when the sentiment index calculations were repeated using the volatility of the Euro Stoxx 50 (V2X) the new sentiment index produced the same

[8] Data accessed on 9th June 2015 from http://www.londonstockexchange.com/exchange/prices-and-markets/stocks/indices/summary/summary-indices-constituents.html?index=UKX , and http://www.londonstockexchange.com/exchange/prices-and-markets/international-markets/indices/home/eurostoxx-50.html. In addition Paun et al. (2015) states that the FTSE 100 has 13.1% of value in oil and gas while the MSCI World has 7.1% and the S&P 500 has 7.9%. This supports the choice of the FTSE 100.

Energy and Emissions Sentiment Index	Current or First Lag	Loading
Volume of Prompt Dec EUA Futures	Lag	-0.36
Volume of non Prompt Dec EUA Futures	Current	-0.40
20 Day EUA Volatility	Current	-0.17
20 Day Brent Oil Volatility	Current	0.38
20 Day NBP Gas Volatility	Lag	0.32
20 Day ARA Coal Volatility	Lag	0.35
Open Interest of Brent Futures	Current	-0.26
Open Interest of NBP Futures	Lag	-0.32
Volatility of the FTSE	Lag	0.38

The table shows the choices of current or first lag of the listed financial proxies and the PCA-derived weights for the linear combination of these proxies to produce the emissions and energy market sentiment index. The first principal component explains 27% of the variance.

Table 3.4: Loadings for the Emissions and Energy Market Sentiment Index

categorization of high or low sentiment for each of the 29 EP decisions. The Euro Stoxx 50 is the index of the top 50 firms of the Euro zone by capitalization, its volatility index is calculated similarly to the VFTSE. The two are very highly correlated and so it is not surprising that the substitution of the V2X and VFTSE did not change the designation of high and low sentiment.

To take into account the possibility that some of the proxies may be more strongly leading indicators of market sentiment than others, we follow the method of Baker and Wurgler (2006). A first stage index F_t is prepared by entering the current values of the nine proxies and their first lags in a principal component analysis (PCA). The first principal component of this PCA of the 18 series is the first stage index, F_t. For each individual proxy, P_t, the correlation between the current value and the first stage index, $\mathrm{Corr}(\mathrm{P}_t, \mathrm{F}_t)$, and the correlation between its first lag and the first stage index $\mathrm{Corr}(\mathrm{P}_{t-1}, \mathrm{F}_t)$ are calculated. For each individual proxy the larger of these two values determines whether to use the current or first lag for each proxy; these are entered into a second PCA which produces the sentiment index as its first principal component.

3.2.4 Measurement of Media Exposure

For the third part of our analysis, we consider to what extent the level of market attention on issues pertinent to the emissions market at the time of policy decisions impacts on price and volatility. Fang and Peress (2009) show that news exposure has an influence on the returns of stocks in the US market. This is in line with the Investor Attention Hypothesis of Barber and Odean (2008), Da et al. (2011) and Vozlyublennaia (2014), which posits that since attention is a scarce commodity, investors are more likely to trade stocks to which their attention has already been drawn. Motivated by this work, we thus construct a media exposure variable based on news stories about the EUA market and emissions trading, a variable we propose as measuring "market attention". Media coverage both informs market participants and is informed by market participants, see Oberlechner and Hocking (2004), and Tetlock (2007); it therefore acts as a guide to the level of market interest in upcoming news events.

A policy decision of the EP is categorized as being of high news importance if the news exposure on the day of the decision is above the median for the set of decisions under consideration. Fang and Peress (2009) defined the news exposure of a particular stock, as a count of stories which appeared in either the Dow Jones Newswire service, or in any of four US newspapers: The New York Times, USA Today, The Wall Street Journal or The Washington Post, which together accounted for 11% of daily circulation of newspapers in US at that time. Motivated by this approach, we consider the following sources of news: the newswire services Agence France Presse (AFP), The Associated Press (AP), Thomson Reuters ONE and Thomson Reuters Financial News Super Focus; and the UK broadsheets The Daily Telegraph, The Financial Times, The Times, The Independent and The Guardian, which account for 18% of daily circulation of newspapers in the UK[9]. The list of broadsheets is taken from Lexis Nexis and excludes Sunday papers as these would give a biased result for that one day of the week which is not a trading day.

We search the Lexis Nexis database for the following terms: "EU ETS", "climate change", "carbon emission", and "CO2". When the search term "EU ETS" was used on its own very low counts were made so that such data was too sparse, hence a wider selection of search terms were used. For an article to be counted at least one of these four search terms must have occurred three times in the article. This provides an objective way to ensure that the article is actually about the EU emissions market and

[9] Source: Audit Bureau Circulations (ABC). Site accessed on 2nd February 2015 at http://www.abc.org.uk/

Origin		Sentiment		News Exposure	
Party Political	10	High	14	High	14
Non-Party Political	19	Low	15	Low	15

The table records the number of decisions of the European Parliament in each of the categories tested.

Table 3.5: Distribution of the Decisions by Origin, Sentiment and News Exposure.

not merely referring to it while discussing other emissions related topics, such as the Chinese emissions trading schemes for instance. We therefore define the following time series:

$Newspaper_t =$ the number of stories on day t in any of the newspapers listed, with each story containing at least three occurrences of at least one of the search terms listed;

$NewsWire_t =$ the number of stories on day t in any of the news wires listed, with each story containing at least three occurrences of at least one of the search terms listed.

In order to measure the effect of the media on EP decisions, we construct a time series which captures the level of coverage of the EU ETS and related issues over the previous three days. We therefore define $News_t$ for the time period under consideration as follows

$$News_t = \sum_{i=t-3}^{t-1} \left(Newspaper_i + Newswire_i\right), \; t = 4, 5, .., 1626$$

This time series is calculated and the median for the 29 days under consideration is calculated. High news coverage is considered to happen on days when $News_t$ is higher than its median.

A summary of the classifications set out in this section and that of Sections 3.2.3 and 3.2.4, is given in Table 3.5 which provides a breakdown of the 29 events dates by origin, sentiment and news exposure.

3.3 Testing Methodology

In this section we set out the technical details of the event study employed to examine price effects and follow this with the specification of the GARCH modelling used to examine volatility effects. We use event study and GARCH methods to test changes in the price and volatility at the times of EP decisions, following Lin and Tamvakis (2010) and Lu and Chen (2011).

3.3.1 Event Study Specification

Following the method of MacKinlay (1997), Kothari and Warner (2007) and, Lin and Tamvakis (2010) we use an event study on the 29 identified dates of EP policy decisions. In addition to this, we perform separate event studies using the categorizations based on: (i) the EP policy decision origin; (ii) the level of market sentiment and (iii) the level of market attention. An event study is chosen as it is suitable to test for the presence of changes in the mean of a time series where the date of the change is known approximately. It will allow us to see when the event is reflected by a change in the mean log returns. There is strong support in Kothari and Warner (2007) for the usefulness of short horizon event studies, such as the one proposed below.

We use an estimation window of 20 days and an event window of 11 days, comprising the 5 days before the decision, the decision day itself and the 5 days after the decision. Lin and Tamvakis (2010) used lengths of 40 days for the estimation window and 20 days for the event window to examine quarterly OPEC meetings. Here we retain the approximate ratio of 2:1 for the estimation window and event window lengths by choosing a 20 day estimation window and 11 day event window. There is an inherent limitation of an investigation of EP decisions, as they do not occur at a constant frequency. The selection for the estimation and event window lengths are chosen as a compromise between obtaining a reasonably accurate estimation for the parameters for expected behaviour without events happening during the estimation window periods, keeping the event windows short enough to detect events more effectively, and selecting a reasonably large number of decisions to test, see Kothari and Warner (2007). At the same time it is necessary to keep an event window long enough to test for price movements before EP decisions possibly due to information leakage and the possibility of price movements after the event day itself. Akin to the phenomenon of post earnings announcement drift of Hirshleifer et al. (2009) the effect of an EP decision on EUA prices may not end on the day of the decision itself, but may continue for a short period after. Setting longer periods for the estimation window will improve the accuracy of the parameter estimates for the statistical testing as suggested by Kothari and Warner (2007), however in this application the cost of this increased accuracy is the loss of the number of EP decisions which can be analysed. In this application we have sample sizes ranging from a minimum of 10 events for the party-political classification to a maximum of only 29 when we consider all decisions of the EP including the backloading rejection on 16th April 2013.

The abnormal returns for a day are calculated as the difference between the day's actual return and the expected returns. In particular we follow Lin and Tamvakis (2010) by using both a zero log return and a constant log return model for the behaviour of EUA prices during typical periods. MacKinlay (1997) states that although a constant return model is a very simple, it is surprisingly useful at identifying changes in price behaviour compared with more sophisticated models. The conclusions drawn from these two models, zero log return and constant log return, are the same, giving practically the same p-values; the results presented in Table 3.7 are for the simpler zero log return model. We define $\Delta EUA_{i,\tau}$ as the observed EUA log return, with i being an index for the particular event and τ being an index for time during this particular event. In this case $i = 1, 2, .., N$, where $N = 29$ when all of the events are under consideration. When we examine only a subset of these, such as days when decisions are party-political in origin, or days with high sentiment or high news then $N = 10$, $N = 14$ or $N = 14$ respectively. We set the event time, $\tau = 0$ on the day of the EP decision, τ then takes values between -25 and 5. $K_{i,\tau}$ is defined to be the expected return based on a model calibrated during the estimation window, which are the 20 days when $-25 \leqslant \tau \leqslant -6$. We therefore define the residual $\epsilon_{i,\tau} = \Delta EUA_{i.\tau} - K_{i,\tau}$. In this application of the event study, as is the case in Lin and Tamvakis (2010) we assume $K_{i,\tau} = 0$. Very similar results and identical conclusions are obtained when using a constant return model for $K_{i,\tau}$, calculated as the mean during the estimation windows. Following the standard approach, the average abnormal return AR_τ at event time τ is defined as

Test	Constant	Constant + Trend
ADF	8.9 x 10^{-27}	4.7 x 10^{-30}
KPSS	< 0.1	< 0.1

The table presents the p-values for the ADF and KPSS tests of stationarity. The Augmented Dickey Fuller (ADF) test has a null of non-stationarity. The Kwiatkowski Phillips Schmidt Shin (KPSS) test has a null of stationarity. The results show strong evidence to accept that the EUA log returns series is stationary. Models with the addition of a constant, and with the addition of a constant and a trend are used for robustness.

Table 3.6: Stationarity Test for EUA Returns

$$AR_\tau = \frac{1}{N}\sum_{i=1}^{N}\epsilon_{i,\tau}. \tag{3.1}$$

The cumulative average abnormal return between two days τ_1 and τ_2, $CAR(\tau_1, \tau_2)$, is therefore defined as

$$CAR(\tau_1, \tau_2) = \sum_{t=\tau_1}^{\tau_2} AR_\tau \ .$$

This is calculated for all 29 events and for the different categories of events, party-political, non-party-political, and high and low sentiment and high and low levels of news exposure. We calculate an associated test statistic

$$T = \frac{CAR(\tau_1, \tau_2)}{\sqrt{\sigma^2(\tau_1, \tau_2)}} \sim N(0, 1)$$

where $\sigma^2(\tau_1, \tau_2) = L\sigma^2$, σ^2 is the variance of the AR_τ calculated during the estimation window, and $L = \tau_2 - \tau_1 + 1$. In our application the value of τ_1 is fixed at $\tau_1 = -5$ while τ_2 varies from $-5, -4, ..., 5$; we present results labelled in the form $CAR\,\tau_2$. The results of the event studies are presented in Table 3.7 both with (Panel A) and without (Panel B) the extreme event of the backloading rejection date, 16th April 2013. Repeating the event studies in this way provides a robustness check for our analysis. We find from both the ADF and the KPSS tests that the time series of the log returns of the EUA is stationary see Table 3.6.

3.3.2 GARCH Model Specification

In addition to the impact on returns, we are also particularly interested in the effect of

EP policy decisions on the volatility of the EUA emissions market. To test this we use a GARCH model with a dummy variable in the variance equation, following Lu and Chen (2011). In line with Engle and Ng (1993) and Chevallier (2011a), the standard GARCH(1,1) model for EUA prices is specified as follows:

$$\Delta EUA_t = \mu + \rho \Delta EUA_{t-1} + \varepsilon_t,\ \varepsilon_t \sim i.i.d.(0, \sigma_t^2),$$

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

where ΔEUA_t is the log return for day t; ρ is the coefficient of first order autocorrelation; μ is the drift;, α_0, α_1 and β are constants, and ε_t is the error term process with mean zero and conditional variance σ_t^2. We test whether there is an effect on the EP decision days by introducing a dummy variable d_t in the variance specification. We test the period before the event day, by setting $d_t = 1$ on each of five days before each event and zero on all other days. We test the period of and after the event by setting $d_t = 1$ on the day of each event and on the following five days. These periods are chosen so that we may make compare the event study results and the GARCH results. That is, we specify

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

where d_t is the value of the dummy variable on day t. We use Marquardt's method implemented in EViews; we present the results before the event in Table 3.8 with the results on and after the event in Table 3.9. Again, as a robustness check we repeat the GARCH modelling while excluding the extreme event of the backloading rejection date, 16th April 2013.

3.4 Empirical Results

Following the method set out in the previous section, Table 3.7 presents the results of the event studies while Tables 3.8 and 3.9 present the results of the GARCH modelling before and after the EP decisions. Our principal finding, is that when all 29 EP decisions are included, these decisions have a very significant effect on EUA prices. From the event study analysis, this effect starts on the day of the policy decision itself, and results in a reduction of average EUA prices, while from the GARCH modelling we see an average increase in volatility before and after these decisions. The decrease in EUA prices is strongly statistically significant, as seen in the cumulative abnormal returns over event dates $\tau = 0, \ldots, 5$. These event study results were found to be robust to a change in the model used to calculate the abnormal returns in Eqn. 3.1, where instead of a zero log returns model we use a constant log returns model to calculate the abnormal returns (calculated as the mean during the estimation window). From the GARCH modelling, an increase in volatility is seen after the event dates with a smaller effect before. There is a very strong result after event days as seen in the higher positive value of the γ parameter, showing that there is, on average, considerable market instability as a result of EP decisions.

As set out in Section 3.3, given the influence, and hence potential source of bias from the backloading event, we check the robustness of our findings by repeating the testing after removing from the data the 16th April 2013, i.e. the date of the backloading rejection by the EP. Panel B of Table 3.7 presents the results of the event studies in this case. As this date falls into the classifications of "non-party-political", "low sentiment" and "low news", we report the updated results for these categories only as the other categories are unaffected. When the effect of the vote on backloading is removed from the analysis the statistical significance of the results is less striking, although the results remain statistically significant at conventional levels. Thus, our findings hold after accounting for the potential bias of the extreme backloading event. In a similar manner, Panel B of Tables 3.8 and 3.9 present the results of the GARCH modelling when the backloading rejection date is removed. When we re-examine the results for the set of 28 decisions we notice that before the event the size of the coefficient for the dummy variable, γ, is lower without the outlier and has lost statistical significance, but the coefficient of the volatility dummy variable on and after the event is practically the same and remains strongly significant. This indicates that the backloading rejection date was an important part of the overall pattern in the data but was not responsible on its own for the pattern.

The drop in EUA prices for the set of all 29 decisions is seen not only on the event day itself but for several more days after these EP decisions. We may conclude that the emissions market is taken by surprise when EP decisions are made. Then, similarly to the post earnings announcement drift in Barber and Odean (2008), Da et al. (2011) and Vozlyublennaia (2014), the change in price continues for several days. We see from the results in Table 3.4 that the cumulative effect of the set of all EP decisions is to reduce the EUA price by approx. 3.6% on the day of the decision. The reduction is larger for the sub group of non-party sources and larger still for decisions made in times of lower sentiment or when news attention was low. This pattern is also followed when the backloading decision is omitted from the analysis.

Our second finding is that when the EP is dealing with a policy decision which is non-party-political, i.e. legislation which originated from the European Parliament's committees, the European Council or the European Commission, there is on average a large reduction in the price of EUAs and an observable increase in the volatility of the EUA returns. These effects are not seen for decisions brought forward by the party-political groups of MEPs. Decisions made in these cases tend not to move the price significantly and there is some evidence that volatility decreases after such decisions. The results are seen to hold when the backloading rejection vote is excluded. This would indicate that if the political groups of the MEPs are themselves the source of the discussion, then the resulting decisions of the EP do not take the market by surprise. This may be caused by the political groups' willingness to publicize their activities. The market is more strongly affected by the non-party-political decisions from more bureaucratic sources which are less likely to seek publicity and so these decisions are less anticipated by the market. This finding has an important implication for policy makers as it shows that non-party-political legislation has the greatest impact on the emissions markets, and these on average cause market shocks.

Our third finding is that EP policy decisions are associated with a decrease in the level of EUA price and an increase in volatility after the decision during times of low market sentiment but not in times of high sentiment. This suggests a particular effect of EP policy decisions during times of low market sentiment, namely that in spite of the sentiment being low, the market is surprised by negative news and prices, on average, move significantly downwards when the EP decisions are made. Conversely there is little evidence of a significant price movement when EP decisions are made in times of high sentiment, which might indicate that the "good news" from the EP was already anticipated in the EUA price. A similar pattern is seen without the backloading event date. These sentiment findings indicate a need for policy makers to consider market dynamics in terms of policy decision timing.

Our fourth finding is that when there are low levels of emissions market attention, as measured by media exposure, the EP decisions again move the price of EUAs significantly downwards after the event and significantly increase volatility both before and after the event. In contrast, when there are high levels of emissions market related news, the EP decisions do not, on average, have an effect on the level of EUA prices but actually lower the volatility after the decision takes place. This suggests that policy decisions that directly or indirectly relate to the structure and functioning of the EUA market, have an impact on price and volatility when general market attention is low. These findings indicate a need to inform market participants more effectively concerning upcoming EP decisions which might have an impact on the market. There is evidence that there is considerable market inattention when there is low general media attention and when the political parties are not the originators of the decision process. This demonstration of market inattention violates the Efficient Market Hypothesis (EMH).

There is no evidence, even at conventional levels, of a "calm before the storm" effect for decisions made during times of high news intensity and for party political sourced decisions, see Table 3.8. In both cases the γ parameter, which indicates the extra effect on volatility in the period being tested, is not significantly different from zero. In contrast, there is very strong evidence of higher than expected volatility before decisions during times of low news. This indicates that the market is unsure what to expect from these decisions which are to take place in the near future. After the decisions of the EP take place there is evidence, at conventional levels, of a reduction in volatility for the high news periods and party-political decisions. There is very strong evidence of an in increased volatility effect for low news periods and non-party-political decisions and evidence only at conventional levels for an increase in volatility for low sentiment decisions. This indicates that the market was in a state of turmoil even after such decisions were made except for decisions made during times of high news or from party-political sources, see Table 3.9.

3.4.1 Discussion and Review of the Results

There are some weaknesses in the testing method used here which would prompt future investigations. Firstly the media analysed is only in the English language. While it is certainly the case that the chosen newspapers and newswires have international respect, it would be interesting to test the exposure in other languages. Another weakness is that we only test 29 decisions, while this is a much larger sample size than Koch et al. (2014) it is always desirable to have more data points. This selection was a compromise between the length of the estimation window and the number of decisions used for the event study, because an increased estimation window size would reduce the number of decisions available for the event study. The decision to use a 5 day post event window is reasonable because the EU ETS futures market has on average 2,000 trades per day. The data suggests that the effect of decisions lasted as long as 5 days, however the aim of the tests was to discover whether there was an effect due to sentiment, rather than to test how long the effect endured. This would be an interesting extension to the work but was not realistic for the data available. The evidence is inconsistent with EMH as the changes to prices and volatility are influenced by sentiment, news coverage and the origin of the decisions. This violates the EMH.

In this chapter there have been 468 hypothesis tests and so our conclusions are vulnerable to the multiple comparisons problem, whereby we may falsely reject true

Panel A	Event Study using all data						
	All Decisions	**Party Political**	**Non Party Political**	**High Sentiment**	**Low Sentiment**	**High News**	**Low News**
CAR -5	-0.004	-0.002	-0.005	0.001	-0.009	-0.006	-0.003
CAR -4	-0.013	-0.010	-0.014*	-0.005	-0.020*	-0.014	-0.012
CAR -3	-0.016	-0.022	-0.013	-0.010	-0.022*	-0.021*	-0.012
CAR -2	-0.012	-0.021	-0.007	0.000	-0.023	-0.009	-0.015
CAR -1	-0.013	-0.018	-0.010	-0.003	-0.022	-0.010	-0.015
CAR 0	**-0.036*** **	-0.028	-0.041**	-0.020	-0.051**	-0.020	-0.049**
CAR 1	**-0.045*** **	-0.019	**-0.059*** **	-0.019	**-0.070*** **	-0.009	**-0.074*** **
CAR 2	-0.039***	-0.013	-0.052***	-0.012	-0.064***	0.000	**-0.070*** **
CAR 3	**-0.047*** **	-0.020	**-0.062*** **	-0.020	**-0.073*** **	0.001	**-0.086*** **
CAR 4	**-0.056*** **	-0.014	**-0.078*** **	-0.018	**-0.082*** **	-0.000	**-0.101*** **
CAR 5	**-0.060*** **	-0.024	**-0.079*** **	-0.036*	**-0.083*** **	-0.006	**-0.105*** **
N =	29	10	19	14	15	14	15

Panel B	Event Study omitting the backloading rejection day			
	All Decisions	**Non Party Political**	**Low Sentiment**	**Low News**
CAR -5	-0.001	-0.001	-0.004	0.003
CAR -4	-0.007	-0.005	-0.008	0.000
CAR -3	-0.011	-0.004	-0.011	-0.001
CAR -2	-0.009	-0.003	-0.018	-0.010
CAR -1	-0.010	-0.006	-0.018	-0.010
CAR 0	-0.019 *	-0.014	-0.018	-0.018
CAR 1	-0.024 **	-0.027 *	-0.029	-0.037 *
CAR 2	-0.021 *	-0.026 *	-0.031	-0.040 *
CAR 3	-0.031 **	-0.038 **	-0.043 *	-0.059 **
CAR 4	-0.037 **	-0.050 **	-0.046 *	-0.068 ***
CAR 5	-0.044 ***	-0.055 ***	-0.051 **	**-0.077 *** **
N =	28	18	14	14

Panel A shows the cumulative abnormal returns from the event study tests comparing the effect of European Parliament (EP) decisions on the mean log returns of EUA prices from five days before, on the day itself and during the five days after the EP decision. Panel B repeats these tests without the extreme value on the backloading rejection day, 16th April 2013. Party Political refers to EP decisions originating from the political groups of MEPs, Non-Party Political refers to all other sources of EP decisions. High sentiment refers to levels of sentiment above the median. The EUA sentiment index uses data from the EUA and Energy markets, and the volatility of the FTSE 100 to construct a sentiment index. News is a measure of the exposure of the EU ETS in broadsheet and newswire stories. The event study measures changes in the cumulative abnormal returns for an event window of 11 days. CAR(n) refers to the cumulative abnormal returns from 5 days before the decision to the n^{th} day, where $n = 0$ on the day of the decision. These tests are repeated with a constant level of change model to calculate the abnormal returns, the results of which yield very similar results and identical conclusions; results are omitted for brevity and are available from the authors. N indicates the number of events in each test. The usual */**/*** indicates 10%, 5% and 1% p-values for the coefficient significance test, bold typeface indicates significant p-values at MHT levels.

Table 3.7: Event Study Results

Panel A GARCH Results Before the European Parliament decisions

	Base Model	All Decisions	Party Political	Non Party Political	High Sentiment	Low Sentiment	High News	Low News
γ (x 10^{-6})	-	19.9*	-5.3	30.6*	12.7	25.7	-2.9	**87.0******
α_0 (x 10^{-6})	**15.4 *****	**12.8*****	**15.4*****	**12.4*****	**14.4*****	**14.1*****	**15.6*****	**12.3*****
α_1	**0.160 *****	**0.157*****	**0.160*****	**0.156*****	**0.159 *****	**0.157*****	**0.160*****	**0.151*****
β_1	**0.839 *****	**0.843*****	**0.839*****	**0.845*****	**0.840*****	**0.842*****	**0.839*****	**0.846*****
N	-	29	10	19	14	15	14	15

Panel B GARCH Results Before the European Parliament decisions omitting the backloading rejection

	Base Model	All Decisions	Non Party Political	Low Sentiment	Low News
γ (x 10^{-6})	-	14.7	21.1*	11.5	59.0***
α_0 (x 10^{-6})	**15.4 *****	**13.3*****	**12.8*****	**14.5*****	**12.2*****
α_1	**0.160 *****	**0.157*****	**0.157 *****	**0.158*****	**0.153*****
β_1	**0.839 *****	**0.843*****	**0.844 *****	**0.841*****	**0.846*****
N	-	28	18	14	14

The table shows the results of GARCH models for the 1,625 daily log returns of EUA prices. Panel A uses all 29 decisions of the European Parliament (EP) selected according to origin, sentiment and news exposure. Panel B repeats these tests, omitting an extreme value on the backloading rejection day, 16th April 2013. The base model is the standard GARCH(1,1) model following Engle and Ng (1993) and Chevallier (2011a) without the dummy variables around the times of EP decisions. This model is shown for comparison purposes. Party Political refers to a categorization of each decision by the EP itself where the decision originates from the political groups of the EP. High sentiment refers to levels of sentiment above the median. The sentiment index uses data from the EUA and Energy markets, and the volatility of the FTSE 100 to construct a sentiment index. News is a measure of the exposure of the EU ETS in broadsheet and newswire stories in the three days before the EP decision. The change of variance is based on the addition of a dummy variable d_t to the variance equation in a GARCH(1,1) model describing the log returns EUA_t by $EUA_t = \mu + \rho EUA_{t-1} + \varepsilon_t$, where μ is a constant, ρ, is the coefficient of first order autocorrelation and $\varepsilon_t \sim i.i.d.(0, \sigma_t^2)$; where the variance σ_t^2 is described by $\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma d_t$, where α_0, α_1 and β are constants, the dummy variable d_t takes the value 1 on the 5 days before the European Parliament (EP) decision and zero otherwise, and γ is the coefficient of the dummy variable which is tested to determine the effect of EP decisions on EUA variance before such a decision. N refers to the number of events (EP decisions) in each model. The usual */**/*** indicate 10%, 5% and 1% p-values for the coefficient significance test. For brevity the mean equation results are not included but are available from the authors.

Table 3.8: GARCH Results for the Five Day Period Before European Parliament Decisions

Panel A GARCH Results After the European Parliament decisions

	Base Model	All Decisions	Party Political	Non Party Political	High Sentiment	Low Sentiment	High News	Low News
γ (x 10^{-6})	-	23.5**	-26.9*	**39.3*** **	5.6	35.5**	-28.8**	**93.9*** **
α_0 (x 10^{-6})	**15.4 *** **	**13.3*** **	**15.6*** **	**13.2*** **	**15.1*** **	**14.1*** **	**17.5*** **	**13.5*** **
α_1	**0.160 *** **	**0.164*** **	**0.159*** **	**0.166*** **	**0.161*** **	**0.162*** **	**0.161*** **	**0.166*** **
β_1	**0.839 *** **	**0.836*** **	**0.841*** **	**0.834*** **	**0.839*** **	**0.837*** **	**0.837*** **	**0.832*** **
N	-	29	10	19	14	15	14	15

Panel B GARCH Results After the European Parliament decisions omitting the backloading rejection

	Base Model	All Decisions	Non-Political	Low Sentiment	Low News
γ (x 10^{-6})	-	22.3**	**37.0*** **	32.5**	**86.0*** **
α_0 (x 10^{-6})	**15.4 *** **	**13.3*** **	**13.1*** **	**14.0*** **	**13.2*** **
α_1	**0.160 *** **	**0.163*** **	**0.166*** **	**0.162*** **	**0.165*** **
β_1	**0.839 *** **	**0.836*** **	**0.835*** **	**0.838*** **	**0.833*** **
N	-	28	18	14	15

The table shows the results of GARCH models for the same tests as in Table 3.8 with the change that the dummy variable d_t takes the value 1 on the day of the decision and on the following 5 days, and is zero otherwise again γ is the coefficient of the dummy variable. This tests for a change of variance after a decision of the European Parliament.

Table 3.9: GARCH Results for the Day of European Parliament Decisions and the Following Five Days

null hypotheses because a large number of tests are carried out simultaneously. In order to be consistent with the application of a multiple hypothesis testing (MHT) as used in Chapters 2 and 4, we apply the MHT framework of Holm (1979), following its use in Cummins (2013b) and Deeney, Cummins, Dowling and Bermingham (2015). Due to the particular distribution of the p-values in this data we find that there is a general cut off level for all the tests of $p = 0.00606$. Coefficients in Tables 3.7, 3.8 and 3.9 which are considered significant at this level are presented in bold type.

With the MHT adjustments in mind we now re-visit the results presented above in Tables 3.7, 3.8 and 3.9. When we remove the effect of the outlier of the backloading rejection day from the event study (Table 3.7 Panel B) we find that only one of the cumulative abnormal returns is considered significant. As this particular result, for EP decisions made during periods of low news, refers to cumulative returns a full week after the these EP decisions are made, it is difficult to consider it to be truly significant. When we examine the GARCH results for changes in volatility, excluding the effect of the backloading rejection, we find that under the MHT framework only those decisions made from non-party-political sources and those decisions made at times of low news attention are considered significant.

In the event study application we have small numbers of events ranging from a minimum of 10 events for the party-political classification to a maximum of only 29 when we consider all decisions of the EP including the backloading rejection on 16th April 2013. This restricts the power of our testing method and so it is not a surprise that the use of a MHT framework drastically reduces the number of rejected null hypotheses. This reduction changes the strength of our conclusions that EP decisions generally, EP decisions coming from non-party-political sources, EP decisions made during times of low sentiment and EP decisions during times of low news exposure all have a negative impact on price level and a positive impact on volatility. These conclusions cannot be supported within the strictures of the MHT framework, although there is considerable and consistent evidence for these conclusions at conventional levels. Therefore we may only report these conclusions with the proviso that the evidence is of only moderate strength and not sufficient to pass the higher standard associated with an MHT approach.

3.5 Conclusions and Policy Implications

Koch et al. (2014) and Koch et al. (2016) are clear that there is much yet to be discovered about the drivers of EUA prices beyond the fundamentals. It is not surprising that there is moderate evidence that policy decisions from the European Parliament have a direct effect on the volatility and level of EUA prices. Bearing in mind the proviso that our conclusions are supported by moderate, rather than very strong evidence, this study shows that EP influence is changed by the type of decision, the current sentiment of the emissions market, and the current level of market attention, as measured by news exposure, in advance of the decision.

The emissions market has some insight into the likely outcome of decisions made by the European Parliament, and so does not react strongly, in three circumstances, (i) when it is the party-political groups in the parliament who propose the legislation, (ii) when market sentiment is high and (iii) when the level of market awareness is high, that is, when there are high levels of media exposure. The decisions made under these circumstances seem to be anticipated correctly by the market and there is little price movement.

Of greater interest are the occasions when EUA market reacts as if it has just been surprised. The decisions that we have termed non-party-political in this study, namely those decisions originating from one of the EP committees, the European Council or the European Commission, significantly lower EUA prices and are strongly associated with heightened price volatility. The GARCH volatility findings indicate a high level of trader uncertainty around the outcome of these decisions and their potential impact on prices, particularly so for decisions which are from non-party-political sources. Better communication by policy makers would help reduce this. Clearly setting out a timeline of planned legislative decisions over the medium-term and what these policies will broadly aim to achieve, can help provide some improved certainty to market participants. Ideally some form of forward guidance might be given. A benefit of this is that current prices would be a more accurate reflection of true value and thus organizations that must buy allowances will be paying an appropriate price. Reducing uncertainty will also encourage market participation by large institutions, thus helping to add depth to the market.

With regard to the sentiment and media findings, these offer some additional important implications. Firstly the finding that sentiment and media coverage might influence price reaction is of interest in terms of informing the timing of decisions. Political decisions are often timed based on judgements of public receptiveness, and perhaps this needs to be considered for EP decisions on the EUA market. EUAs are not like typical commodities; the supply of EUAs is under political control and the demand for them is caused by regulation. Hence they have a high level of regulatory uncertainty attached to their valuation. The sentiment literature in equity markets, for example Baker and Wurgler (2006), has consistently recognized that more uncertain assets are more prone to the influence of sentiment. The presence of high uncertainty in the pricing of EUAs, and not just for the EUA market, but also other highly regulated markets subject to political influence, suggests a greater need for awareness of these behavioural drivers of price.

It is clear that EP decisions have a significant and important influence on EUA price levels and volatility. We have provided a systematic investigation of this influence in this study. Providing greater certainty to market participants, possibly through forward guidance, would enhance market participation, while improved awareness of behavioural influences regarding the market's reaction to EP decisions, can help strengthen the operation of the EUA market. A next step is to delve more qualitatively into the nature of individual EP decisions and ascertain particular facets of those decisions that might be driving market reactions. There is also scope for integrating market sentiment deeper into our understanding of emissions markets pricing.

We have shown that there is moderate evidence that sentiment, as well as political origin and news exposure, influences the market's reaction to decisions of the European Parliament regarding the EU emissions trading scheme. This is an important issue as the largest moves in EUA price have always been associated with regulatory matters rather than the day to day movements of the energy markets. In our next chapter we examine the influence of sentiment from a different perspective and at a higher frequency.

Chapter 4

Twitter Sentiment and the EU Carbon Market

4.1 Introduction

Sentiment measured from Twitter originates in a completely different manner from sentiment measured by proxies which have been used until now in this thesis. On account of this, Twitter offers a new opportunity to test the effect of sentiment in the EU emissions market. Twitter also offers the possibility of using intra-day data to examine sentiment, which until now has been examined at monthly frequency in Chapter 2 and at daily frequency in Chapter 3. For these two reasons, diversity and granularity, Twitter is an ideal source of sentiment information to examine the EU emissions market.

The subject of this research, the EU emissions market, is important for several reasons. It is the principal method by which the EU addresses the reduction of its greenhouse gas emissions. The market itself is quite large; during the final year of the December 2015 futures contract, € 25bn was traded on that single contract. The cost of EU emission allowances (EUAs) is part of the cost of many goods in the EU, for example electricity. Research on this new asset class informs the design of other large trading schemes around the world, most notably the Chinese national emissions trading scheme which is set to become the largest emissions market in the world.

The rest of this chapter is arranged as follows. In Section 4.1.1 we summarize recent literature and in Section 4.1.2 we discuss the emissions market as the context of this study. In Section 4.2 we describe the unstructured Twitter data and the construction of the sentiment impact measures derived from this data. In Section 4.3 we describe the EUA intra-day price data, the sampling frequency and the control variables. In Section 4.4 we identify outliers in the data and then set out the statistical models. Vector autoregression (VAR) and Granger causality testing are used to test whether sentiment has an influence on EUA returns. GARCH and Threshold GARCH are used to test whether sentiment has an effect on volatility. In Section 4.5 we present the results for the emissions market and climate change sentiment analysis separately. We then present results concerning the control variables and the implications of our use of a Multiple Hypothesis Testing framework. Section 4.6 concludes.

4.1.1 Background Literature

The research presented here is the first investigation to explicitly examine sentiment, as derived from social media, and the emissions market, and to do so using EUA, energy and equity market index data at intra-day frequency. Mansanet-Bataller et al. (2011) and Koch et al. (2014) have used the EU Eurostat Economic Sentiment Index as a measure of economic outlook. This index is gathered across the EU using a monthly survey examining economic expectations in several markets across all EU members. In both papers the sentiment measured concerns the whole economy and is not specific to the EU ETS or indeed to the wider energy market. Our use of Twitter allows us to be more targeted in our measurement of sentiment pertinent to climate change and, more importantly, the EU ETS itself. Our work is also one of very few studies to take account of the multiple comparisons problem inherent in the testing framework; which is an important statistical robustness measure given the novelty of this research. This multiple comparisons problem, as identified earlier, is the issue that some true null hypotheses may be rejected falsely when many hypotheses are tested at the same time. To correct for this we use a multiple hypothesis testing framework previously used in

Sections 2.4.2 and 3.4.1 based on the work of Holm (1979), Romano et al. (2010) and Cummins (2013a,b). We use this approach because this is a relatively new area for research and so, we wish to be prudent and careful with our conclusions. In order to measure the effect of sentiment, we add sentiment information to a fundamental model of EUA prices which has been informed by the literature.

There have been several fundamental drivers of EUA prices identified in the literature. Oil, coal and gas prices have been found to be influential by Alberola et al. (2008), Fezzi and Bunn (2009), Bredin and Muckley (2011), Chevallier (2011a), Creti et al. (2012), Aatola et al. (2013) and Ahamada and Kirat (2015). Stock markets have been found to be influential by Creti et al. (2012), Zhu et al. (2015) and Sousa and Aguiar-Conraria (2015). There have also been many papers examining the microstructure of the European emissions markets, including Daskalakis and Markellos (2009), Bredin et al. (2014) and, Chevallier and Sevi (2014). These show that there is a link between volume and volatility at the microstructure level and that the jumps in EUA prices are due to regulatory announcements. Also working at intra-day frequency, Mizrach and Otsubo (2014) suggest that order book imbalances can predict returns for up to three days, this would contradict the EMH, while Ibikunle et al. (2016) show that efficiency is improving as the market matures. In addition the ambient temperature has been found to be influential by Bredin and Muckley (2011), Chevallier (2011a) and Ahamada and Kirat (2015). While it is possible to obtain intra-day financial data it was not possible to obtain intra-day temperature data, hence we base the EUA price modelling in this chapter on the literature's suggestion of oil, coal, gas and market indices, see Section 4.3.1.1. We build on the findings of Chapter 3 which gave some insight into the effect of regulatory announcements on EUA prices. Our overall aim is to examine the effect of sentiment in professionally traded markets. In order to do this we examine sentiment expressed in tweets. There has been quite a body of literature to support the use of social media, and Twitter in particular, as a method of measuring sentiment.

Social media analysis is particularly suited to the European emissions market because of the interplay of economic and political influences in the market as attested to by Benz and Trück (2009), Koch et al. (2014), Zhu et al. (2015) and Deeney et al. (2016a). The demand for EUAs depends on the expectation of future industrial production which drives greenhouse gas output (Mansanet-Bataller et al. 2011 and Koch et al. 2014). This is largely an economic matter, but the inclusion of particular industries in the EU ETS and possible changes in regulations are a political matter. Therefore the price of EUAs depends on both economics and politics, both of these subjects have been investigated in the literature using sentiment measured from tweets. Examples of the use of social media analysis applied to political issues are Parameswaran et al. (2013), Siapera et al. (2015), Quinn et al. (2016) and Jull et al. (2016), who use DataSift, the same source as this investigation, to examine political attitudes to war, utility pricing and health issues (see Section 4.2.3 for more details). Corea and Cervellati (2015) and Corea (2016) use Twitter sentiment from DataSift[1] to investigate stock prices. In an unpublished study, Rao and Srivastava (2012) examine several commodities, including oil, using Twitter sentiment and Google search volume. They find correlations between sentiment and oil prices. Bollen et al. (2011) and Sprenger, Tumasjan, Sandner and Welpe (2014) use Twitter to measure market sentiment and its effect on the Dow Jones Industrial Average. Yang et al. (2015) show that the people who form a community by communicating with each other using Twitter, send tweets whose sentiment is predictive of stock markets. Sprenger, Sandner, Tumasjan and Welpe (2014) use the daily count of tweets as confirmation that a news event has happened and as a method of finding out precisely when an event happened. All these examples have in common the fact that they all link political or financial issues with online sentiment, and they are all very recent. These investigations support the use of Twitter as a means of measuring sentiment in the EU ETS.

[1] This leading supplier of news and media analytics is based in California USA. DataSift provided tweets with individual sentiment scores for the period 17th Dec 2012 to 16th Dec 2013. See www.datasift.com

4.1.2 Context

The literature cited above has shown that social media can provide useful information for the study of a wide variety of topics. We now focus on the financial markets relevant work and in particular on our context of the EU emissions market. We examine whether and why sentiment, measured by social media, has an influence on the financial markets and how we might test this in general. We then specialise the discussion to make this relevant for our study of sentiment effects on emissions markets. Of particular interest is the behaviour of the emissions markets on the day the European Parliament rejected the backloading proposal, which caused a sudden and sharp drop in EUA prices.

Social media sentiment is already used extensively in trading, a striking example is seen on Tuesday 23rd April 2013 when the Associated Press Twitter account was hacked and a false story posted claiming that there had been an attack on the White House. This was accompanied by a drop in US stock prices[2] which was quickly corrected. More recently on 7th October 2016 there was a flash crash in the sterling/US dollar exchange rate apparently due to one news story and the reaction of an algorithmic trading programme[3]. The influence of Twitter is not confined to sudden shocks but is part of many firms' trading strategies[4,5]. Lynn et al. (2015) provide a basis for social media sentiment analysis, suggesting that there are several aspects to interactions on social media. Of interest here are the aspects of identity, relationship, reputation, conversation and sharing. We see that tweets convey a writer's wish to reveal themselves to some extent, to form relationships with others, to build up their reputation and to share opinions and information. A further examination of the rationale behind sharing commercially valuable information is given by Chen et al. (2014) who examine the *Seeking Alpha* blog. Chen et al. (2014) list four reasons why writers are prepared to place valuable information on a public forum: the writer gets attention, fame and a

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[2]BBC report of the event http://www.bbc.com/news/world-us-canada-21508660 and Bloomberg News report http://www.bloomberg.com/news/articles/2013-04-24/how-many-hft-firms-actually-use-twitter-to-trade both accessed on 8th August 2016.

[3]The BBC report of this event http://www.bbc.com/news/business-37582150 and Bloomberg News report http://www.bloomberg.com/news/articles/2016-10-06/pound-plunges-6-1-percent-in-biggest-drop-since-brexit-result

[4]A special report by CNBC was published at the end of June 2012, see http://www.cnbc.com/trading-on-twitter/ accessed on 11th August 2016.

[5]Twitter messages between farmers has been used by traders to estimate harvests. http://www.cnbc.com/id/41948275 accessed on 11th August 2016

following; in the case of the blog *Seeking Alpha*, posters of messages get paid if people read their blogs; writers get a chance to put their opinions into circulation and perhaps fix errors; and finally, writers get a chance to support their own positions so that the market will move in their favour.

We see therefore that sentiment concerning equity, commodity and energy markets is expressed on Twitter. We propose that sentiment regarding the EU ETS is also expressed on Twitter and that this sentiment is associated with the price and volatility of the EUAs. A parsimonious and direct explanation is that sentiment influences emissions traders. There is considerable evidence showing that professional traders are subject to behavioural biases in their decisions as has been outlined earlier in Section 2.1. Coval and Shumway (2005) show loss-aversion from intra-day trading data on the Chicago Board of Trade; O'Connell and Teo (2009) show currency trader overconfidence; Coates and Herbert (2008) and Coates (2012) show that different testosterone levels, which are linked to risky behaviours, are associated with different trading outcomes; Cummins et al. (2015) and Dowling et al. (2016) show there are psychological price barriers even in the professionally traded oil markets and in the metals markets. Of greatest relevance to this chapter is the finding by Palao and Pardo (2012) showing that EUA traders cluster their orders and prices around multiples of five; that is, there is a behavioural bias present in carbon traders to select multiples of 5c for the price and multiples of 5 for order sizes, especially when there is uncertainty in the market and when there is low liquidity, neither of which is a rational explanation for this behaviour. Palao and Pardo (2012) do not explain this behaviour as a result of sentiment but as a method of quickly and cheaply managing information by restricting the number of choices from which to select the specifications for a trade. Having confirmed that there are irrational behavioural biases by professional traders in many markets including the energy markets and the EU emissions market, we propose that sentiment directly affects EUA traders' decisions and hence EUA prices.

To test whether sentiment has an effect in the professionally traded emissions market, we measure sentiment at intra-day frequency using Twitter. We relate this sentiment with intra-day EUA futures prices, while taking account of recognized control variables. By finding that sentiment has an effect on the price and volatility of the professionally traded EUA futures market, we show that the EMH does not provide a complete description of EUA market behaviour and that sentiment must become part of the explanation for EUA price dynamics. In this investigation we propose that sentiment is directly related to the price and volatility of EUA futures. This is based on a similar model used in Deeney, Cummins, Dowling and Bermingham (2015) (Chapter 2) where an oil market sentiment index modelled on Baker and Wurgler (2006) was found to be directly related to the price of crude oil futures.

The preliminary stage of the sentiment measure construction involves a scoping test to identify search terms which are useful for selecting tweets concerning climate change and the European emissions market, (see Section 4.2.1). The scoping test produces 17 terms[6] giving 1,522,562 tweets which produce the climate change sentiment measures. A more specific list of 5 search terms,[7] focusing on the emissions market, yields 20,884 tweets which produce the Emissions Market sentiment measures used in our investigation. We use the sentiment score assigned by DataSift for each tweet, as well as the sign of that score, as measures of sentiment. In addition we use the number of tweets as our measure of Twitter traffic intensity. The positive and negative sentiment scores are treated separately because the literature suggests that positive and negative sentiments behave differently, see Soroka (2006), Akhtar et al. (2013) and Sprenger, Sandner, Tumasjan and Welpe (2014). These scores are used to form four time series based on the sum and count of positive and negative tweets. A fifth time series based on the Twitter traffic intensity is included. These five series are used to test whether sentiment series from the emissions market tweets and from the climate change tweets have an effect on EUA price level and volatility.

The World Bank (2014) report on the EU emissions market summarized 2013 as a year which had a formal endorsement of backloading and many uncertainties, in

[6]The terms used for the climate change sentiment were: backloading, carbon market, carbon price, carbon trading, climate change, CO2, drought, emission, EU ETS, flood, fossil fuel, geothermal, GHG, global warming, greenhouse gas, renewable and UNFCCC

[7]The terms used for the Emissions Market sentiment were: backloading, carbon market, carbon price, carbon trading and EU ETS

particular the backloading rejection by the EP. Baker and Wurgler (2006) suggest that sentiment is at its most effective when fundamental data is lacking. This supports our choice of 2013 as our test year in which to examine the effect of sentiment on the EU emissions market.

Having considered the context used to examine sentiment in this particular professionally traded futures market, and in particular the events surrounding the rejection of backloading by the European Parliament, we now summarise the findings which are explained in detail in Section 4.5.

The first finding is that there is strong evidence of bi-directional Granger causality between changes in emissions market sentiment and changes in EUA prices. Further, we establish that periods of strong (weak) emissions market sentiment correspond with periods of high (low) EUA return volatility. The second finding is that there is only very weak evidence that Twitter sentiment concerning the general topic of climate change, rather than specifically the EU emissions market, is associated with EUA returns, but the strength of climate change sentiment is associated with EUA volatility in a similar manner to that of the emissions market. The third finding is that while energy commodity prices, particularly NBP gas, Brent oil and to a lesser extent the FTSE, show weak evidence of accounting for EUA prices, they show no evidence of predicting these changes. This suggests that the emissions market assimilates new information from the energy market efficiently because there is some evidence that the energy variables, of NBP gas, Brent oil and the level of the FTSE explain contemporaneous EUA prices, but this ability is lost for information one hour into the future. Thus we may conclude that the market has absorbed the information and adjusted prices in less than an hour.

4.2 Twitter Data

In this section the methods for selecting tweets, gathering sentiment scores for individual tweets, combining these scores into sentiment measures and calculating sentiment impact are described. This entire process is carried out twice, once for tweets concerning the general topic of climate change and once for tweets specifically about the emissions market. Tweets are selected by searching for particular words or combinations of words, referred to as search terms, which occur anywhere in the text of any tweet posted between 17th December 2012 and 16th December 2013. Location and language are used as additional selection criteria. The sentiment analysis used is that provided by DataSift[8], which gives a sentiment score for each measurable tweet. If positive sentiment is detected the score is an integer between 1 and 20 indicating the intensity of the positive sentiment, if the sentiment is detected as negative, the score is a negative integer between -1 and -20. It is important to treat negative and positive sentiment separately as the literature indicates that they do not simply cancel each other, see Soroka (2006), Sprenger, Sandner, Tumasjan and Welpe (2014) and Akhtar et al. (2013). Sentiment time series are constructed to describe the sentiment on a minute-by-minute basis, these are aggregated later into observation intervals of length m minutes so as to be compared with the time series of EUA prices and control variables using the same observation interval. The use of intra-day sentiment data is one unique element of this investigation. Four sentiment measures are constructed for both the climate change tweets and the emissions market tweets for the 525,600 minutes covering the period under investigation. The four one-minute-frequency time series for both sets of tweets are respectively based on: (i) the sum of the positive scores during each minute, (ii) the sum of the negative scores during each minute, (iii) the count of the number of tweets containing positive sentiment during each minute, and (iv) the count of the number of tweets containing negative sentiment during each minute. The latter two series, based on tweet counts, reduce our reliance on the scaling accuracy of the DataSift sentiment algorithm. A fifth measure that we consider is the count of the total number of tweets during each minute, irrespective of whether these tweets had measurable sentiment or not. It thus produces a count of Twitter traffic. This is used to test whether DataSift's sentiment scoring method improves upon a simple count of Twitter traffic.

In order to create a simple and realistic model of the behaviour of sentiment, we

[8]This leading supplier of news and media analytics based in California, USA supplied tweets with sentiment scores for the period 17th Dec 2012 to 16th Dec 2013. See www.datasift.com

follow the method of Mitra et al. (2009) and Yu et al. (2013). This allows the sentiment associated with a particular tweet to remain effective for a period after the tweet was posted, and for this impact to decrease with time. The details of these procedures are given below in Section 4.2.3.

4.2.1 Selection of Tweets

To select the tweets for the analysis an initial scoping list of 44 words and phrases are used as search terms, see Table 4.1. These terms concern climate change, global warming, renewable energy and the emissions market, and are collected from the indexes of several published books namely, Kaplan (1983), Stern (2006), Serletis (2007), Ellerman et al. (2010), Richter (2010) and Chevallier (2011a). Tweets which contain any one of the search terms are selected, this includes occurrences where the search term is prefixed with a hashtag, e.g. *"#EU ETS"*. The scoping list search terms are: *backloading, biofuels, biogas, biomass, cap and trade, carbon, clean tech, climate, CO2, dioxide, drought, electricity, emission, emitter, energy market, environment, EU ETS, EU Parliament, EUETS, flood, fossil fuel, geothermal, glacier, global warming, greenhouse gas, hydrocarbons, hydroelectric, ice cap, IPCC, Kyoto Protocol, methane, pollution, power plant, power sector, renewable, sea ice, sea level, smelting, sustainab, trading, UNFCCC, warming, wave energy* and *wind turbines*. Note that "EUA" is not used as a search term despite its obvious desirability, because it is an acronym for the USA in French, Spanish, Catalan and Portuguese; it is likely that this would lead to confusion. For each of these search terms a random sample of 100 tweets found by the search term are manually checked for subject accuracy. If at least 70 of these tweets are accurate for their stated subject the search term is used for the next stage of the Twitter selection process. It is found that many search terms produce tweets which are not intended. For example *"IPCC"* selects many tweets concerned with the Intergovernmental Panel on Climate Change but also produces tweets concerned with the Independent Police Complaints Commission, which is from the UK. It is also found that *"carbon"* produces tweets concerning greenhouse gases as well as carbon steel, carbon fibre, carbon filters and the description of a colour. Those search terms which produce tweets that are accurate concerning their subject in 70 or more cases are used to produce the climate change list of 17 words namely: *backloading, carbon market, carbon price, carbon trading, climate change, CO2, drought, emission, EU ETS, flood, fossil fuel, geothermal, GHG, global warming, greenhouse gas, renewable* and *UNFCCC.*

In addition to restricting the search to tweets containing any of these 17 search terms, climate change tweets are selected to come from Europe and to be written in English. The geographical origin of the tweets is determined by the time zone in the tweet metadata, and the language is determined by the language detection system of DataSift. The geographical restriction is to ensure subject accuracy. Twitter metadata does include a location field which is entered by the user, however the description of the location is entirely at the user's discretion and is often null or refers to an unusable location name. The geo-location function is another possible source of location data. The difficulty with this source is that it is not available to laptop and PC users, but only to mobile phone users many of whom have disabled the function. This would probably produce a sample with fewer tweets from people who post tweets from their desks. The time zone is a particularly useful way to describe the location of the poster of the tweet as it is copied from the computer's own settings and is likely to be correct. Furthermore, on reading samples of time zones in the initial scoping list, it is clear that almost all time zones are the names of capital cities e.g. *Paris*, and not as the name of a time zone such as *Central European Time*. Hence we can be very confident that the tweets originated in Europe. The restriction to English is to ensure that the authors may check the subject accuracy of samples of the tweets. Again for reasons of accuracy DataSift is used to verify the language rather than the user's self-description.

As well as building a set of sentiment measures based on the 17 words for the climate change tweets, a second set of sentiment measures, based specifically on the emissions market is produced from tweets containing any of the 5 words: *backloading, carbon market, carbon price, carbon trading* and *EU ETS.* The search terms to produce these two sets of tweets, namely the climate change tweets and the emissions market

	Terms used for Tweet Search
Scoping	backloading, biofuels, biogas, biomass, cap and trade, carbon, clean tech, climate, CO2, dioxide, drought, electricity, emission, emitter, energy market, environment, EU ETS, EU Parliament, EUETS, flood, fossil fuel, geothermal, glacier, global warming, greenhouse gas, hydrocarbons, hydroelectric, ice cap, IPCC, Kyoto Protocol, methane, pollution, power plant, power sector, renewable, sea ice, sea level, smelting, sustainab, trading, UNFCCC, warming, wave energy and wind turbines
Climate Change	backloading, carbon market, carbon price, carbon trading, climate change, CO2, drought, emission, EU ETS, flood, fossil fuel, geothermal, GHG, global warming, greenhouse gas, renewable and UNFCCC
Emissions Market	backloading, carbon market, carbon price, carbon trading and EU ETS

The table presents the search terms used for the scoping, climate change and emissions market tweet searches. The Initial Scoping set of 44 terms were used to verify search term accuracy. Selections were made so that the set of search terms in the climate change sentiment and emissions market lists were at least 70% accurate for subject when random samples of 100 tweets for each term were checked, and the list of search terms for the Emissions Market were specific to the EU ETS and not to a wider topic of climate change.

Table 4.1: Search Terms for Initial Scoping, Climate Change and Emissions Market Tweets

tweets, are listed in Table 4.1, their descriptive statistics are given in Table 4.2. In total, 1,522,562 tweets concerning the topics of climate change, global warming, and emissions markets formed the source for the climate change sentiment measures. The smaller set of 5 search terms specifically related to the emissions market, rather than the broader topic of climate change, returned 20,884 tweets. The sentiment measures from this smaller set of tweets is found to be very useful in explaining the level and volatility of EUA returns, but there is no evidence from correlation or VAR tests that the climate change sentiment measures are associated with EUA prices. There is evidence that a high number of climate change tweets is associated with higher volatility. Thus from this stage onwards in the investigation we mainly concern ourselves with emissions market sentiment as this has a much richer association with both the direction and volatility of EUA returns than the climate change sentiment. Descriptive statistics for the emissions market and climate change tweets are found in Table 4.2, histograms are found in Figures 4.6 on page 105 and 4.8 on page 108.

4.2.2 Verifying the Subject Matter of the Emissions Market Tweets

A very useful aspect of using tweets to measure sentiment is that samples of the selected

N = 365	Emissions Market Tweets Per Day	Climate Change Tweets Per Day
Total	20,884	1,522,562
Mean	57.22	4,171.40
Max	1,586	22,970
Min	2	2,074
Median	29	3,931
Standard Deviation	123.74	1,671.14
Skewness	7.86	5.26
Excess Kurtosis	79.77	49.52
Positive Tweets	21%	20%
Negative Tweets	18%	26%
Unclassified	61%	54%

The table presents descriptive statistics for the number of emissions market and climate change tweets per day and the percentages of positive, negative and unclassified tweets. This includes the entire data set and is not restricted to trading hours.

Table 4.2: Distribution of Emissions Market and Climate Change Tweets Per Day

tweets can be read individually to check for subject accuracy. This is the reason only English language tweets are chosen. In practice it is not possible to read each tweet but samples of 100 tweets found by each search term in the scoping list are tested for accuracy. For each search term 100 tweets are randomly selected and if 70 or more of these tweets are on the stated topic, the search term is used in the list of 17 search terms which yield the climate change tweets. A smaller set of 5 search terms are used to specifically identify tweets which can only be concerned with the emissions market.

Since these emissions market tweets are fewer in number than the climate change tweets and since it is found that the sentiment of these tweets is an influence on EUA returns and volatility, it is considered prudent to carry out some tests to check that these tweets were actually on the correct topic of the EU ETS. The daily frequency distribution of these tweets is compared with the number of newspaper stories per day concerning the EU ETS following Sprenger, Sandner, Tumasjan and Welpe (2014) who use the number of tweets to check the timing of actual news events. Following this example we verify that the days with the largest numbers of emissions market tweets correspond to days on which there are important events in the EU ETS as measured by news stories found by Nexis Lexis. This verification is carried out using Lexis Nexis to search for articles in European newspapers containing the phrases “Emission Allowances” or “EU ETS” or “Carbon Emissions”. An exact replication of the search terms was not possible due to the search criteria availability in Lexis Nexis. As these stories are written by professional journalists and selected by professional editors it is reasonable to assume that they are relevant to events in the EU ETS. If the tweets are concerned with events in the EU ETS then we would expect that large numbers of tweets would be posted on the days when there are important events in the EU ETS as confirmed by large numbers of newspaper stories on these days retrieved using Lexis Nexis. This is indeed the case. On days on which there are high numbers of emissions market tweets, there are high numbers of newspaper stories about the EU ETS, see Table 4.3. It might be argued that the similarity between the numbers of news stories and tweets is due to a common correlation between the day of the week and the number of stories in the media. An example of this would be that there are more sports stories on a Monday after the weekend or fewer financial stories on days when the markets are closed. It may also be argued that both tweets and print media follow a general trend. The day of the week and trend effect is measured by regressing the number of emissions market tweets per day against dummies for six of the days of the week and a trend term; this is repeated for the number of newspaper stories each day. It is found for example that there are significantly fewer stories on a Friday compared with a Monday. There is a very strong day of the week effect in the number of both tweets and newspaper stories released concerning the emissions market, but there is no evidence of a significant trend during the year. This is somewhat unusual given the general increase in Twitter activity, however the investigation deals with only a tiny proportion, 0.0008%, of the total number of tweets[9]. The 10 days with the largest excess numbers of emissions market tweets are presented in Table 4.3 along with the corresponding numbers of newspaper stories. Excess numbers of tweets or newspaper stories are the number actually published on that day less the number expected given the day of the week and the trend, i.e., the residuals. The dates are sequenced in decreasing order of number of excess tweets, and it can be seen that this corresponds closely with the largest numbers of excess newspaper stories. It is also seen by reading the new stories that on these days there were highly significant events for the EU ETS.

[9] Source http://www.internetlivestats.com/twitter-statistics/ accessed on 6th September 2016

This provides strong evidence that the emissions market tweets are verifiably concerned with the EU ETS, based on: (i) the origin of the search terms producing these tweets, (ii) the distribution of the numbers of tweets coinciding almost exactly with important EU ETS events, and (iii) reading large samples of the tweets. This study adds to the literature by using the greater granularity of the intra-day Twitter information to examine at what specific time within the day particular events happened, not just on which days. This allows a much faster and more accurate estimation of returns and volatility than estimations available using daily data, and as such is of practical benefit to traders. Having carried out the previous tests which indicate that the emissions market tweets are associated with the emissions market, the next task is to produce time series of the changes in sentiment of these tweets which may be compared with time series of EUA, oil, coal, gas and the FTSE returns.

4.2.3 Sentiment Scores and the Calculation of Sentiment Impact

We now use the sentiment scores from both sets of tweets to produce intra-day time series which can be used to test whether sentiment has a direct effect on the price and volatility of EUAs. The sentiment scores are provided by DataSift; such scores have been used in published research as a source of sentiment information. The accuracy of the DataSift sentiment algorithm, which measures the sentiment of tweets, has been attested to by Parameswaran et al. (2013) who find it two to three times as accurate as traditional data retrieval schemes. Quinn et al. (2016) use sentiment supplied by DataSift to analyse public mood from tweets regarding a new public utility. Siapera et al. (2015) use DataSift's sentiment scores to analyse tweets concerning violence in the Middle East. Jull et al. (2016) use DataSift to measure issues relating to public health. Corea and Cervellati (2015) use Twitter sentiment measured by DataSift to predict the NASDAQ and find that it improves an existing benchmark model. Corea (2016) finds that the volume of tweets as collected by DataSift is a useful addition to stock prediction models. We can therefore have confidence that the sentiment scores assigned by DataSift are reliable. The descriptive statistics for both emissions market

Date	Excess Tweets	Excess News Stories	Event / Headline
16th April 2013	1,475.7	62.7	Backloading rejected by European Parliament (EP)
3rd July 2013	992.1	49.1	Backloading Accepted by EP to be put to individual states
15th April 2013	699.0	19.7	EU ETS faces crunch vote
19th June 2013	391.1	20.1	EP votes to freeze the number of permits auctioned; Shenzhen starts the first of seven Chinese ETS and Kazakhstan plans a national ETS
2nd July 2013	384.7	12.7	Zombie carbon markets to be shocked back to life; ETS tension mounting ahead of new EP vote on allowance backloading; mixed far curves (futures market) as region awaits CO_2 vote.
17th April 2013	367.4	54.1	Backloading Rejected by European Parliament (EP)
19th February 2013	337.7	39.7	The International Emissions Trading Association supported the European Commission's backloading proposal
12th April 2013	327.4	51.6	EU Commission is using an outdated list to grant free EUAs; Agricultural Bank of China to support Green Development
10th December 2013	253.7	110.3	Britain must press on with fracking; Sinopec buys credits after formal opening of Beijing carbon trading exchange
11th April 2013	238.4	63.6	CE Delft, the research group, suggests that low CO_2 prices can be corrected by cutting free allowances; advance publicity about the EU ETS facing a crunch vote on 16th April

The table shows a list of the days which have the largest number of excess emissions market tweets. Excess tweets are the differences between the actual daily count of tweets and the numbers expected from a regression model based on the day of the week and a trend term. The number of excess news stories is shown for comparison.

Table 4.3: The Ten Days with the Most Excess Emissions Market Tweets

tweets and climate change tweets have been summarized in Table 4.2, we note that there are broadly similar proportions of positive, negative and unclassified tweets in both. Further comments on the polarity of the climate change and emissions market tweets are to be found in Section 4.2.4. We see that there are substantial numbers of tweets which are unclassified, in these cases DataSift has found un-opinionated statements. This is entirely normal in the field of natural language processing.

Sentiment measured from tweets is precisely in line with the definition of Baker and Wurgler (2007, p.129), "a belief about future cash flows and investment risks which are not justified by the facts at hand", as it is based on the expressed opinions of a community of people. In sentiment analysis, such as used by DataSift, the sentiment detection programme extracts opinionated text from tweets and ignores factual text. DataSift assigns an integer between -20 and +20 to each tweet which it detects as containing sentiment. It uses a proprietary sentiment detection programme where a positive number indicates a tweet with positive sentiment and a negative number indicates a tweet with a negative sentiment. We initially construct four one-minute-frequency time series of sentiment for both the emissions market tweets and the climate change tweets comprising, respectively, (i) the sum of the positive scores during each minute, (ii) the sum of the negative scores during each minute, (iii) the count of the number of tweets containing positive sentiment during each minute and (iv) the count of the number of tweets containing negative sentiment during each minute. We add a fifth series, Count All, which is the sum of the number of tweets per minute, so as to produce a measure of Twitter traffic intensity. The search-based method of Da et al. (2015) is analogous this fifth measure Count All, in that it is a measure of the interest in the particular topics identified by the search terms. In Da et al. (2015) these search terms are words such as "recession", "bankruptcy", "unemployment", "price of gold", "donation" or "savings". The sums of positive and negative sentiment scores, the counts of positive and negative tweets and the total number of tweets per minute are not immediately useful as time series because there are many zeros in these series, particularly for the emissions market tweets due to the fact that there are many fewer of these tweets than minutes in the year. There is of course a more fundamental problem, namely that sentiment one minute after a tweet has been posted cannot reasonably be considered to return to zero because the person holding the sentiment may be assumed to hold on to their opinion for longer than one minute. In order to model sentiment more realistically we calculate sentiment impact following Mitra et al. (2009) and Yu et al. (2013). We set the parameters so that the impact of each sentiment measure decreases during every minute, becoming negligible, i.e. 1% of original impact, after a set number of days termed the decay length. As we will use the Twitter traffic intensity to test the efficacy of DataSift's sentiment algorithms, we treat the count of tweets (traffic intensity) exactly the same as the four sentiment series when we calculate the sentiment impact measures. We define for both the emissions market sentiment and the climate change sentiment, the sentiment impact,

$$SentimentImpact_t^{Pos,Sum} = \sum_{i=0}^{t-D} Sent_{t-i}^{Pos,Sum} e^{-ri} \tag{4.1}$$

$$SentimentImpact_t^{Neg,Sum} = \sum_{i=0}^{t-D} Sent_{t-i}^{Neg,Sum} e^{-ri} \tag{4.2}$$

$$SentimentImpact_t^{Pos,Count} = \sum_{i=0}^{t-D} Sent_{t-i}^{Pos,Count} e^{-ri} \tag{4.3}$$

$$SentimentImpact_t^{Neg,Count} = \sum_{i=0}^{t-D} Sent_{t-i}^{Neg,Count} e^{-ri} \tag{4.4}$$

$$SentimentImpact_t^{All\,Count} = \sum_{i=0}^{t-D} Sent_{t-i}^{All\,Count} e^{-ri} \tag{4.5}$$

where $SentimentImpact_t^{*,*}$ is the impact of the indicated sentiment measure at minute t, $Sent^{*,*}{}_{t-i}$ is the sum of the sentiment scores or counts during minute $t-i$; r is the rate of decay of the sentiment impact and is chosen so that $e^{-rD} = 0.01$ when D is the number of minutes in the decay length, see Yu et al. (2015). Thus the sentiment of a particular tweet has a decreasing sentiment impact for several days (the decay length) after which its influence is zero. Patton and Verardo (2012) have found a decay length for the effect of news in the equity market of 2 to 5 days and Yu et al. (2013) confirm these time periods. To ensure robustness we use decay lengths from two days to one week; these give similar results.

These four series of sentiment impacts and the impact measure based on traffic intensity, of both emissions market and climate change tweets, are aggregated at m minute observation intervals by summing each of the sentiment impact measures for these minutes following the pattern of

$$SentImpact^{*,*}(m)_{t/m} = \sum_{i=t-m+1}^{t} SentImpact_i^{*,*},$$

subject to $\frac{t}{m} \epsilon \mathbb{N}$, where m is the number of minutes in the observation interval. This allows a range of granularities for the analysis of prices and sentiment which are chosen so as to suit the EUA data availability, and chosen with m dividing into 600 so that an observation interval does not straddle two trading days; the length of the trading day is 600 minutes. The statistical properties of the resulting series at different observation interval lengths is given in Tables 4.4 and 4.5. The descriptive statistics show that the series of sentiment impacts are reasonably stable when the length of the observation interval is changed. The series themselves and their first differences were found to be stationary using the Augmented Dickey Fuller test. The choice of $m = 60$ for the main results is to suit the EUA data and this choice is described in Section 4.3. In the testing phase, several other values near to one hour frequency are used to ensure the results are robust.

To examine the effect of sentiment on volatility we consider sentiment as being either strong or weak, a binary variable. While it may be considered preferable to use the sentiment impact variables directly in the GARCH and Threshold GARCH variance equations, it is found that convergence is not attained using the Marquardt steps method implemented in EViews, thus high/low sentiment is used. The use of a binary variable does have the advantage that it places less reliance on the scaling accuracy of the DataSift sentiment algorithms. The practice of characterizing sentiment with a binary variable has been quite useful and is found widely in the literature, for example it is indicated by the sign of the Fama French RMRF[10], which is excess return on the market; this indicates a bull or bear market on a daily basis. Kim et al. (2014) finds that investor disagreement predicts lower stock market returns during times of low investor sentiment but it does not do so in times of high investor sentiment. Baker and Wurgler (2006) finds that high or low sentiment is a predictor of firm value for firms which are otherwise difficult to value. Here we use more detail than simply high or low, but assign strong or weak to the positive and negative sentiment measures separately, as well as strong or weak for the intensity of Twitter traffic. For each of the four sentiment impact measures and the traffic intensity impact measure for both emissions market and climate change sentmient, we define sentiment as strong or weak using the $StrongSent^{*,*}(m)_t$ variable in Equations 4.6 to 4.10, for simplicity of labelling we later refer to this variable as $StrongSent_t^{*,*}$. Sentiment or traffic intensity for each of the measures is considered to be strong if the magnitude of the sentiment impact at that time is larger than the magnitude of the mean value of the sentiment impact. Recall that each of the terms of each series has the same sign as each other term, except possibly for terms equal to zero. This method is repeated using the median instead of the mean and gives identical conclusions. Explicitly for each sentiment impact measure we define

$$StrongSent_t^{Pos,Sum} = \begin{cases} 1, & SentImpact_t^{Pos,Sum} > MeanSentImpact^{Pos,Sum} \\ 0, & otherwise \end{cases} \tag{4.6}$$

$$StrongSent_t^{Neg,Sum} = \begin{cases} 1, & SentImpact_t^{Neg,Sum} < MeanSentImpact^{Neg,Sum} \\ 0, & otherwise \end{cases} \tag{4.7}$$

$$StrongSent_t^{Pos,Count} = \begin{cases} 1, & SentImpact_t^{Pos,Count} > MeanSentImpact^{Pos,Count} \\ 0, & otherwise \end{cases} \tag{4.8}$$

[10]The RMRF is the value weighted return on all NYSE, AMEX and NASDAQ stocks minus the one month Treasury bill rate.

$$StrongSent_t^{Neg,Count} = \begin{cases} 1, & SentImpact_t^{Neg,Count} > MeanSentImpact^{Neg,Count} \\ 0, & otherwise \end{cases} \tag{4.9}$$

$$StrongSent_t^{All\ Count} = \begin{cases} 1, & SentImpact_t^{All\ Count} > MeanSentImpact^{All\ Count} \\ 0, & otherwise \end{cases} \tag{4.10}$$

where $MeanSentImpact^{*,*}$ is the mean of the particular sentiment impact measure taken over the whole period under investigation; we use an observation interval of one hour, i.e.$m = 60$, for the reported tests in Section 4.5. The sum of negative sentiment impacts is necessarily a series of non-positive terms, hence it is considered strong when below its mean. The sum of positive sentiment impact and the counts of the numbers of positive, negative and traffic intensity is a series of non-negative terms, and as such is considered strong when above its mean.

Having defined useful time series for both the climate change and emissions market sentiment impact series, we now make some interesting observations.

4.2.4 Initial Observations of Climate Change Sentiment and Emissions Market Sentiment

It is seen in Figure 4.3 that there is no obviously unusual behaviour in the climate change sentiment counts or scores on 16th April, 1st February or 3rd July on which the EUA returns have their largest daily changes, see Figures 4.1 and 4.2. The large negative spike in climate change sentiment, on 5th December 2013 (C) in Fig 4.3, is due to public reaction to flooding in Britain after a winter storm; there is no particularly unusual behaviour in the returns of EUAs on that day. These observations suggest that climate change sentiment is not strongly associated with EUA prices. This suggestion, that climate change sentiment is largely unconnected to the EUA prices, is developed later in Section 4.5. We see in Table 4.2, that there are slightly more negative tweets about climate change than positive, while the reverse is true for the emissions market

20 Minute N=7,620	Sum Pos	Sum Neg	Count Pos	Count Neg	Total Tweets
Mean	36.51	-29.94	8.84	6.47	39.60
Max	1036.62	0.00	244.41	108.03	842.07
Min	0.00	-476.77	0.00	0.00	1.33
Median	18.17	-18.83	4.51	4.08	23.63
Std Dev	69.77	37.74	16.33	8.17	59.77
Skewness	7.37	-4.56	7.18	4.92	6.46
Kurtosis	81.68	39.25	79.49	45.28	65.75

Hourly, N = 2,540	Sum Pos	Sum Neg	Count Pos	Count Neg	Total Tweets
Mean	37.23	-30.53	9.02	6.60	40.40
Max	1026.79	0.00	242.27	107.57	837.30
Min	0.01	-476.77	0.00	0.00	1.36
Median	18.52	-19.04	4.57	4.11	23.96
Std Dev	71.41	38.59	16.71	8.35	61.21
Skewness	7.33	-4.54	7.14	4.87	6.41
Kurtosis	79.74	38.34	77.56	43.87	64.11

Daily, N = 254	Sum Pos	Sum Neg	Count Pos	Count Neg	Total Tweets
Mean	36.51	-29.94	8.84	6.47	39.60
Max	1036.62	0.00	244.41	108.03	842.07
Min	0.00	-476.77	0.00	0.00	1.33
Median	18.17	-18.83	4.51	4.08	23.63
Std Dev	69.77	37.74	16.33	8.17	59.77
Skewness	7.37	-4.56	7.18	4.92	6.46
Kurtosis	81.68	39.25	79.49	45.28	65.75

The table presents descriptive statistics for each of the five emissions market sentiment impact measures based on the positive and negative tweet sentiment scores, and the counts of positive and negative tweets and the total number of tweets. Impacts are weighted means calculated from the sentiment measure provided by DataSift using $SentimentImpact_t^{*,*} = \sum_{i=0}^{t-D} Sent_{t-i}^{*,*} e^{-ri}$ following Eqn 4.5 , where where $Sent_{t-i}^{*,*}$ is one of the sentiment measures summed during minute $t-i$ these being the sum of the positive scores per tweet, sum of negative scores per tweet, the count of positive tweets, the count of negative tweets or the count of the all tweets; r is the rate of decay of sentiment impact and is chosen so that $e^{-rD} = 0.01$ when D is the number of minutes in the decay length. Results are presented for data at 20 minute, hourly and daily frequency.

Table 4.4: Descriptive Statistics for Emissions Market Sentiment

	Sum Pos	Sum Neg	Count Pos	Count Neg	Total Tweets
Sum Pos	1	-0.75	0.99	0.78	0.90
Sum Neg	-0.74	1	-0.75	-0.99	-0.86
Count Pos	0.98	-0.77	1	0.80	0.92
Count Neg	0.76	-0.99	0.78	1	0.88
Total Tweets	0.89	-0.89	0.91	0.90	1

The table shows the correlations between the five sentiment impact measures for the whole year. The top right shows the results for hourly data, the bottom left shows results for daily data. The negative sentiment impact is recorded as a negative number hence the negative correlation between sum of positive and sum of negative sentiment impact actually means that larger values of positive sentiment occur together with larger values of negative sentiment.

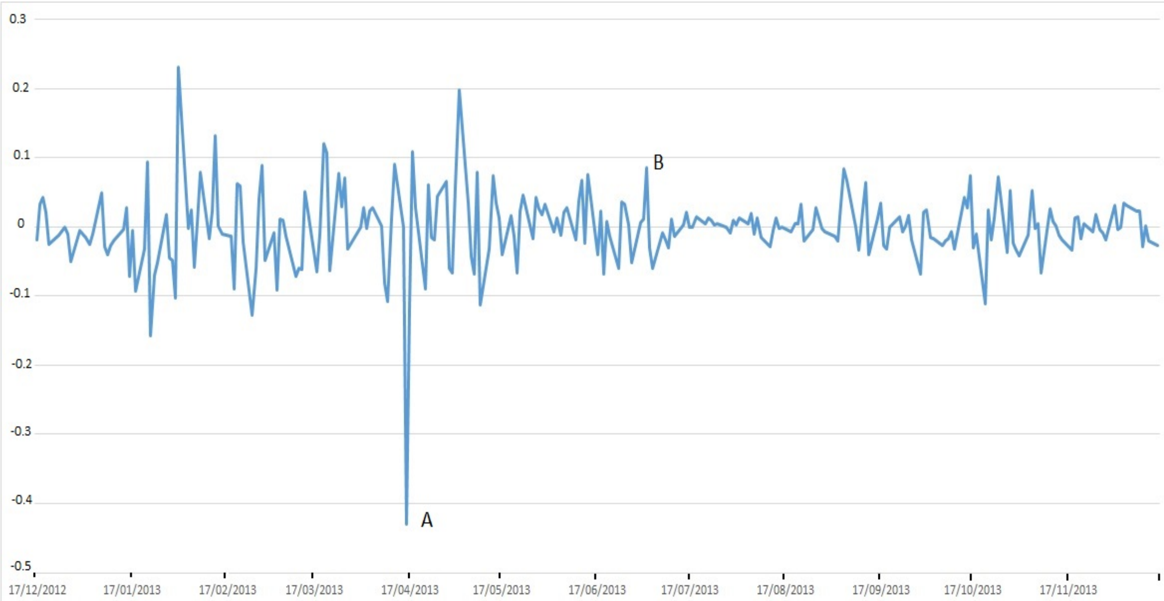
Table 4.5: Correlation Matrix for Sentiment Impact at Hourly and Daily Frequency

The figure shows the EUA price for prompt December 2013 in Euro per tonne of CO_2. "A" marks the large drop in price on 16th April 2013.

Figure 4.1: Price of EUAs from 17th December 2012 to 16th December 2013

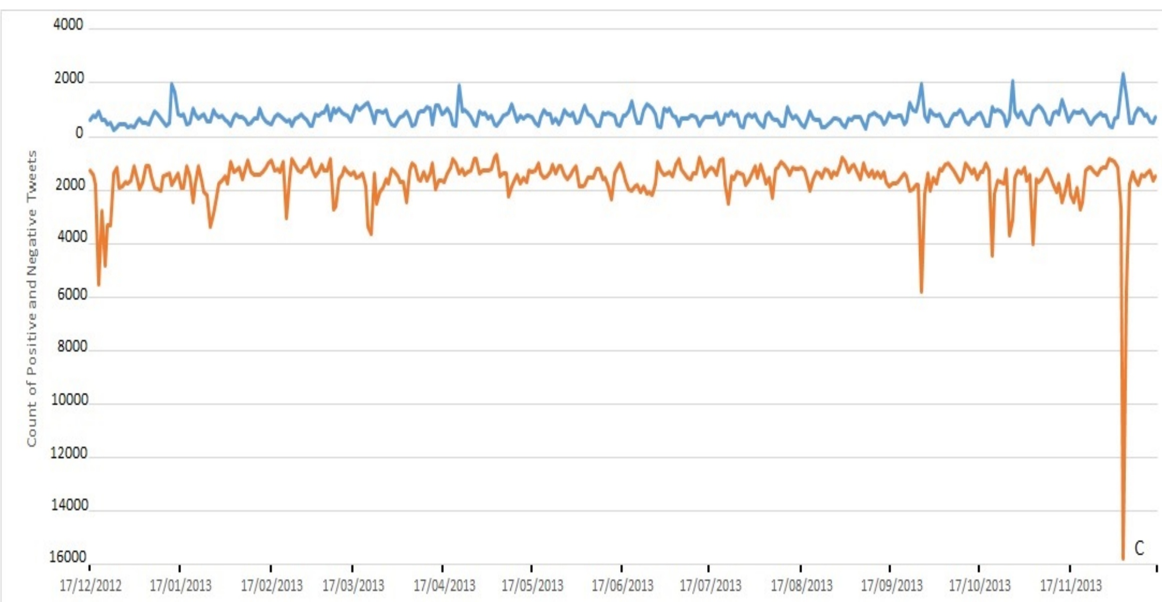
tweets. This is not surprising as the emissions market is of interest primarily to traders and aficionados of the EU ETS who are more likely to take a dispassionate attitude to events, than is the general public in its opinions about climate change. It is plausible that those who posted the large number of tweets in response to the storm on 5th December 2017, related that event to climate change. This is because many people associate extreme weather events with climate change.

The smaller set of five search terms specifically for the emissions market produces sentiment measures which are seen to have a much clearer connection with the EUA market. In Figure 4.4 we see that a large spike in the number of negative sentiment tweets happens on the same day, 16th April (A), as there is a large negative change in EUA returns (Figure 4.2). We also see that there is a large spike in the number of positive sentiment tweets and a positive change in EUA returns on 3rd July (B). This is confirmed later in the statistical tests outlined in Section 4.4. It is proposed later in Section 4.4.1 that these two days be treated as outliers, so strong is their influence.



The figure shows a plot of the log returns of EUA December 2013 futures prices. "A" indicates the largest single daily price movement on 16th April 2013. "B" indicates the price increase on 3rd July 2013.

Figure 4.2: Log Returns of EUA from 17th December 2012 to 16th December 2013



The figure displays the daily number of positive and negative climate change tweets during the period 17th Dec 2012 to 16th Dec 2013. The number of positive tweets is shown above the x-axis and the number of negative tweets is shown below the x-axis. "C" indicates the peak of negative tweets on 5th December 2013.

Figure 4.3: Counts of Positive and Negative Climate Change Tweets from 17th December 2012 to 16th December 2013

The figure displays the daily number of positive and negative emissions market tweets during the period 17th Dec 2012 to 16th Dec 2013. The number of positive tweets is shown above the x-axis and the number of negative tweets is shown below the x-axis. "A" indicates the peak of negative tweets on 16th April 2013 and "B" indicates the peak of positive tweets on 3rd July 2013.

Figure 4.4: Counts of Positive and Negative Emissions Market Tweets from 17th December 2012 to 16th December 2013

4.3 Emission Allowance, Energy and Market Data

In this section we discuss the EUA tick data and the choice of the size of the observation interval, the control variables, and some possible confounding influences. Following standard practice we use prompt December futures for EU emission allowance (EUA) prices as these are the most liquid of the EUA futures contracts, following Mizrach and Otsubo (2014) among others; the price data is supplied by the Intercontinental Exchange in London.

4.3.1 EUA Trading Frequency

Compared with major energy commodities like oil, EUA futures are infrequently traded[11] (see Table 4.6). It is not the objective of this research to examine the microstructure of the EUA futures market. Very useful work on this has already been carried out by Bredin et al. (2014), Chevallier and Sevi (2014), Mizrach and Otsubo (2014) and Ibikunle et al. (2016). In order to determine whether sentiment is a significant driver of

[11] As an illustration of this there were 286,493 transactions on the Brent futures January 2013 contract carried out on one day, Wednesday 5th December 2012. There were 446,506 EUA futures December 2013 contracts traded in the year from 17th Dec 2012 to 16th Dec 2013.

returns and volatility, it is preferable to avoid microstructure effects. We must therefore choose a suitably large value for m, the observation interval. Also in order to avoid the bid-ask bounce, the EUA price is calculated during every minute as being equal to the price during the previous minute, if there are no trades, or the mean of the trades during that minute weighted by trading volume.[12] This process is also followed for the control variables of prompt month Brent, NBP gas and ARA coal futures as well as the FTSE which are discussed in Section 4.3.1.1.

When a time series with an observation interval of m minutes is created for EUA December 2013 futures contracts, it is found that there may be many observation intervals with no trading activity, for example when we use $m = 10$ approximately 5% of these observations do not include trades, see Table 4.6. The choice of m, the length of the observation interval measured in minutes, is critical to the number of zeros in the time series. Previous work by Andersen et al. (2001) looking at the Dow Jones found the median duration (time between trades) was 23.1 seconds between trades, and a 5 minute observation interval was used to produce a time series. Similarly, Wang et al. (2008) use a 5 minute observation interval for crude oil futures. Both of these markets have far more frequent trades than the EU ETS. In Table 4.6 we see that if a series of length $m = 5$ minutes is chosen then almost one sixth of these observation intervals would have no trades recorded and hence would have zero as the value for the log return while there would likely be non-zero entries for the control variables and for sentiment; this would bias our findings on the possible connections between these variables. The issue is completely avoided by using daily frequency but this would lose much of the information available in the dataset. A reasonable minimal standard is to require that at least 99% of the periods have an EUA transaction. This would be achieved with $m \geqslant 20$.

In addition to avoiding a large number of zeros in the time series we wish to avoid the microstructure effects of the EUA futures market. By examining serial correlation and order imbalances Chordia et al. (2005) find that predictive inefficiencies should not persist beyond 60 minutes on the New York Stock Exchange. This suggests that

[12] The calculations are repeated using the median price with no noticeable changes to the results.

Timescale, m	N	Mean No of Transactions	No. of Zeros	% Zeros
1 minute	151,800	2.9	83,765	55.18%
5 minutes	30,360	14.7	4517	14.88%
10 minutes	15,180	29.4	732	4.82%
15 minutes	10,120	44.1	200	1.98%
20 minutes	7,620	58.8	71	0.93%
60 minutes	2,530	176.5	6	0.24%
600 minutes	253	1,764.8	0	0

The table shows the numbers of transactions per observation interval for a series of choices of m the length of the observation intervals in minutes. N is the number of such intervals during the year of our investigation. There were 446,506 transactions for EU emissions allowances on the futures market from 17th Dec 2012 until the expiry of these contracts on 16th Dec 2013. We count only transactions which took place during trading hours of 0700 to 1700 London time and exclude the backloading day 16th April 2013 as it was exceptional.

Table 4.6: Frequency of EUA Transactions

$m = 60$ would be a safe choice to avoid microstructure effects. A simple but effective way to decide on the length is to select a value of m which reduces serial correlation but retains intra-day frequency. There is very strong negative serial correlation for the first lag of the EUA futures returns when the frequency of the time series is set at $m = 5$, 10, 15 and $m = 20$ minutes; this is expected for high frequency data. There is very little evidence of serial correlation when $m = 60$ minutes from either PACF plots or Durbin Watson tests. We thus conclude that the serial correlation, which is a feature of the microstructure of the EUA market, is not strongly present at hourly frequency and we use a value of $m = 60$ for our reported tests, however as a robustness check the analysis will be repeated using a range of values for m.

4.3.1.1 Energy and Market Controls

Selecting from the the control variables used in Bredin and Muckley (2011), Chevallier (2011a), Creti et al. (2012), Aatola et al. (2013), Ahamada and Kirat (2015), Oestreich and Tsiakas (2015) and, Koch et al. (2016), and taking into account data availability, we use Brent oil, NBP [13] gas and ARA[14] coal prompt month futures as well as the FTSE 100 for the control variables. We analyse log returns of EUA prices, the four control variables of oil, gas, coal and the FTSE, and changes in sentiment, in a six variable VAR model following the empirical evidence presented in Chevallier (2011a,b,

[13] NBP is the price of natural gas in the UK, the market is directly connected to the mainland and so NBP prices reflect prices across Europe.

[14] ARA is is API2 standard coal for delivery to Amsterdam, Rotterdam or Antwerp.

20 Minute N=7,620	EUA	Brent Oil	ARA Coal	NBP Gas	FTSE
Mean x 10 $^{-6}$	14.2	-7.26	-2.72	-1.53	5.71
Max	0.263	0.012	0.176	0.044	0.008
Min	-0.295	-0.001	-0.200	-0.083	-0.008
Median	0	0	0	0	0
Std Dev	0.014	0.002	0.003	0.002	0.001
Skewness	0.465	-0.074	-79.946	-8.388	-0.158
Kurtosis	100.63	6.43	2478.01	505.19	6.53

Hourly, N=2,540	EUA	Brent Oil	ARA Coal	NBP Gas	FTSE
Mean x 10^{-6}	42.68	-21.77	-8.15	-4.58	17.12
Max	0.230	0.015	0.176	0.042	0.013
Min	-0.433	-0.012	-0.200	-0.086	-0.009
Median x 10^{-6}	0	0	0	0	76
Std Dev	0.021	0.003	0.0006	0.003	0.002
Skewness	-2.53	0.122	-4.639	-5.16	-0.11
Kurtosis	97.67	5.29	840.21	178.03	5.496

Daily, N = 254	EUA	Brent Oil	ARA Coal	NBP Gas	FTSE
Mean x 10^{-6}	426.81	-217.66	-81.48	-45.76	171.24
Max	0.268	0.025	0.176	0.046	0.026
Min	-0.448	-0.024	-0.203	-0.078	0.017
Median x 10^{-6}	-461.78	-43.87	0	-152.74	195.99
Std Dev	0.065	0.008	0.018	0.010	0.006
Skewness	-0.564	-0.030	-1.836	-1.214	0.176
Kurtosis	13.46	3.37	91.44	17.12	4.03

The table presents descriptive statistics for log returns of EUA futures and the control variables of Brent oil, NBP gas, ARA coal and the FTSE. Results are presented for data at 20 minute, hourly and daily frequency.

Table 4.7: Descriptive Statistics for Log Returns of EUAs and Control Variables

2013), Cummins (2012), Aatola et al. (2013) and, Sousa and Aguiar-Conraria (2015). A VAR model is suited to the serial correlation which is a natural consequence of the construction method of the sentiment impact series attested to in the literature by Mitra et al. (2009) and, Yu et al. (2015).

We find that the correlations between the five sentiment measures, and the energy and market control variables, are found to be not significantly different from zero, except for the correlations between the FTSE and Count Pos and Count Neg (see Table 4.9). These two results from the 20 correlation tests were only just significantly different from zero at the 5% level. This possibly hints that the FTSE is susceptible to the sentiment of the Emissions Market but is by no means conclusive and is not considered significant in the MHT framework. This supports our argument that sentiment itself influences EUA prices rather than being effective due to fundamental effects.

	LnR EUA	LnR Brent	LnR Coal	LnR Gas	LnR FTSE
LnR EUA	1	0.046*	0.003	0.069*	0.032
LnR Brent	0.116	1	-0.010	0.080*	0.181
LnR Coal	0.032	-0.072*	1	0.012	-0.022
LnR Gas	0.095*	0.098*	-0.047*	1	0.020
LnR FTSE	-0.043*	0.234	0.056*	-0.052*	1

The table presents the correlations of the log returns of the EUA and control variables. The top right presents results for hourly data, the bottom left presents results for daily data. The 5% significance level (indicated *) is 0.0389 for a sample size of N=2,540 (hourly, top right) and 0.1231 for a sample of N=254 (daily, bottom left).

Table 4.8: Correlation Matrix for EUA and Control Variables

	Brent	NBP Gas	Coal	FTSE
Sum Pos	0.005	-0.019	-0.001	0.010
Sum Neg	-0.003	0.020	-0.004	-0.009
Count Pos	0.015	-0.008	0.002	-0.048*
Count Neg	0.013	-0.007	0.000	0.044*
Count All	0.009	-0.010	-0.000	-0.032

The table presents the correlations of the five sentiment measures and the control variables. The significance level at 5% is indicated (*) by values whose absolute value is above 0.0389 for a sample size of N=2,540.

Table 4.9: Correlation Matrix for Sentiment and Control Variables

4.4 Statistical Testing

Having selected intra-day control variables we wish to test for an association between carbon market sentiment, measured from tweets, and the returns of EUA futures contracts. As this is the first investigation into the effect of such explicitly defined sentiment in the EU ETS we propose a straightforward model, that sentiment drives both price and volatility of EUA prices. A similar direct association was found between sentiment and oil prices in Deeney, Cummins, Dowling and Bermingham (2015). In order to investigate the dynamic links between sentiment and EUA returns we use a vector autoregression (VAR) model to examine the effects of lagged variables and the possible Granger causality between sentiment and returns as used by Sousa and Aguiar-Conraria (2015). This is necessary to take account of the serial correlation which is induced in the sentiment impact measures due to their method of construction. In order to test the possible links between sentiment and the volatility of EUA returns we use GARCH and Threshold GARCH models, see Chevallier (2011a). A Threshold GARCH model is useful as it allows the model to respond differently to negative shocks and positive shocks. It is found that there is a significant improvement using the Threshold GARCH

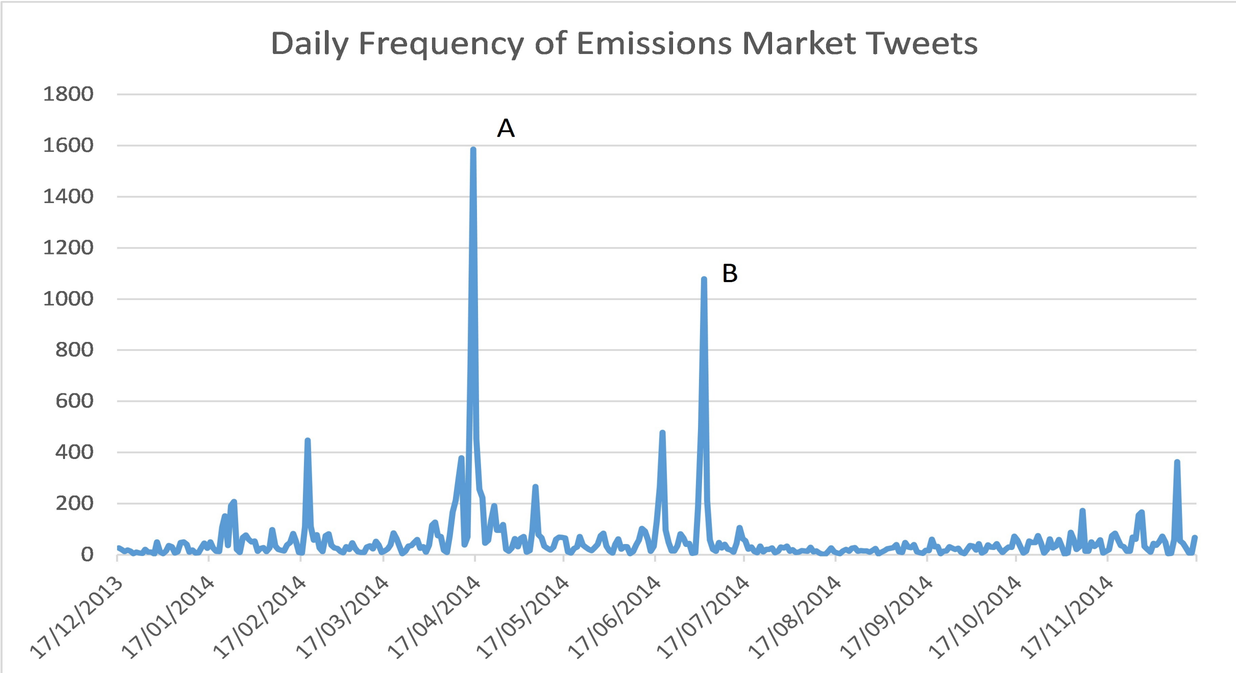


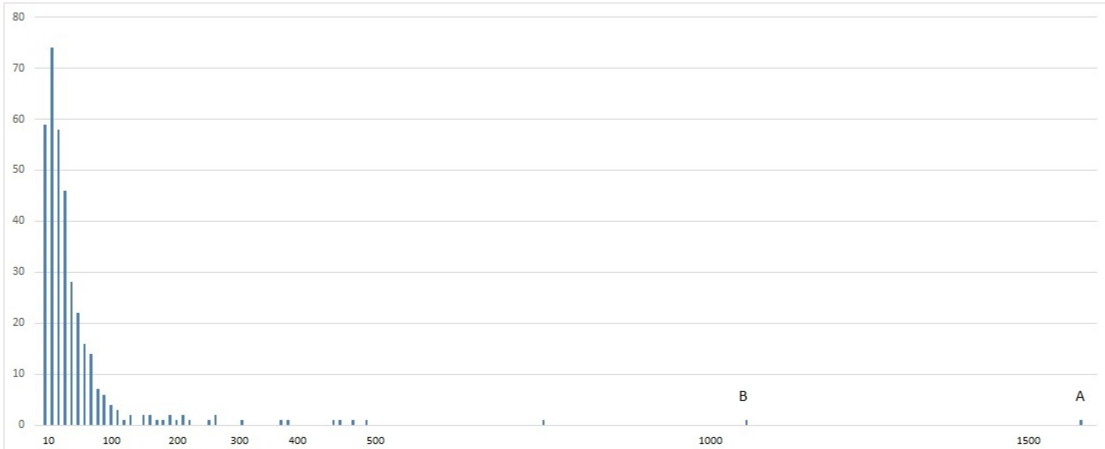
Figure 4.5: Daily Frequency of Emissions Market Tweets

model compared with the GARCH model.

In order to directly test the association of the control variables and emission allowances we use a simple multivariate regression. This confirms the VAR results and the choice of control variables. As we are carrying out many hypothesis tests we use a multiple hypothesis testing framework to take account of the multiple comparisons problem, see Section 4.5.4. Following standard practice we restrict or attention to trading hours, which are from 0700 to 1700 London time following Zhu et al. (2015).

4.4.1 Identification of Outliers

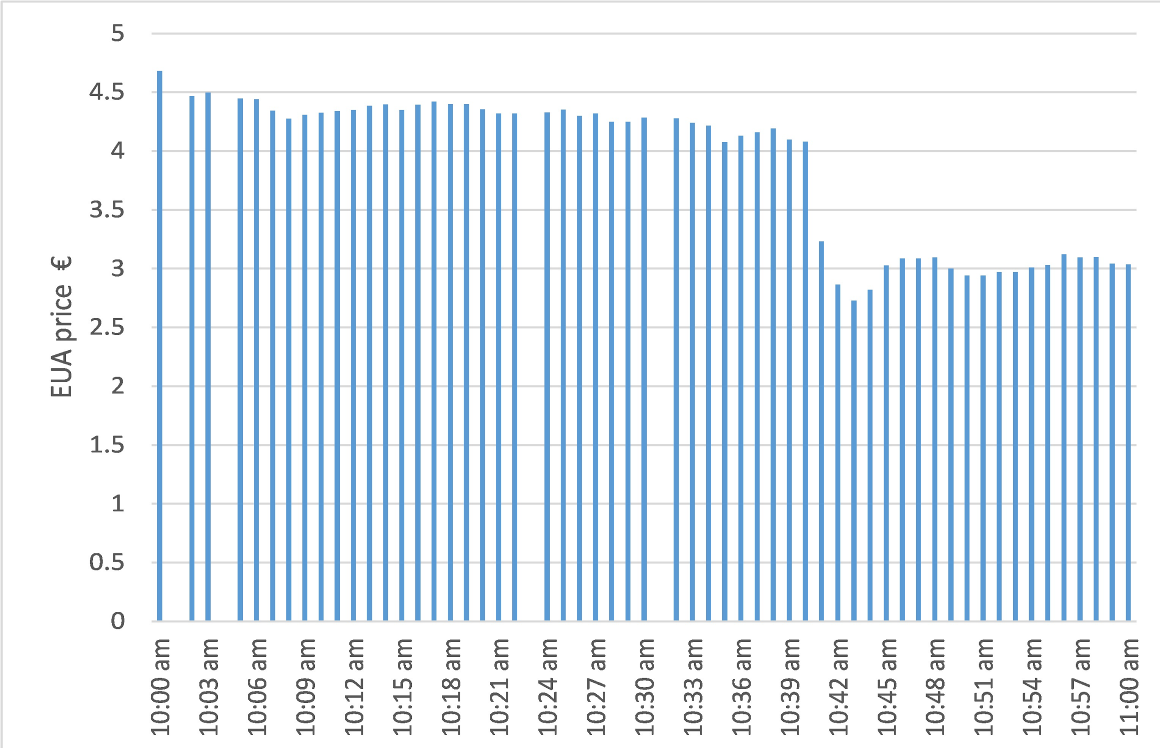
It is suggested by examining the histograms of the number of tweets per day, that there may be outliers in both the numbers of emissions market tweets and the climate change tweets (Figures 4.6 and 4.8). This is supported by the events in the European Parliament as described in Section 4.3. In Figure 4.6, a histogram of the number of emissions market tweets per day, we see that the days 16th April (A) and 3rd July (B) would appear to be outliers while 15th April may also be an outlier. In Figure 4.8, a histogram of the number of climate change tweets per day we see that the days 5th December (C), 6th December (D) and 27th September (E) may be outliers. We now discuss the identification of outliers in these two sets of data separately.



The figure displays the histogram of the frequency of occurrences of emissions market tweets per day. “A” indicates 16th April 2013 (1,586 tweets), “B” indicates 3rd July 2013 (1,079 tweets) and the next highest number of tweets on a single day (762) occurred on 15th April 2013.

Figure 4.6: Histogram of the Daily Frequency of Emissions Market Tweets

We see from the list of excess emissions market tweets in Table 4.3 that the 16th April 2013 and the 3rd July are in 1st and 2nd position for the largest number of emissions market tweets for the year under consideration. It is also the case that the 15th April and the 2nd of July are in 3rd and 5th positions. This suggests that the large numbers of tweets are connected with extreme events at these two times. Furthermore we see on a scatter plot of changes in emissions market Twitter intensity and EUA returns (Figure 4.10) that these two days are farthest away from the centre of the data. We therefore have reasonably strong evidence suggesting that these days 16th April and 3rd July are outliers. The explanation for this extreme behaviour is that on 16th April 2013 there was a narrow rejection of backloading by the European Parliament which caused a huge drop in EUA December 2013 futures prices from €4.76 at the close of business on 15th to €3.09 at the close of business on 16th; the drop in the price of the June 2013 expiry futures was even larger but we use December futures as they are the most liquid of the futures. This was accompanied by the largest number of emissions market tweets on a single day (1,586) see Figure 4.5. On 3rd July 2013 the European Parliament decided to send the backloading decision back to national parliaments. This caused the price of EUAs to rise from €4.29 to €4.69 a rise of 9.3%. While this is a less dramatic change in EUA prices it was accompanied by the second-largest number



The plot shows the price of EUAs during each minute from 10am GMT to 11am GMT on 16th April 2013, the day of the rejection of the backloading proposal by the European Parliament. The missing lines are due to minutes during this hour when there were no trades.

Figure 4.7: Price of EUA Futures during the backloading decision of the European Parliament

of tweets on a single day (1,079).

The sudden collapse in the price of EUAs occurred at 10:41am GMT and can be seen in Figure 4.7. This was due to the European Parliament rejecting a plan which had been intended to support the price of EUAs under a proposal of the European Commission to withhold 900 million EUAs from the market and release them at a later date in Phase I of the EU ETS. This process, known as “backloading”, was proposed as a way to address the historical oversupply of allowances that resulted from the general over-allocation of allowances by Member States to their industries during Phases I and II of the scheme. Backloading was aimed at supporting EUA prices while holding on to the support of EU states who wanted to maintain the supply of EUAs in the long term. Given the size of this price change it is an ideal opportunity to verify that there is an association between Twitter sentiment and EUA price changes. Later in the year, on 3rd July 2013, there was a decision of the European Parliament to pass discussions about backloading to national parliaments. This increased EUA prices by a lesser amount than the previous fall. These two days had the largest number of emissions market tweets per day for the year and as such represent important subjects for further investigation. The large number of emissions market tweets (see Figure 4.5) suggests that there is a very close association between tweets regarding the EU ETS and the EUA price.

While these two days provide an illustration that emissions market tweets and EUA price returns are strongly associated, they have the characteristics of outliers which would be capable of driving the results of tests. In order to investigate the unexceptional behaviour of EUA returns it is prudent to run such tests both with and without these two backloading events.

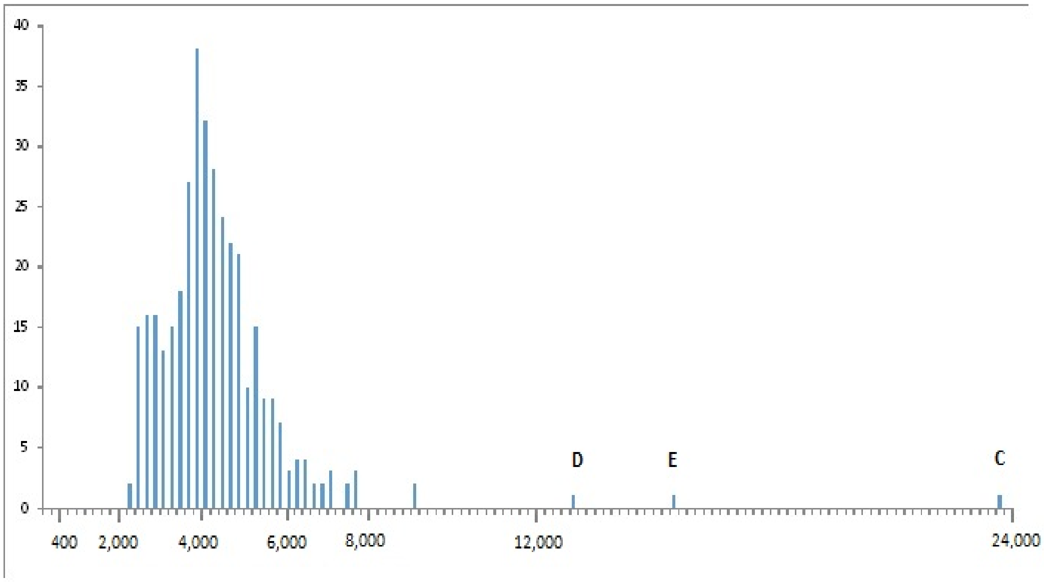
On examination of the climate change tweets daily histogram in Figure 4.8 we note that there are three days which have exceptionally large numbers of tweets, the 5th (C) and 6th (D) December 2013 and 27th September 2013 (E). These dates do not have unusual behaviour in EUA returns. The cause of the large number of tweets in December was flooding around Britain which produced a huge public reaction[15], the sentiment of which was measured as negative (see Figure 4.4). On 27th September 2013 the Intergovernmental Panel on Climate Change (IPCC) released its report IPCC (2013) indicating that it was "extremely likely" that humans were responsible for climate change. This also produced a large response in the print media[16]. While there is less analytic evidence for these three days being outliers it is prudent to repeat the analysis of the effect of climate change sentiment on EUA returns both with and without these three days.

4.4.2 VAR Model and Granger Causality

Following Chevallier (2011a,b, 2013), Cummins (2013b), Aatola et al. (2013) and, Sousa and Aguiar-Conraria (2015) we use a VAR model to examine the interactions between the EUA price, emissions market sentiment and the control variables; we also test for Granger causality. Most recently Chen, Muckley and Bredin (2017) addresses the issue

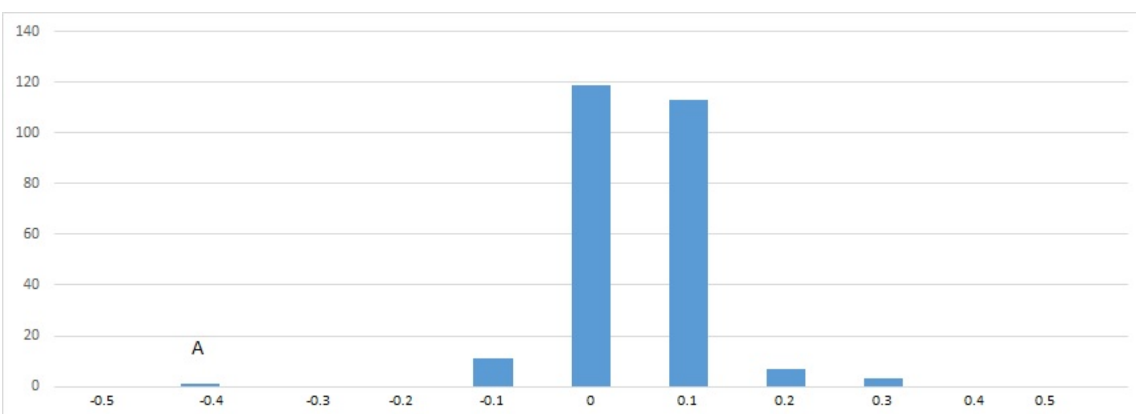
[15]In total 1,895 sources in the UK media reported flooding in a search conducted using Lexis Nexis for 5th and 6th December 2013.

[16]In total 1,259 sources were found by Lexis Nexis for the search term "climate change" on 27th September 2013.



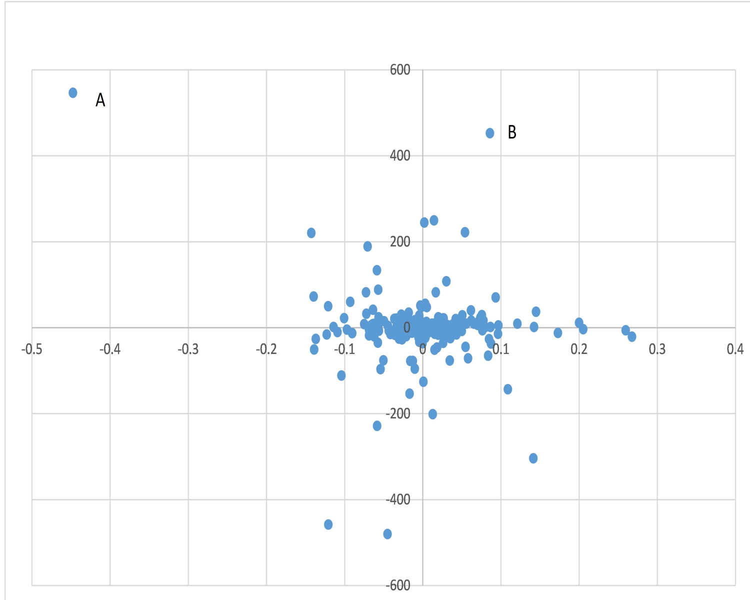
The figure displays the histogram of the frequency of occurrences of climate change tweets per day. “C” indicates 5th December 2013 (22,970 tweets), “D” indicates 6th December 2013 (12,611 tweets) and “E” indicates 27th September 2013 (15,083 tweets).

Figure 4.8: Histogram of the Daily Frequency of Climate Change Tweets



The figure presents the histogram of daily log returns of EUA futures. “A” indicates the log returns on 16th April 2013.

Figure 4.9: Histogram of Daily Log Returns of EUAs



The scatter plot shows the log returns of EUA price (horizontal) and the change in the number of tweets per day. The proposed outliers are indicated as A and B.

Figure 4.10: Scatter Plot of the Daily Log Returns and Daily Change in the Number of Emission Market Tweets

of the existence of long run behaviour in EUA tick data. Chen, Muckley and Bredin (2017) use a test by Lo (1991) and find no evidence for long run memory, this encourages the use of a VAR model. The lack of evidence of long run memory repeats findings by Nazifi and Milunovich (2010) who had previously found that there was no long term relationship between EUA prices and energy commodities.

Following Sousa and Aguiar-Conraria (2015), Chevallier (2011b) and Aatola et al. (2013) we analyse the three energy prices Brent, NBP gas and ARA coal futures, the FTSE, and the EUA futures prices in a dynamic VAR setting to take in to account the possible lagged associations between the EUA prices and the control variables. This will allow likely serial correlation to be accounted for in the model which will be present in the sentiment measures.

For both emissions market sentiment and climate change sentiment, the four sentiment impacts are used, namely the sentiment impact based on the sum of the positive sentiment scores, the sum of the negative scores, the count of the positive tweets and the count of the negative tweets. The correlations between positive and negative emissions market sentiment measurements are tested at hourly and daily frequency and

Variable	ADF	ADF + Trend	KPSS	KPSS + Trend
$\triangle EUA$	9.8 x 10^{-9}	2.8 x 10^{-7}	> 0.1	> 0.1
$\triangle Brent$	5.3 x 10^{-16}	4.9 x 10^{-16}	> 0.1	> 0.1
$\triangle NBP$	6.8 x 10^{-29}	1.6 x 10^{-30}	> 0.1	> 0.1
$\triangle FTSE$	1.6 x 10^{-28}	5.1 x 10^{-30}	> 0.1	> 0.1
$\triangle Coal$	1.9 x 10^{-27}	1.5 x 10^{-28}	> 0.1	> 0.1
$\triangle PosSumSent$	1.3 x 10^{-9}	1.3 x 10^{-8}	> 0.1	> 0.1
$\triangle NegSumSent$	2.3 x 10^{-9}	1.9 x 10^{-8}	> 0.1	$= 0.1$
$\triangle PosCountSent$	1.9 x 10^{-12}	1.9 x 10^{-11}	> 0.1	> 0.05
$\triangle NegSumSent$	2.0 x 10^{-10}	2.1 x 10^{-10}	> 0.1	> 0.1
$\triangle AllCountSent$	8.8 x 10^{-11}	4.8 x 10^{-10}	> 0.1	> 0.1

The table presents the p-values of the stationarity tests for the variables. The Augmented Dickey Fuller (ADF) test has a null of non-stationarity. The Kwiatkowski Phillips Schmidt Shin (KPSS) test has a null of stationarity. The results show strong evidence to accept that the variables are stationary. Models with the addition of a constant, and with the addition of a constant and a trend are used for robustness.

Table 4.10: Stationarity Test Results

are presented in Table 4.5. These show that positive and negative sums and counts are strongly correlated, hence these variables are tested separately. The two measures based on counts of tweets rather than sum of scores lose information by replacing the scaled sentiment measure assigned to each tweet with a count-based measure, this approach serves as a useful robustness check as it removes reliance on the accuracy of the scaling of the sentiment measure. An additional fifth measure is used which is the number of tweets per observation interval. This allows the efficacy of the sentiment analysis to be tested. In order to compare the relative size of the influences of sentiment and the energy market, variables are standardized. All variables are tested for stationarity using the ADF and KPSS tests, see Table 4.10. We use the FTSE as a measure of economic activity and omit the price of electricity because Aatola et al. (2013) and Fezzi and Bunn (2009) suggest that electricity price is endogenous. The Akaike information criteria are used to decide the optimal lag lengths for the VAR. Explicitly the VAR equations are

$$\Delta EUA_t = \alpha + \sum_{i=1}^{11} \{\beta EUA, EUA_i \Delta EUA_{t-i} + \beta EUA, Sent_i \Delta Sent_{t-i} + \beta EUA, Brent_i \Delta Brent_{t-i}$$

$$+\beta EUA, Coal_i \Delta Coal_{t-i} + \beta EUA, Gas_i \Delta Gas_{t-i} + \beta EUA, FTSE_i \Delta FTSE_{t-i}\} + \epsilon_t$$

$$\Delta Sent_t = \alpha + \sum_{i=1}^{11}\{\beta Sent, EUA_i \Delta EUA_{t-i} + \beta Sent, Sent_i \Delta Sent_{t-i} + \beta Sent, Brent_i \Delta Brent_{t-i}$$

$$+\beta Sent, Coal_i \Delta Coal_{t-i} + \beta Sent, Gas_i \Delta Gas_{t-i} + \beta Sent, FTSE_i \Delta FTSE_{t-i}\} + \epsilon_t$$

$$\Delta Brent_t = \alpha + \sum_{i=1}^{11}\{\beta Brent, EUA_i \Delta EUA_{t-i} + \beta Brent, Sent_i \Delta Sent_{t-i} + \beta Brent, Brent_i \Delta Brent_{t-i}$$

$$+\beta Brent, Coal_i \Delta Coal_{t-i} + \beta Brent, Gas_i \Delta Gas_{t-i} + \beta Brent, FTSE_i \Delta FTSE_{t-i}\} + \epsilon_t$$

$$\Delta Coal_t = \alpha + \sum_{i=1}^{11}\{\beta Coal, , EUA_i \Delta EUA_{t-i} + \beta Coal, Sent_i \Delta Sent_{t-i} + \beta Coal, Brent_i \Delta Brent_{t-i}$$

$$+\beta Coal, Coal_i \Delta Coal_{t-i} + \beta Coal, Gas_i \Delta Gas_{t-i} + \beta Coal, FTSE_i \Delta FTSE_{t-i}\} + \epsilon_t$$

$$\Delta Gas_t = \alpha + \sum_{i=1}^{11}\{\beta Gas, EUA_i \Delta EUA_{t-i} + \beta Gas, Sent_i \Delta Sent_{t-i} + \beta Gas, Brent_i \Delta Brent_{t-i}$$

$$+\beta Gas, Coal_i \Delta Coal_{t-i} + \beta Gas, Gas_i \Delta Gas_{t-i} + \beta Gas, FTSE_i \Delta FTSE_{t-i}\} + \epsilon_t$$

$$\Delta FTSE_t = \alpha + \sum_{i=1}^{11}\{\beta FTSE, EUA_i \Delta EUA_{t-i} + \beta FTSE, Sent_i \Delta Sent_{t-i} + \beta FTSE, Brent_i \Delta Brent_{t-i}$$

$$+\beta FTSE, Coal_i \Delta Coal_{t-i} + \beta FTSE, Gas_i \Delta Gas_{t-i} + \beta FTSE, FTSE_i \Delta FTSE_{t-i}\} + \epsilon_t$$

where the log return variables of EUA, Brent, Coal, Gas, FTSE are as before.

The VAR analysis is repeated for each of the four measures of sentiment and also for the Twitter traffic intensity measures of both emissions market sentiment and climate change sentiment.

4.4.3 Control Variable Association with EUA Prices

The choice of control variables is tested both contemporaneously and predictively. These control variables are chosen from the literature as detailed above in Section 4.3.1.1 notably Bredin and Muckley (2011), Chevallier (2011a), Creti et al. (2012), Aatola et al. (2013), Lutz et al. (2013), Ahamada and Kirat (2015), Oestreich and Tsiakas (2015) and, Koch et al. (2016). Here we aim to verify that these variables are useful at high frequency and further, we wish to test if they have predictive value. In order to examine the efficacy of the control variables contemporaneously we use a multivariate regression equation

$$\Delta EUA_t = \alpha + \beta_{Brent}\Delta Brent_t + \beta_{NBP}\Delta NBP_t + \beta_{Coal}\Delta Coal_t + \beta_{FTSE}\Delta FTSE_t + \varepsilon_t. \tag{4.11}$$

where ΔEUA_t is the log return series of the EUA Dec 2013 futures, $\Delta Brent_t$ is the log return of the prompt month Brent oil futures, ΔNBP is the log return of the prompt month National Balance Point natural gas price, ΔARA_t is the log return of first month API2 grade Coal for delivery to Amsterdam, Rotterdam or Antwerp, $\Delta FTSE$ is the log return of the FTSE, and the β coefficients are calculated by OLS regression. To test whether there is any association between one hour lagged control variables and EUA returns we test the equation

$$\Delta EUA_t = \alpha + \beta_{Brent}\Delta Brent_{t-1} + \beta_{NBP}\Delta NBP_{t-1} + \beta_{Coal}\Delta Coal_{t-1} + \beta_{FTSE}\Delta FTSE_{t-1} + \varepsilon_t \tag{4.12}$$

The data for the control variables are supplied by the Intercontinental Exchange (ICE). The size of the observation interval is measured in minutes and denoted m, this allows the testing to be carried out at a range of frequencies. To avoid the influence of microstructure we choose $m = 60$, a range of values near to this is used as a robustness test. Results are presented for one hour ahead predictions. In order to compare the relative size of the influences of the controls, variables are standardized. All variables are tested for stationarity using the ADF and KPSS tests.

4.4.4 GARCH Specification

It has long been the case that sentiment and volatility have been considered to be almost synonymous, see Brown (1999), Whaley (2000) and, Baker and Wurgler (2006). We examine this connection by adding sentiment to a volatility model and measuring any improvement in the model using a likelihood ratio test. This method of adding a variable to the variance equation is based on a suggestion by Reider (2009) and similar use by Lu and Chen (2011), Kumari and Mahakud (2015) and Deeney et al. (2016a). GARCH models have been found to be very useful for data which has volatility clustering such as equity markets and commodity futures. We use a standard GARCH(1,1) and a Threshold GARCH(1,1) to test whether the inclusion of sentiment information improves the volatility modelling. We use a binary indicator of strong or weak level of sentiment which takes the value +1 when the sentiment is higher than the mean, and zero otherwise; for the sum of negative sentiment which is measured using negative numbers, we set the dummy variable to +1 when the sentiment impact is below the mean, see Equations 4.6 to 4.10. As a robustness check, the analysis is repeated using the median in the place of the mean. We use the usual four measures of sentiment impact based on the count of positive tweets, the count of negative tweets, the sum of the positive sentiment scores and the sum of the negative sentiment scores. In addition we also test the count of all tweets.

There is an inconsistency between the assumption of constant volatility required for regression and VAR models, and the use of GARCH models which examine the variability in volatility and often find such variability. An important principle in statistics is that "All models are wrong; some models are useful" (Box et al.; 1978). Thus we have in the literature widespread use of models using the assumption of constant volatility. For example the following use VAR models for EUA data Chevallier (2011a,b, 2013), Cummins (2012), Aatola et al. (2013) and, Sousa and Aguiar-Conraria (2015). Most recently Chen, Muckley and Bredin (2017) use an event study methodology which likewise assumes a constant volatility. At the same time we have papers using GARCH models which test for, and usually find, variations in the volatility of EUA data, such as Miclaus et al. (2008), Paolella and Taschini (2008), Benz and Trück (2009), Regnard and Zakoian (2011), Wang and Wu (2012) Lutz et al. (2013), Venmans (2015) and Zeitlberger and Brauneis (2016). Indeed in the oil literature there are papers which use both assumptions of constant volatility and examine how the volatility changes using GARCH models such as Aboura and Chevallier (2013), Wolfe and Rosenman (2014) and Kim (2015). We can have confidence that the EUA data is reasonably close to constant volatility as the ADF and KPSS tests failed to find evidence of non-stationarity and we are further assured that our testing is reasonable due to the support from the literature.

4.4.4.1 GARCH(1,1)

We fit the standard GARCH(1,1) model as used by Benz and Trück (2009), Oberndorfer (2009) and Chevallier (2011a), and then add a sentiment term to test whether this improves the model measuring the improvement with a likelihood ratio test. The equations for the GARCH model are

$$\Delta EUA_t = \mu + \rho \Delta EUA_{t-1} + \epsilon_t,\ \epsilon_t \sim i.i.d.(0, \sigma_t^2)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma StrongSent_{t-1} \tag{4.13}$$

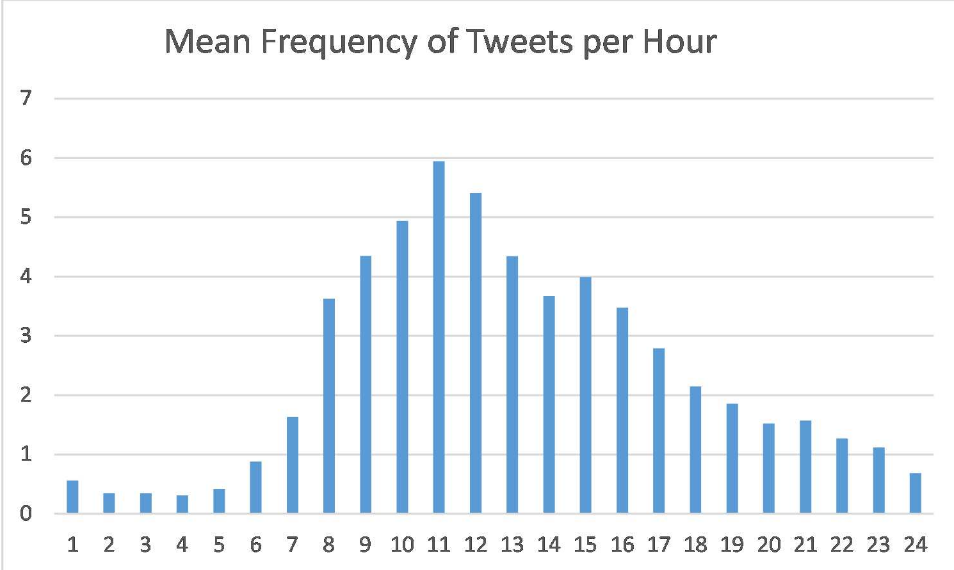
where ΔEUA_t is the log returns of the EUA price, μ is the drift, ρ is the coefficient of first order auto-correlation, $\alpha_0, \alpha_1, \beta, \gamma$ are constants, ϵ_t is the error term with mean zero and conditional variance σ_t^2, and $StrongSent_{t-1}$ is one of the binary indicators of sentiment defined in Equations 4.6 to 4.10. These take the value 1 when the sentiment impact is larger than the mean and zero otherwise. For the sum of negative sentiment impact, which is non-positive, $StrongSent_t$ takes the value 1 when it is below the mean. We test a series of 4 sentiment impacts based on the count of positive and negative tweets, the sum of the sentiment of positive and negative tweets and also use the total number of tweets.

4.4.4.2 Samuelson Hypothesis and Time Patterns in the Data

The volatility of EUA returns are likely to be influenced by the Samuelson hypothesis and by the time of day. To verify that the Samuelson hypothesis, suggested by Samuelson (1965), Andersen et al. (2001), Chang et al. (2009) and, Duong and Kalev (2008) is not confounding the results, we repeat the volatility tests with dummy variables for each of the 12 months, recall that the data covers 13 consecutive months from Dec 2012 to Dec 2013. We then repeat the analysis again with data only up to the end of November 2013 following Chevallier and Sevi (2014). This did not change the conclusion that there was a highly significant effect of sentiment on volatility. There is often a high level of volatility due to high frequency of transactions, after opening and before closing of markets each day, see Cont (2011), and so to avoid this influencing our conclusions, we test the effect of the time by allocating dummy variables for each of the nine hours after the first trading hour each day. There is little evidence that time of day has any influence on price level. Time of the day is shown to influence volatility, but it does not change the conclusion that sentiment has an influence on volatility. A lesser concern is that the deviation of the present temperature from the seasonal average has been shown to be an influence on EUA prices, see Bredin and Muckley (2011), Mansanet-Bataller et al. (2011) and Alberola et al. (2008), however intra-day temperatures and intra-day average temperatures were not available. As a robustness test the analysis is repeated with the control variables in the mean equation, the same conclusions followed.

4.4.4.3 Threshold GARCH (1,1)

The explanation for different effects of positive and negative sentiment is present in the



The plot shows the mean number of emissions market tweets per hour during the year. Hours are in local time labelled for the end of each hour.

Figure 4.11: Mean Frequency of Tweets per Hour

literature, notably the "negativity effect" mentioned by Chevalier and Mayzlin (2006), Soroka (2006), Akhtar et al. (2013) and Sprenger, Sandner, Tumasjan and Welpe (2014) (see Section 4.2). This is based on the idea that market participants are over-optimistic on average, recall that there were more positive emissions market tweets than negative, see Table 4.2, and so respond more strongly to bad news than to the good news they had been expecting, see Liu et al. (2014) and Feng et al. (2011). This behaviour is modelled well by a Threshold GARCH model which allows negative shocks to add to the variance independently from positive shocks. The particular form of the Threshold GARCH model used here is selected as it is the same as the GARCH model with the addition of one variable. This makes it possible to test the improvement of the Threshold GARCH compared with GARCH using a likelihood ratio test. Threshold GARCH is used by Alberola et al. (2009), Chevallier (2009) and, Byun and Cho (2013) to model EUA price dynamics. It is found that the addition of the threshold term $(\alpha_2(\epsilon_{t-1}^{-})^2)$, term significantly improves the Threshold GARCH model compared with the GARCH model in all five applications, see Table 4.14. Following the same nomenclature as Eqn 4.13 we test the following Threshold GARCH specification following (Chevallier; 2009),

$$\Delta EUA_t = \mu + \rho \Delta EUA_t + \epsilon_t, \ \epsilon_t \sim i.i.d.(0, \sigma_t^2)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 (\epsilon_{t-1}^-)^2 + \beta \sigma_{t-1}^2 + \gamma StrongSent_{t-1} \tag{4.14}$$

where ϵ_{t-1}^- is the value of the previous residual when it is negative and zero otherwise, so that the coefficient α_2 measures the excess volatility due to a negative residual. The same robustness tests are carried out as for the GARCH model regarding the Samuelson hypothesis and U-shaped daily volatility.

4.5 Results

We find there is very strong evidence that sentiment measured from tweets concerning the emissions market has an effect on the level and volatility of EUA prices. Using a vector autoregressive (VAR) model we find that changes in the sentiment measured from tweets concerning the EU emissions market predicts EUA returns and we find there is bi-directional Granger causality between changes in negative sentiment and EUA returns. There is very strong evidence from the Threshold GARCH model that stronger than average levels of emissions market sentiment are associated with higher levels of volatility of EUA returns. There is only very weak evidence that climate change sentiment influences the levels of EUA futures but there is evidence that strong climate change sentiment is associated with high levels of EUA returns volatility. Thus we see that tweets from the emissions market have a richer insight into EUA behaviour than the more general category of climate change tweets. We find that there is some weak evidence that the returns of oil, gas and to a lesser extent the FTSE, can explain EUA returns, but that there is no evidence of predictability for a period of one hour (or longer). This suggests that the emissions market efficiently assimilates energy information into prices.

We repeat our tests to consider the effect of including or excluding the outliers and find that the observations in Section 4.4.1 were correct. The inclusion or exclusion of

16th April and 3rd July does change the conclusions for the positive emissions sentiment measures, but not for the negative emissions sentiment measures or the count of emissions tweets. These days had large spikes in the number of emissions market tweets. This supports the decision to omit the outliers from reported results. The inclusion or omission of the outliers of 5th and 6th December 2013 and 27th September does not change the climate change sentiment results. These days produced large spikes in the numbers of tweets posted concerning climate change.

In this investigation many hypothesis tests are carried out which leaves the conclusions open to the multiple comparisons problem. In Section 4.5.4 we see the effect that this has on the conventionally significant results. Coefficients which are considered significant under the more stringent conditions of the MHT framework are in bold text in tables of results. We now examine the results for emissions market sentiment and climate change sentiment separately.

4.5.1 Results for Emissions Market Tweets

We discuss the findings for the emissions market sentiment in greater detail first looking at the outliers, then discussing the connection between changes in sentiment and changes in EUA prices, and finally looking at the effect of strong sentiment on volatility. The use of a multiple hypothesis testing framework follows in Section 4.5.4.

4.5.1.1 Outliers for Emissions Sentiment

When the VAR tests and Granger causality tests are carried out, including and excluding the two outliers of 16th April and 3rd July, we find that there is a considerable difference in the outcomes. Table 4.11 shows that for the two positive sentiment measures, Sum Pos and Count Pos, there is a much reduced significance when the two outliers are omitted. The results for the count of tweets measure is less significant but remains. This indicates that these two outliers are driving these results. There is however, very little change for the two measures of negative sentiment for the VAR analysis.

We see in Table 4.12, the summary of the Granger causality tests, that there is no

	Including Outliers											Excluding Outliers										
Lags	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Sum Pos		+		+	-															+	-	
		+			-																	
Count Pos		+		+	-								+								-	
				+	-																-	
Sum Neg	-	-			+				+	+		-	-			+				+	+	
		-			+					+			-			+					+	
					+					+						+					+	
Count Neg		+			-				-	-				-		-				+	-	
		+			-					-						-					-	
					-					-						-					-	
All Tweets		+	-	+	-	-				-			+			-					-	+
		+	-	+	-																-	+
			-	+	-																-	+

The table presents a summary of the p-values and signs of the sentiment coefficients in the EUA equations of the VAR analysis. + indicates a positive coefficient. - indicates a negative coefficient. The number of + or - signs arranged vertically indicates the level of significance, one for 10%, two for 5% and three for 1%. The left side of the table shows the results when the two outliers of 16th April and 3rd July are included, the right side shows results when these two days are excluded. The numbers indicate the lag length for the sentiment measured in hours. The total lag length of 11 was chosen by Akakie information criteria.

Table 4.11: Summary of VAR Analysis for Emissions Market Sentiment Measures and Inclusion / Exclusion of Outliers

significant evidence that either of the positive sentiment measures Granger-cause EUA prices when the two outliers are excluded. There is little change to the conclusions for the two negative sentiment measures or to the count of tweets measure when the outliers are excluded. The VAR and Granger causality results confirm the indications which were discussed in Section 4.4.1 that the events of 16th April and 3rd July are outliers, hence they are omitted from the results presented below, these results are included in the Appendices.

4.5.1.2 VAR and Granger Causality Results for Emissions Market Tweets

A VAR analysis is well suited to this application because there is a high degree of serial correlation in the sentiment impact variables due to their construction. The results of the VAR analysis are summarized in Tables 4.11 and 4.13. The data is tested for

	Including Outliers	Excluding Outliers
Sum Pos	0.1029	0.2331
Count Pos	0.0450	0.1706
Sum Neg	0.0000	0.0001
Count Neg	0.0000	0.0001
Count All	0.0000	0.0014

The table presents the p-values of the Granger Causality tests of whether the changes in the various measures of emissions market sentiment Granger Cause EUA futures returns.

Table 4.12: Summary of Granger Causality Results for Emissions Market Sentiment

stationarity using the ADF and KPSS tests which find the time series to be I(0). The lag lengths are selected by the Akaike information criteria. There was little evidence of serial correlation in the residuals. The results of VAR analysis are found in Appendices B and D. The results for Granger causality including outliers are found in Appendix C, the results without the outliers is found in Tables 4.14, 4.15 and 4.16.

We find that there is very strong evidence with p-values of 5.4 x $10^{-6}$and 4.2 x 10^{-7}, that the changes in the Sum Neg and Count Neg sentiment impacts measures Granger-cause EUA returns, and we find strong evidence that changes in the count of tweets, which measures traffic intensity, also Granger-causes EUA returns. This information is presented in Figures 4.14, 4.15 and 4.16 where the direction of the arrow indicates the direction of Granger causality. There is very high significance with p-values below 1%, of this finding of bi-directional causality between each of the sentiment measures and EUA prices except in one case, count of all tweets, when the p-value is 0.0104. The forward direction Granger causality from emissions market sentiment to EUA price returns is explained by the market using sentiment as a source of information about the future. The reverse direction from EUA price returns is explained by the reaction of the emissions market to price movements, in that a positive price movement is perceived as being positive by quite a number of those posting tweets. This pattern of bi-directional causality was observed by Brown and Cliff (2004) in the stock market.

The VAR results show that many of the lags of the changes in the sum of negative sentiment, count of negative sentiment and count of tweets, and a smaller number of the lags of sum of positive and count of positive sentiment, are associated with EUA returns. The signs of the coefficients vary both within the lag and within the sentiment measure. This anomaly is addressed later in Section 4.5.4. There is no evidence of a similar effect with positive sentiment, either sum or count, see Table 4.14 and Figures 4.12 and 4.13; this may be a consequence of the negativity effect which posits that negative news has a greater effect on prices than positive, see Soroka (2006), Sprenger, Sandner, Tumasjan and Welpe (2014), Chevalier and Mayzlin (2006) and Akhtar et al. (2013). We thus conclude that because of the VAR and Granger causality tests we have established a direct association between the emissions market sentiment measures and the price of EUAs. These results are different from Sousa and Aguiar-Conraria (2015) who find that in the EU ETS the economy, in their case the FTS Eurofirst 300, Granger-causes emissions prices at the 5% level. Fezzi and Bunn (2009) and Mansanet-Bataller et al. (2007) also find that energy prices are associated with carbon prices in the EU ETS. However these studies use daily frequency but here we use hourly frequency.

We find that there are no significant coefficients even at the conventional 10% level, from any of the control variables to EUA returns. This is in agreement with the results of the regression analysis in Section 4.5.3, which finds that the log returns of energy commodities and the FTSE do not predict changes in EUA prices.

Sentiment does not affect only EUA returns. When we examine the count of negative tweets, which gives similar results to sum of negative tweets, we see from Table 4.23 that there is significant influence from changes in sentiment to Brent and gas returns, and to a lesser extent the FTSE. This confirms the choice of the control variables and supports the placing of EUAs within the energy commodity arena. We recall that sentiment in the oil markets is found to be a significant driver of oil prices in Chapter 2, in that case sentiment was measured from proxies within the oil market. Thus it comes as no surprise that sentiment in another part of the energy market, namely emissions market sentiment, would be associated with Brent and gas prices.

There are many other interactions which are not the focus of this investigation but which deserve comment. We find that there is an association between the FTSE and Brent using intra-day data. Chapter 2 also finds evidence that there is an association between the Hang Seng returns and oil returns, but not between European stock indices

	Sum Pos	Sum Neg	Count Pos	Count Neg	Count All
Sent$_{t-1}$	-0.025	-0.148*	-0.040	0.015	-0.105
	(0.7594)	(0.0805)	(0.6359)	(0.863)	(0.3063)
Sent$_{t-2}$	0.125	-0.193**	0.151*	0.017	0.169*
	(0.1107)	(0.0174)	(0.0595)	(0.842)	(0.0599)
Sent$_{t-3}$	-0.089	0.126	-0.075	-0.148*	-0.038
	(0.2487)	(0.1191)	(0.3355)	(0.069)	(0.6677)
Sent$_{t-4}$	0.011	-0.109	0.042	-0.006	0.000
	(0.8883)	(0.1793)	(0.5931)	(0.939)	(0.9969)
Sent$_{t-5}$	-0.075	**0.252*** **	-0.078	**-0.231*** **	-0.167*
	(0.3287)	(0.0018)	(0.3173)	(0.004)	(0.0590)
Sent$_{t-6}$	-0.057	0.043	-0.050	0.008	-0.049
	(0.4553)	(0.5882)	(0.5231)	(0.921)	(0.5776)
Sent$_{t-7}$	-0.118	0.028	-0.097	-0.011	-0.107
	(0.1247)	(0.7251)	(0.2129)	(0.891)	(0.2251)
Sent$_{t-8}$	0.055	0.023	0.088	0.108	0.046
	(0.4769)	(0.7736)	(0.2610)	(0.183)	(0.5991)
Sent$_{t-9}$	0.128*	0.203**	0.113	0.145*	0.145
	(0.0963)	(0.0112)	(0.1494)	(0.076)	(0.1010)
Sent$_{t-10}$	-0.144*	**0.341*** **	-0.169*	**-0.330*** **	**-0.288*** **
	(0.0670)	(0.0000)	(0.0359)	(0.000)	(0.0014)
Sent$_{t-11}$	0.082	-0.047	0.122	0.144	0.282***
	(0.3147)	(0.5717)	(0.1480)	(0.105)	(0.0061)

The table shows the results of VAR analysis of the five sentiment measures' coefficients for log returns of EUA futures. The p-values are given in brackets, */**/*** indicate significance at the 10%, 5% and 1% levels, bold indicates significance using the MHT framework . The p-values for each coefficient are given in brackets below the coefficients.

Table 4.13: VAR Results for the Five Emissions Market Sentiment Measures' Effect on EUA Returns

ΔEUA	χ^2	p-value	ΔEUA	χ^2	p-value
ΔSum Pos	14.00	0.233	ΔCount Pos	15.27	0.171
ΔBrent	7.74	0.736	ΔBrent	7.67	0.742
ΔCoal	3.61	0.980	ΔCoal	3.71	0.978
ΔGas	10.68	0.470	ΔGas	10.67	0.472
ΔFTSE	5.99	0.874	ΔFTSE	6.10	0.867
ΔSum Pos	χ^2	p-value	**ΔCount Pos**	χ^2	p-value
Δ EUA	18.56*	0.070	Δ EUA	19.80**	0.0482
Δ Brent	20.17**	0.043	ΔBrent	23.14**	0.0169
Δ Coal	3.19	0.988	ΔCoal	3.82	0.975
Δ Gas	10.96	0.446	ΔGas	8.47	0.670
Δ FTSE	15.66	0.154	ΔFTSE	10.94	0.448
Δ Brent	χ^2	p-value	**Δ Brent**	χ^2	p-value
ΔSum Pos	**32.63*** **	0.0006	ΔCount Pos	**28.40*** **	0.0028
Δ EUA	8.83	0.637	Δ EUA	9.20	0.603
Δ Coal	**30.82*** **	0.0012	Δ Coal	**30.89*** **	0.0011
Δ Gas	10.57	0.480	Δ Gas	10.46	0.490
Δ FTSE	24.35**	0.0113	Δ FTSE	24.82***	0.010
Δ Coal	χ^2	p-value	**Δ Coal**	χ^2	p-value
ΔSum Pos	1.39	1.000	ΔCount Pos	1.74	0.999
Δ EUA	3.35	0.985	Δ EUA	3.43	0.984
Δ Brent	4.48	0.954	Δ Brent	4.50	0.953
Δ Gas	5.26	0.918	Δ Gas	5.25	0.918
Δ FTSE	12.64	0.317	Δ FTSE	12.57	0.322
Δ Gas	χ^2	p-value	**Δ Gas**	χ^2	p-value
ΔSum Pos	7.29	0.775	ΔCount Pos	7.01	0.798
Δ EUA	6.04	0.871	Δ EUA	6.01	0.873
Δ Brent	8.96	0.626	Δ Brent	9.06	0.616
Δ Coal	8.13	0.702	Δ Coal	8.17	0.698
ΔFTSE	21.73**	0.0266	ΔFTSE	21.65**	0.0272
ΔFTSE	χ^2	p-value	**ΔFTSE**	χ^2	p-value
ΔSum Pos	24.36**	0.0113	ΔCount Pos	23.59**	0.0146
Δ EUA	6.90	0.807	Δ EUA	6.68	0.824
Δ Brent	8.32	0.684	Δ Brent	8.14	0.700
Δ Coal	5.90	0.880	Δ Coal	5.82	0.885
Δ Gas	19.34*	0.055	Δ Gas	19.22*	0.0572

The table presents the χ^2 and p-values for Granger causality tests based on the VAR analysis. The null hypothesis of the test is no causality, hence significantly low values of probability indicate Granger causality from the variable in the row to the variable at the top of each of the 12 sub-tables. Here we present the results for sum of positive and count of positive sentiment impact. */**/*** indicate p-values at the 10%, 5% and 1% significance levels, bold indicates significance using a Multiple Hypothesis Testing framework outlined in Section 4.5.4.

Table 4.14: Granger Causality With Positive Emissions Sentiment Measures Excluding Outliers

ΔEUA	χ^2	**p-value**	**ΔEUA**	χ^2	**p-value**
ΔSum Neg	**42.77*** **	5.4×10^{-6}	**ΔCount Neg**	**50.95*** **	4.2×10^{-7}
ΔBrent	8.22	0.608	**ΔBrent**	9.40	0.585
ΔCoal	3.56	0.965	**ΔCoal**	3.04	0.990
ΔGas	11.58	0.314	**ΔGas**	10.41	0.494
ΔFTSE	4.57	0.918	**ΔFTSE**	5.57	0.901

ΔSum Neg	χ^2	p-value	**ΔCount Neg**	χ^2	p-value
Δ EUA	**28.30*** **	0.002	**Δ EUA**	**63.92*** **	1.7×10^{-9}
Δ Brent	16.59*	0.084	**ΔBrent**	23.90**	0.0132
Δ Coal	1.12	1.000	**ΔCoal**	2.00	0.999
Δ Gas	11.23	0.340	**ΔGas**	11.16	0.430
Δ FTSE	3.49	0.967	**ΔFTSE**	13.79	0.245

Δ Brent	χ^2	p-value	**Δ Brent**	χ^2	p-value
ΔSum Neg	21.63**	0.017	**ΔCount Neg**	16.90	0.111
Δ EUA	9.83	0.455	**Δ EUA**	10.28	0.505
Δ Coal	**29.88*** **	0.001	**Δ Coal**	**29.05*** **	0.002
Δ Gas	7.56	0.672	**Δ Gas**	10.51	0.485
Δ FTSE	22.56**	0.014	**Δ FTSE**	26.11***	0.006

Δ Coal	χ^2	p-value	**Δ Coal**	χ^2	p-value
ΔSum Neg	1.07	1.000	**ΔCount Neg**	1.09	1.000
Δ EUA	3.40	0.970	**Δ EUA**	3.45	0.983
Δ Brent	4.44	0.925	**Δ Brent**	4.45	0.955
Δ Gas	5.08	0.886	**Δ Gas**	5.39	0.911
Δ FTSE	12.50	0.253	**Δ FTSE**	12.22	0.348

Δ Gas	χ^2	p-value	**Δ Gas**	χ^2	p-value
ΔSum Neg	4.10	0.943	**ΔCount Neg**	6.30	0.853
Δ EUA	6.38	0.782	**Δ EUA**	6.34	0.850
Δ Brent	8.51	0.579	**Δ Brent**	8.78	0.642
Δ Coal	7.63	0.665	**Δ Coal**	8.28	0.688
ΔFTSE	17.01*	0.074	**ΔFTSE**	21.18**	0.0316

ΔFTSE	χ^2	p-value	**ΔFTSE**	χ^2	p-value
ΔSum Neg	11.48	0.321	**ΔCount Neg**	20.54**	0.0385
Δ EUA	6.76	0.748	**Δ EUA**	10.34	0.500
Δ Brent	9.62	0.475	**Δ Brent**	10.51	0.485
Δ Coal	5.12	0.883	**Δ Coal**	5.05	0.929
Δ Gas	17.29*	0.068	**Δ Gas**	17.18	0.103

The table presents the χ^2 and p-values for Granger causality tests based on the VAR analysis. The null hypothesis of the test is no causality, hence significantly low values of probability indicate Granger causality from the variable in the row to the variable at the top of each of the 18 sub-tables. Here we present the results for sum of negative, count of negative and count of all tweets sentiment impact. */**/*** indicate p-values at the 10%, 5% and 1% significance levels, bold indicates significance using a Multiple Hypothesis Testing framework outlined in Section 4.5.4.

Table 4.15: Granger Causality using Negative Emissions Sentiment Measures Excluding Outliers

ΔEUA	χ^2	**p-value**
ΔCount All	23.10**	0.0104
ΔBrent	7.63	0.665
ΔCoal	3.64	0.962
ΔGas	10.63	0.387
ΔFTSE	5.33	0.868

ΔCount All	χ^2	p-value
Δ EUA	**34.34*** **	0.0002
ΔBrent	21.88**	0.0157
ΔCoal	1.56	0.999
ΔGas	17.26*	0.0689
ΔFTSE	10.19	0.424

Δ Brent	χ^2	p-value
ΔCount All	**98.61*** **	0.0001
Δ EUA	9.83	0.455
Δ Coal	**30.06*** **	0.0008
Δ Gas	7.79	0.649
Δ FTSE	24.85***	0.0056

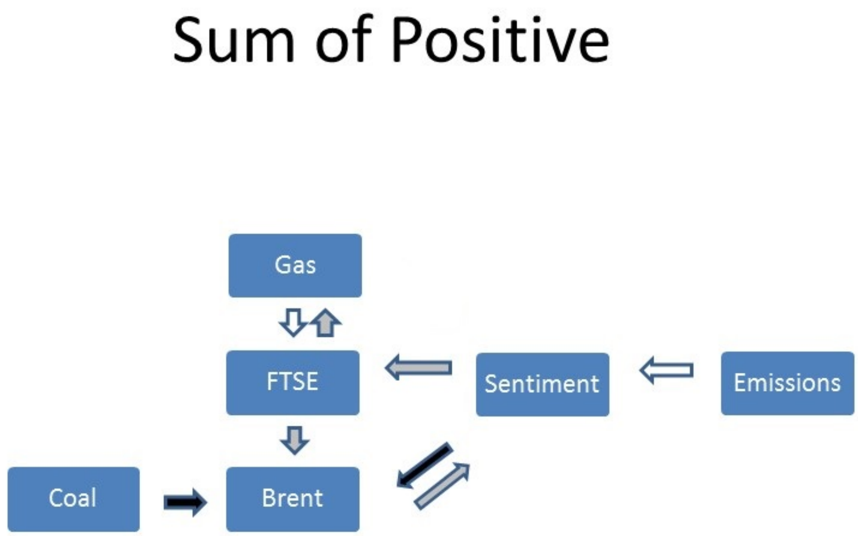
Δ Coal	χ^2	p-value
ΔCount All	1.93	0.997
Δ EUA	3.58	0.964
Δ Brent	4.46	0.924
Δ Gas	5.01	0.891
Δ FTSE	12.10	0.279

Δ Gas	χ^2	p-value
ΔCount All	5.53	0.853
Δ EUA	6.28	0.791
Δ Brent	8.26	0.603
Δ Coal	7.64	0.664
ΔFTSE	17.27*	0.0686

ΔFTSE	χ^2	p-value
ΔCount All	20.18**	0.0276
Δ EUA	6.68	0.755
Δ Brent	9.70	0.468
Δ Coal	5.26	0.873
Δ Gas	18.23*	0.0512

The table presents the χ^2 and p-values for Granger causality tests based on the VAR analysis. The null hypothesis of the test is no causality, hence significantly low values of probability indicate Granger causality from the variable in the row to the variable at the top of each of the 18 sub-tables. Here we present the results for sum of negative, count of negative and count of all tweets sentiment impact. */**/*** indicate p-values at the 10%, 5% and 1% significance levels, bold indicates significance using a Multiple Hypothesis Testing framework outlined in Section 4.5.4.

Table 4.16: Granger Causality using Count of Emissions Tweets Excluding Outliers



The figure summarizes the results of Granger causality tests for the Sum of Positive sentiment measure. In this and in Figures 4.14, 4.13, 4.15 and 4.16 a black arrow denotes significance at the 1% level, grey 5% and white 10%.

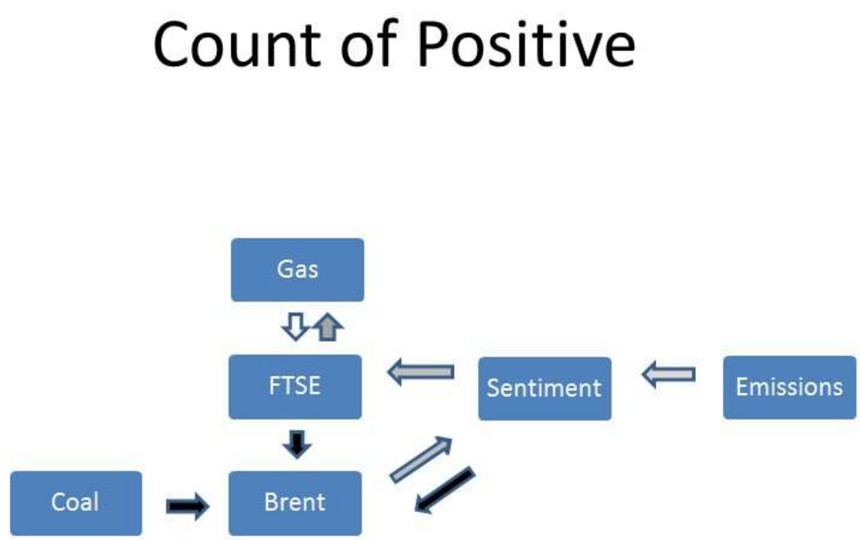
Figure 4.12: Granger Causality Results for Sum of Positive Emissions Market Sentiment

and Brent. We recall that Chapter 2 used monthly data, while here intra-day data is used. We also note that there is a highly significant effect of lagged sentiment on itself. This is expected given the method construction of sentiment impact in Equations 4.1 to 4.5. We find that there is a strong link between the FTSE and Brent which is expected as both are indicators of economic activity. We also note that the coal market does not seem to be influenced by the rest of the energy market.

4.5.1.3 GARCH and Threshold GARCH Results for Emissions Market Tweets

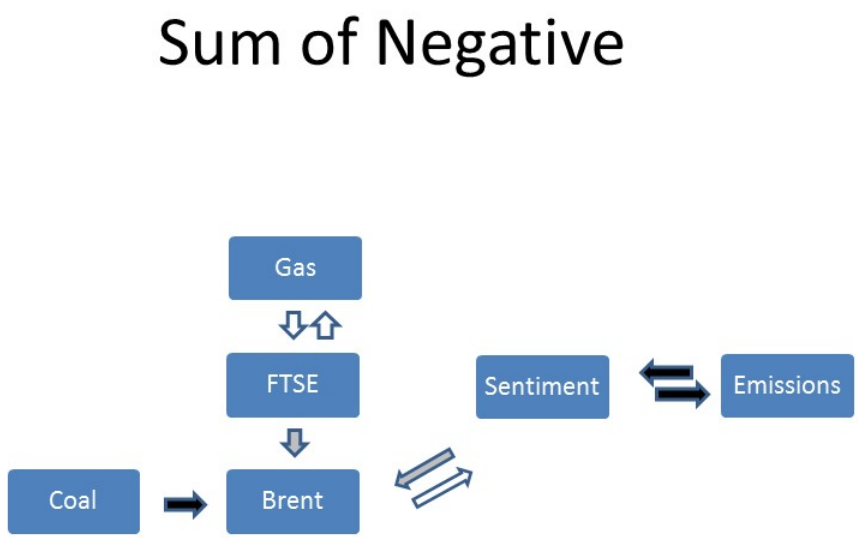
We find that measures of sentiment impact based on positive and negative, sums and counts of tweets improve predictions of the variance of EUA returns.

We see from Table 4.17 that the improvement due to adding the dummy variable, $StrongSent_t$, is highly significant for all four sentiment measures, but not for the



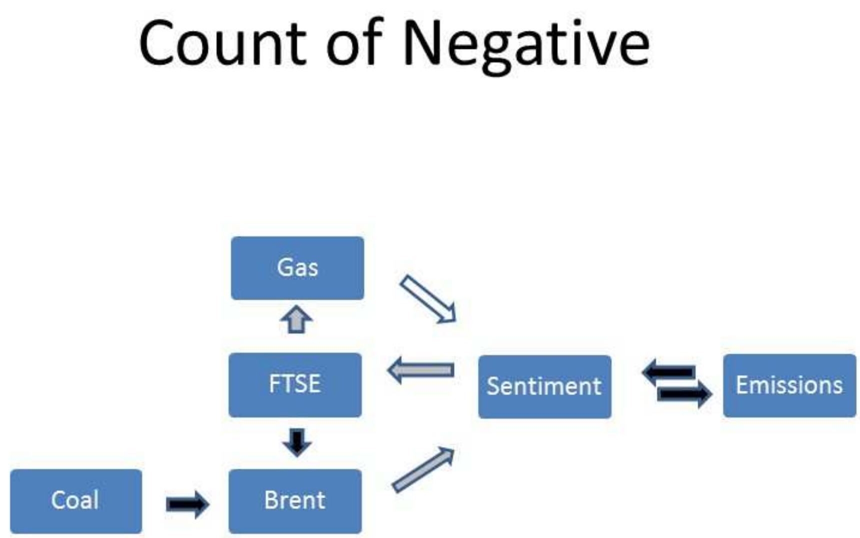
A black arrow denotes significance at the 1% level, grey 5% and white 10%.

Figure 4.13: Granger Causality Results for Count of Positive Emissions Market Sentiment



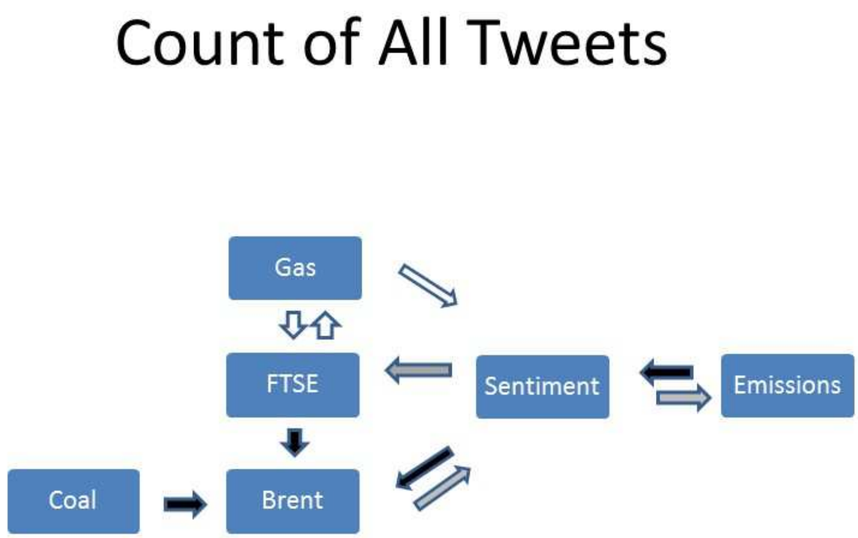
A black arrow denotes significance at the 1% level, grey 5% and white 10%.

Figure 4.14: Granger Causality Results for Sum of Negative Emissions Market Sentiment



A black arrow denotes significance at the 1% level, grey 5% and white 10%.

Figure 4.15: Granger Causality Results for Count of Negative Emissions Market Sentiment



A black arrow denotes significance at the 1% level, grey 5% and white 10%.

Figure 4.16: Granger Causality Results for Count of All Emissions Market Tweets

$StrongSent_t$ dummy variable based on count of tweets. However, we also note that the sum of the α_1 and β terms is larger than 1 for all six applications, and therefore the GARCH volatility model is invalid. The Threshold GARCH model results presented in Table 4.5.1.3 show that this more sophisticated model does not suffer from this problem. It is not a surprise that a Threshold GARCH model is a better fit for the data than a GARCH model since it allows negative residuals to have an additional contribution to the variance. This concept is found in the literature by Soroka (2006), Chevalier and Mayzlin (2006), Akhtar et al. (2013) and Sprenger, Sandner, Tumasjan and Welpe (2014) who support the idea of the negativity effect which proposes that negative shocks have more effect on returns than positive shocks. The results from the Threshold GARCH model presented in Table 4.5.1.3 are that there is a highly significant and large association between $StrongSent_t$ and higher EUA returns variance for all of the sentiment measures, Sum Pos, Sum Neg, Count Pos or Count Neg. That is, we see that strong sentiment of any kind is associated with increased EUA variance. It is noticeable that this is not the case for $StrongSent_t$ based on Count of All Tweets. This suggests that the sentiment algorithms of DataSift have more information than a simple traffic intensity measure.

We note that the size of the γ coefficient is of the same order of magnitude as the α_0 term which is the minimum volatility. We can therefore conclude that the increase in volatility during hours of strong sentiment is non trivial.

Recall that we define an hour as having strong sentiment for a particular sentiment impact, if the sentiment impact is larger than the mean value for the year, and we record these hours with a value of 1 for the dummy variable $StrongSent_t$ used in Equations 4.13 and 4.14. The tests were repeated using the median in place of the mean and the same conclusions were reached.

Samuelson (1965) and, Carchano and Pardo (2009) suggest that there is an increase in volatility near the maturity date of futures contracts, indeed Chevallier (2011a) finds evidence of the Samuelson hypothesis for EUA futures. In order to make sure that this effect is not driving the results, the GARCH and Threshold GARCH tests are repeated

GARCH	No Sentiment	Sum Positive	Sum Negative	Count Positive	Count Negative	Count of Tweets
Mean Eqn						
μ(**x 10**$^{-3}$)	**0.564*****	**0.587*****	**0.601*****	**0.604*****	**0.578*****	**0.558*****
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
ρ	0.0496**	0.0502**	0.0565**	0.0516**	0.0599**	0.0490**
	(0.028)	(0.026)	(0.018)	(0.024)	(0.013)	(0.030)
Variance Eqn						
γ (**x 10**$^{-6}$)	-	**10.6*****	**10.3*****	**14.3*****	**12.1*****	-1.35
	-	(0)	(0)	(0)	(0)	(0.422)
α_0(**x 10**$^{-6}$)	6.35***	5.45***	5.74***	5.99***	5.60***	6394***
	(0)	(0)	(0)	(0)	(0)	(0)
α_1	**0.307*****	**0.316*****	**0.318*****	**0.320*****	**0.326*****	**0.307*****
	(0)	(0)	(0)	(0)	(0)	(0)
β	**0.769*****	**0.760*****	**0.757*****	**0.752*****	**0.752*****	**0.770*****
	(0)	(0)	(0)	(0)	(0)	(0)
Log likelihood	6998.44	7003.793	7004.733	7006.092	7006.084	6998.561
Durbin-Watson	2.109	2.110	2.123	2.113	2.130	2.108
Likelihood Ratio	-	0.0011	0.0004	0.0001	0.0001	0.6228

The following GARCH model was fitted, with the mean equation $EUA_t = \mu + \rho EUA_{t-1} + \epsilon_t,\ \epsilon_t \sim i.i.d.(0, \sigma_t^2)$ where the variance of the ϵ_t term is given by $\sigma_t^2 = \alpha_0 + \alpha_1\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma StrongSent_t$. The table records the effect of strong sentiment measured by tweets concerning the emissions market. An hour is considered to have strong sentiment and has the dummy variable $StrongSent_t = 1$ when the specific sentiment impact is larger than the mean for the positive number series and less than the mean for the sum of negative scores. In this case the positive γ coefficient indicates that a more extreme sentiment score is associated with a larger variance. The data here is uses a 3 day delay without the backloading events. This data is not standardized so that we may compare the $\alpha_0$and γ parameter sizes. p-values of zero are due to calculation limitations.

Table 4.17: GARCH Results for Emissions Market Strong and Weak Sentiment

with dummy variables for all but the initial month; this does not change the conclusions. As a further robustness test the GARCH and Threshold GARCH tests are repeated without the December 2013 data. This gives the same conclusions as before. U-shaped volatility in commodity markets during the course of the trading day has been noted by Wolfe and Rosenman (2014) and, Batten and Lucey (2010). We include hour of the day dummies for nine of the ten hours and find that while there is a significant effect on the volatility from some of these dummies, there is still a significant effect from sentiment as measured by any of the sentiment measures. We conclude that stronger sentiment, i.e. higher than average positive sentiment, or lower than average negative sentiment, as measured by Twitter text, is associated with an increase in volatility of EUA returns. This has implications for risk management as well as option pricing.

Threshold GARCH	No Sentiment	Sum Positive	Sum Negative	Count Positive	Count Negative	Count All Tweets
Mean Equation						
μ **(x 10^{-3})**	0.271	0.261	0.299	0.276	0.275	0.271
	(0.271)	(0.279)	(0.227)	(0.257)	(0.261)	(0.272)
ρ	0.0486**	0.0480**	0.0527**	0.0496**	0.0560**	0.0486**
	(0.0266)	(0.0286)	(0.0211)	(0.0248)	(0.0152)	(0.0267)
Variance Equation						
γ **(x 10^{-6})**	-	**11.9*** **	**10.3*** **	**15.3*** **	**12.3*** **	34.4
	-	(0)	(0)	(0)	(0)	(0.9843)
α_0 **(x 10^{-6})**	**5.95*** **	**4.86*** **	**5.52*** **	**5.36*** **	**5.38*** **	**5.95*** **
	(0)	(0)	(0)	(0)	(0)	(0)
α_1	**0.202*** **	**0.201*** **	**0.209*** **	**0.203*** **	**0.213*** **	**0.202*** **
	(0)	(0)	(0)	(0)	(0)	(0)
α_2	**0.184*** **	**0.198*** **	**0.191*** **	**0.202*** **	**0.197*** **	**0.183*** **
	(0)	(0)	(0)	(0)	(0)	(0)
β	**0.777*** **	**0.770*** **	**0.764*** **	**0.762*** **	**0.760*** **	**0.777*** **
	(0)	(0)	(0)	(0)	(0)	(0)
Log likelihood	7012.92	7020.404	7019.483	7022.786	7021.06	7012.92
Durbin-Watson	2.108	2.107	2.117	2.110	2.123	2.108
L R Sentiment		0.0001	0.0003	0.0000	0.0001	1

The following GARCH model was fitted using Marquardt steps with the mean equation $EUA_t = \mu + \rho EUA_{t-1} + \epsilon_t$, $\epsilon_t \sim i.i.d.(0, \sigma_t^2)$ where the variance of the ϵ_t term is given by $\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 (\epsilon_{t-1}^{-})^2 + \beta \sigma_{t-1}^2 + \gamma StrongSent_{t-1}$. Where $\epsilon_{t-1}^{-} = \epsilon_{t-1}$ when $\epsilon_{t-1} < 0$, and zero otherwise, thus α_2 is a measure of the added of volatility due to a previous negative residual. The figures presented refer to the data without the two backloading events on 16th April and 3rd July and with a delay period of three days, similar results are obtained with a five day delay period (available from authors). LR Sentiment is the p-value of a likelihood ratio test comparing the addition of the sentiment variable to the Threshold GARCH model without the sentiment measure (first column).

Table 4.18: Threshold GARCH Results for Emissions Market Strong and Weak Sentiment

4.5.2 Results for Climate Change Tweets

The sentiment measured from climate change tweets is remarkably different from that measured from the emissions market tweets. At the conventional level of significance, 5%, there is no evidence of an association with the price of EUAs in any of the VAR or Granger causality tests, but there is strong evidence of a link with volatility. We follow a similar analysis as for emission market tweets.

4.5.2.1 Outliers for Climate Change Tweets

There is no evidence that the inclusion or exclusion of the days with the most climate change tweets makes any difference to the conclusions of the analysis of the effect of climate change tweets (Table 4.20). These outliers on 5th and 6th of December 2013 or on 27th September 2013 recorded large numbers of tweets due to severe flooding around the British coast in December 2013 and the publication of the IPCC report linking climate change to anthropogenic greenhouse gas emissions earlier the same year.

4.5.2.2 VAR and Granger Causality Results for Climate Change Tweets

When a VAR model is used we find very weak evidence of a link between changes climate change sentiment and EUA returns, see Table 4.20. The p-values are always above 5%, the conventional boundary for significance. The p-values for the two positive measures are above 10%. It is also noted that the data has been standardized and hence the very small size of the coefficients indicates that any effect is tiny. There is no evidence of an association between changes in climate change sentiment and EUA returns using the Granger causality tests, the results of which are in Appendix E. Further examination of the relationship between the first differences of the sentiment measures including the Twitter traffic measure and EUA returns, using a basic correlation matrix, fails to show an association, see Table 4.19. Given these results we conclude there is only very weak evidence of an association between changes in negative climate change sentiment and EUA returns, or between changes in the number of climate change tweets and EUA returns. None of these results are considered significant in the MHT framework.

	Sum Pos	**Sum Neg**	**Count Pos**	**Count Neg**	**Count All**
Climate Change	-0.00879	0.0236	-0.020	-0.0229	-0.0340*
Emissions Market	0.0489**	**0.1830*** **	0.0354*	**-0.1867*** **	**-0.0771** **

The table shows the correlations between changes in the five sentiment measures and the log returns of EUA prices. The 5% significance level is 0.0389 for a sample size of N=2,539. The p-values are given in brackets, */**/*** indicate significance at the 10%, 5% and 1% levels, bold indicates significance using the MHT framework .

Table 4.19: Correlations Between Climate Change Sentiment and EUAs

No Outliers	**Sum Pos**	**Sum Neg**	**Count Pos**	**Count Neg**	**Count All**
Sent$_{t-1}$	-0.000	-0.001*	-0.000	-0.001*	-0.001*
	(0.3647)	(0.0801)	(0.4419)	(0.0679)	(0.0653)
Sent$_{t-2}$	-	0.000	-	0.001	0.001
		(0.3025)		(0.2703)	(0.1714)

With Outliers	**Sum Pos**	**Sum Neg**	**Count Pos**	**Count Neg**	**Count All**
Sent$_{t-1}$	0.000	0.001*	0.000	-0.001*	-0.001*
	(0.4188)	(0.0902)	(0.4939)	(0.0823)	(0.0864)
Sent$_{t-2}$	-	-0.001	-	0.001	0.001
		(0.1455)		(0.1109)	(0.1861)

The table shows the results of VAR analysis of the five Climate sentiment measures' coefficients for log returns of EUA futures without and with the outliers. The p-values are given in brackets below the coefficients.

Table 4.20: VAR Results for the Climate Sentiment Measures Omitting Outliers

4.5.2.3 GARCH and Threshold GARCH Results for Climate Change Tweets

There is a very different result when we examine the volatility of the EUA returns. Using the Threshold GARCH model we find that there is a strong association between higher than average sentiment levels and higher EUA returns volatility. This is found using the $StrongSent_t$ variable which takes the value 1 when sentiment is above the mean and zero otherwise. In the case of Sum Neg we define $StrongSent_t$ equal to 1 when the sentiment impact is below the mean, as these are a sequence of negative numbers. Similar results are found when $StrongSent_t$ is defined using the median. We see from Table 4.21 that the improvement due to adding the dummy variable, $StrongSent_t$, is highly significant, however we note that the sum of the α_1 and β terms is larger than 1 for all six applications, and therefore the volatility model is invalid, similar to the case with the emissions market GARCH analysis in Section 4.5.1.3. The Threshold GARCH model does not suffer from this deficiency as is seen in Table 4.22. It is not unexpected that the Threshold GARCH model is a better fit for the data as it has been observed that negative shocks have a larger effect on volatility than positive. The results from the Threshold GARCH model are that there is a highly significant and large association between $StrongSent_t$ and higher EUA returns variance for $StrongSent_t$ based on any of the sentiment measures, including the traffic intensity measure, count of tweets. That is, we see that strong sentiment, of any kind, is associated with increased EUA variance. This fails to show that DataSift's sentiment analysis has added information to a simple traffic intensity measure.

The regression, VAR and Granger causality results for climate change sentiment show that there is a failure to find a connection with EUA returns, however there is a connection between strong and weak levels of climate change sentiment and EUA returns volatility. This indicates that those who post tweets concerning climate change are aware of turbulence in the EU emissions market but do not have an accurate insight into the direction of EUA returns.

Having established the association between emissions market sentiment and both EUA returns and volatility, and also the less useful association between climate change

GARCH	No Sentiment	Sum Positive	Sum Negative	Count Positive	Count Negative	Count of Tweets
Mean Eqn						
μ(x 10^{-3})	**1.111*** **	**1.181*** **	**0.976*** **	**1.21*** **	**1.00*** **	**1.02*** **
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ρ	**-0.0487*** **	-0.0501***	-0.0435**	-0.0487**	-0.0438***	-0.0504***
	(0.001)	(0.007)	(0.025)	(0.010)	(0.025)	(0.009)
Variance Eqn						
γ (x 10^{-6})	-	**7.74*** **	**25.0*** **	**9.16*** **	**21.9*** **	**42.3*** **
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α_0(x 10^{-6})	**13.8*** **	**10.4*** **	**7.57*** **	**10.3*** **	**9.15*** **	**9.59*** **
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α_1	**0.8543*** **	**0.836*** **	**0.836*** **	**0.836*** **	**0.838*** **	**0.798*** **
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β	**0.5612*** **	**0.566*** **	**0.540*** **	**0.563*** **	**0.539*** **	**0.517*** **
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log likelihood	6702.24	6705.20	6725.16	6705.98	6719.68	6741.10
Durbin-Watson	1.91	1.91	1.91	1.91	1.91	1.90
Likelihood Ratio	-	0.0015	0.000	0.006	0.000	0.000

The following GARCH model was fitted, with the mean equation $EUA_t = \mu + \rho EUA_{t-1} + \epsilon_t,\ \epsilon_t \sim i.i.d.(0, \sigma_t^2)$ where the variance of the ϵ_t term is given by $\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma StrongSent_t$. The table records the effect of strong climate change sentiment measured by tweets concerning the emissions market omitting outliers. An hour is considered to have strong sentiment and has the dummy variable $StrongSent_t = 1$ when the specific sentiment impact is larger than the mean for the positive number series and less than the mean for the sum of negative scores. In this case the positive γ coefficient indicates that a more extreme sentiment score is associated with a larger variance. The data here is uses a 3 day delay without the backloading events. This data is not standardized so that we may compare the $\alpha_0$and γ parameter sizes. p-values of zero are due to calculation limitations.

Table 4.21: GARCH Results for Climate Change Sentiment Strong and Weak

Threshold GARCH	No Sentiment	Sum Positive	Sum Negative	Count Positive	Count Negative	Count All Tweets
Mean Equation						
μ (x 10^{-3})	0.163	0.216	0.179	0.237	0.168	0.235
	(0.488)	(0.351)	(0.42)	(0.305)	(0.462)	(0.295)
ρ	-0.0034	-0.0054	-0.0021	-0.0042	-0.0020	-0.0096
	(0.860)	(0.771)	(0.914)	(0.820)	(0.916)	(0.592)
Variance Equation						
γ (x 10^{-6})	-	**9.01*****	**14.8*****	**9.93*****	**12.3*****	**23.7*****
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α_0 (x 10^{-6})	**11.8*****	**8.33*****	**6.49*****	**8.33*****	**7.80*****	**7.11*****
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α_1	**0.363*****	**0.354*****	**0.410*****	**0.356*****	**0.399*****	**0.402*****
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α_2	**0.771*****	**0.776*****	**0.727*****	**0.776*****	**0.741*****	**0.702*****
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β	**0.607*****	**0.605*****	**0.587*****	**0.603*****	**0.588*****	**0.575*****
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log likelihood	6753.03	6758.44	6765.74	6759.04	6762.26	6777.16
Durbin-Watson	2.01	2.01	2.01	2.01	2.01	2.00
L R Sentiment	-	0.007	0.000	0.005	0.001	0.000

The table presents the results of Threshold GARCH analysis of climate change strong and weak sentiment (omitting outliers). The Threshold GARCH model was fitted using Marquardt steps with the mean equation $EUA_t = \mu + \rho EUA_{t-1} + \epsilon_t,\ \epsilon_t \sim i.i.d.(0, \sigma_t^2)$ where the variance of the ϵ_t term is given by $\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \alpha_2(\epsilon_{t-1}^-)^2 + \beta\sigma_{t-1}^2 + \gamma StrongSent_{t-1}$. Where $\epsilon_{t-1}^- = \epsilon_{t-1}$ when $\epsilon_{t-1} < 0$, and zero otherwise, thus α_2 is a measure of the added of volatility due to a previous negative residual. The figures presented refer to the data without the two backloading events on 16th April and 3rd July and with a delay period of three days, similar results are obtained with a five day delay period (available from authors). LR Sentiment is the p-value of a likelihood ratio test comparing the addition of the sentiment variable to the Threshold GARCH model without the sentiment measure (first column).

Table 4.22: Threshold GARCH Results for Climate Change Sentiment Strong and Weak

sentiment and EUA volatility, we examine the links between the control variables and EUA returns.

4.5.3 Control Variables

In order to verify the choice of control variables we examine an association between the returns of the control variables and the returns of EUA futures. There is evidence at conventional levels of contemporaneous association between Brent, gas and the FTSE, and EUA returns, see Table 4.23; the FTSE drops out when the outliers are excluded. There is no evidence of predictability in the data; it is seen that the F-tests for predictive models show there is, at best, very weak evidence that the coefficients are not all zero, in addition the R^2 values are very small. This result confirms our choices for control variables and suggests that the EU ETS market quickly and efficiently assimilates information from the energy market into EUA prices.

In order to avoid the very high volatility and serial correlation associated with the microstructure of the carbon market we use hourly data. The regression results are robust to selecting the observation interval from the following choices of $m = 40$, 50, 60 minutes while maintaining a one step ahead prediction. These values are chosen as they divide 600 minutes which is the length of the trading day. There is an unreported test of the effect of the hour of day on EUA returns which is found insignificant. The usual ADF and KPSS tests are carried out to confirm the stationarity of the data; Durbin Watson tests and PACF plots show that there is no evidence of serial correlation in EUA returns at $m = 60$ minutes.

4.5.4 Review of Results and Discussion

The general pattern of results in this investigation is in line with previous research from Simon and Wiggins III (2001), Chevalier and Mayzlin (2006), Akhtar et al. (2013), Bathia and Bredin (2013) and Smales (2015), suggesting that negative news or negative sentiment is stronger in its effect than positive news or sentiment. Here we find that negative emissions market sentiment measures, based on either the sum of the scores for negative tweets or counts of negative tweets, do affect EUA prices and show bi-

Regression	Including Outliers		Excluding Outliers	
	Contemporaneous	**Predictive**	**Contemporaneous**	**Predictive**
N	2,540	2,539	2,520	2,519
Brent	0.037**	0.005	0.030*	0.007
	(0.047)	(0.801)	(0.091)	(0.681)
NBP Gas	0.066*	0.023	0.064*	0.023
	(0.074)	(0.125)	(0.080)	(0.139)
Coal	0.003	0.009	0.003	0.008
	(0.796)	(0.274)	(0.799)	(0.293)
FTSE	0.024*	-0.022	0.021	-0.016
	(0.100)	(0.201)	(0.137)	(0.310)
R-squared	0.70%	0.11%	0.74%	0.11%
F-test	0.001334	0.580115	0.00089	0.59862
Durbin Watson	2.02	2.02	2.01	2.01
Log likelihood	-3594.676	-3600.68	-3296.674	-3303.143

The table presents the results of the contemporaneous regression $\Delta EUA_t = \alpha + \beta_{Brent}\Delta Brent_t + \beta_{NBP}\Delta NBP_t + \beta_{Coal}\Delta Coal_t + \beta_{FTSE}\Delta FTSE_t + \varepsilon_t$ and the one hour predictive regression $\Delta EUA_t = \alpha + \beta_{Brent}\Delta Brent_{t-1} + \beta_{NBP}\Delta NBP_{t-1} + \beta_{Coal}\Delta Coal_{t-1} + \beta_{FTSE}\Delta FTSE_{t-1} + \varepsilon_t$. The data has been tested for stationarity and has been standardized. Results are presented including and excluding the two Backloading events of 16th April 2013 and 3rd July 2013. *, **, *** indicate p-values of below 10%, 5% and 1% which are calculated using Newey West standard errors, p-values are in brackets.

Table 4.23: Regression Results for the Control Variables

directional causality with EUA returns. In addition we find that any of the measures of sentiment, either emissions market or climate change, affect the volatility of EUA returns.

There are however limitations to this study. We have only discussed tweets in English; it would be very interesting to extend this work to other languages. There is a limitation to the use of Twitter in that those who post tweets may not be representative of the general population of those who influence EUA prices, for example Mislove et al. (2011) show that the posters of tweets in the USA are not representative of the general population.

It is clear from Figure 4.11, that there are intra-day effects in the sentiment series. Most obviously the number of tweets posted per hour changes during the course of the day. The question of interest is whether the intra-day effects have any influence on the conclusions drawn from the data. As well as checking for time patterns in the EUA volume of trades, volatility and price levels, we tested the controls and the emissions market sentiment data to check for patterns within the day. The EUA volume of trades showed an interesting pattern of increasing towards lunchtime, then falling back and gradually increasing to a maximum at the last hour of trading. There was no evidence that the price returns varied in any systematic manner during the day; there was some evidence that volatility increased in the last hour as would be expected. There was strong evidence of the usual U-shaped volume of trades for Brent oil and NBP gas, that is, there are higher volumes of trades at the opening and closing of the markets. There was no evidence of any systematic changes in the prices of any of the controls or EUAs compared to the hour of the trading day. There is some evidence in the literature of the mood of individuals and investors changing due to time of day effects, see Hill and Smith (1991) and, Sun et al. (2016). We found that the number of tweets rose to a peak at 11am and gradually fell afterwards, see Figure 4.11. This coincided with an increase in all measures of sentiment but there was no evidence that the time of the day had any effect on the distribution of the sentiment measures or the returns of EUAs.

A final consideration, and one which we now address, is that of the multiple comparison problem, namely that if a large number of hypothesis tests are carried out simultaneously then many null hypotheses may be falsely rejected merely as a result of chance. In this investigation we have carried out 5,388 hypothesis tests comprising 20 multivariate regressions, 4,560 VAR, 600 Granger causality tests and 208 Threshold GARCH tests; note that the large number of tests for VAR are due to the lag length. We therefore use a Generalized Holm Multiple Hypothesis Testing (MHT) framework to assure that the conclusions of the investigation are robust. For a more technical treatment of MHT issues, see Holm (1979), Romano et al. (2010), Cummins (2013a), Cummins (2013b) and Deeney, Cummins, Dowling and Bermingham (2015). This technique establishes a threshold p-value for each hypothesis test so that we may have a very high degree of confidence in the conclusions. Due to the particular distribution of the p-values in this application we find that any test's p-value is significant in the MHT framework if it is below 0.005435, this is based on a 10% chance that we will admit no more than 5% erroneous false rejections; these parameters follow Deeney, Cummins, Dowling and Bermingham (2015). This method yields 167 rejections of null hypotheses rather than 194, 360 or 570 which would have been rejected at the conventional levels of 1%, 5% or 10% which are criticized in Baker (2016). With this in mind we re-visit our findings and note that p-values which are considered significant using MHT are in bold in the results tables.

The results of the regression tests are not found to be significant within the MHT framework, so that the finding that Brent, gas and FTSE returns explain EUA returns is not considered reliable, hence it is only reported as being weak evidence. The results of the VAR analysis are found to be significant in the MHT framework so that we are assured that the association between changes in each of the three measures of sum and count of negative emissions market sentiment and the count of all emissions market tweets, and EUA returns is reliable, as are the associated Granger causality findings. Furthermore we find that the only coefficients which are considered reliable in the VAR analysis have negative signs for the count of negative sentiment and positive signs for the sum of negative sentiment. That is, we find that there is highly reliable evidence that an increase in the number of negative emissions market tweets is associated with a decrease in EUA returns and an increase in the negative sentiment score is associated with a decrease in EUA returns. Thus we find that emissions market sentiment is a positive indicator of EUA price. The connection between emissions market and climate change sentiment and the volatility of EUA returns is unchanged in the MHT framework as the p-values are all within the new threshold of the MHT framework. We thus have greater confidence to rely on the existing finding that stronger (weaker) emissions market and climate change sentiment intensity is associated with higher (lower) volatility.

4.6 Conclusions

This investigation has a number of novel aspects. It is the first investigation to explicitly look at the influence of sentiment in the EU ETS, and to the best of our knowledge it is the first time intra-day data has been used to look at the fundamental drivers of EUA returns. Furthermore it is one of relatively few investigations to use a Multiple Hypothesis Testing framework to overcome the multiple comparisons problem.

There are three findings in this investigation. Firstly, we find that emissions market sentiment, as measured from Twitter, does have a statistically significant ability to explain EUA prices while accounting for the multiple comparisons problem. Furthermore we find Granger causality in both directions from three of the five emissions market sentiment measures to and from the EUA price. We find that the coal price seems to be disconnected from the rest of the energy market though it does influence Brent. This is different to what was found by Sousa and Aguiar-Conraria (2015) but may be the result of the use of intra-day data. We also find that strong (weak) emissions market sentiment significantly explains periods of high (low) volatility of the EUA returns.

Secondly, we fail to find reliable evidence that Twitter sentiment extracted from tweets concerned with climate change has any association with EUA returns. Only those tweets specifically concerned with emissions trading have explanatory power. We do find, similar to emissions market sentiment, that strong (weak) levels of climate change sentiment are associated with high (low) levels of EUA volatility. This indicates that people posting tweets about climate change have only a very slight insight into the EU ETS, that is, we detect volatility from their tweets but do not detect reliable evidence as to the price direction. This may be considered surprising as the EU Emissions Trading Scheme, which is the world's largest emissions market, is the principal means by which the EU aims to reduce greenhouse gas emissions. It perhaps calls for a greater degree of education and communication between traders, regulators and the public.

Finally, we find that there is weak evidence that Brent oil, NBP gas and to a lesser extent FTSE explain contemporaneous EUA prices, but none of these has the ability to predict EUA prices for one hour. This suggests that the emissions market is quick to incorporate information from the energy and stock markets.

In this chapter we have shown that sentiment measured from social media can explain price returns and volatility in the professionally traded EU emissions market. This indicates that sentiment does have an effect in another professionally traded market and that the presence of professional traders is not enough to ensure a perfectly efficient market. This finding suggests that the Efficient Market Hypothesis does not hold in explaining the oil and emissions markets.

Chapter 5

Conclusions

5.1 Introduction

In this thesis it is shown that sentiment has influence in the professionally traded oil and emissions markets. This is done using two distinct methods to measure sentiment, the use of these diverse methods adds considerably to the reliability of our conclusions as does the use of multiple hypothesis testing procedures. We compare these two methods, arguing that they give a consistent and reliable insight into the effect of sentiment in futures markets. We conclude that information asymmetry and position limits, and in the case of the emissions market inattention, are sufficient conditions for sentiment to have an effect in these professionally traded futures markets. This extends the application of a behavioural finance approach in the energy commodity markets. We now draw together our understanding of sentiment and the mechanism by which it effects returns and volatility in energy commodity futures markets.

5.2 Topic Identification, Subject Identification and Sentiment Measurement

The first task when measuring sentiment about a particular topic is to ensure that the sentiment which is measured concerns the correct topic. The second task is that those holding the sentiment should be identified and thirdly the sentiment itself should measured accurately.

This thesis examines sentiment about Brent and WTI crude oils, and about the EU emissions market. The proxies which are chosen for the oil and emissions markets are specific to these markets and in most cases specific to the individual asset. For the oil market the following proxies are chosen: volume of trades, historic volatility, put-call ratio, an oil speculation indicator and a local market volatility index (Table 2.1); all of these except the local market volatility index are specific to oil futures contracts. In the case of the emissions market we use the following as proxies: the volume of trades of EUAs, the volatility of energy commodities, the open interest of energy commodities and the volatility of the FTSE (Section 3.2.3); these are specific to the energy and emissions markets. In the case of tweets we follow an objective process to identify which search terms to select. We produce evidence that the tweets selected by these search terms are concerned with climate change and specifically the EU ETS. The process of selecting search terms is summarized in Table 4.1. The initial list comprises terms associated with the emissions market from several published books, namely Kaplan (1983), Stern (2006), Serletis (2007), Ellerman et al. (2010), Richter (2010) and Chevallier (2011a). These are tested for subject accuracy and yield 17 search terms capable of selecting tweets concerned with climate change. These are further reduced to five specific terms which select tweets concerned with the emissions market. As a test of accuracy the frequency distribution of the emissions market tweets is shown to be remarkably similar to that of news stories concerning the EU ETS, also several hundred of the resulting tweets are read and found to concern the EU ETS.

In the case of the proxy-based sentiment used in chapters 2 and 3 the data is taken from the markets. Here it is the case that the sentiment is being held by the market itself. In the case of the Twitter sentiment, we are measuring sentiment from people who are interested in climate change and from people who are interested in the EU emissions market. These are distinct holders of sentiment. In the first case, using proxies, we have a market which is the summation of the participants in the market and in the other cases, using tweets, we have a specific set of people who use a particular social media platform. These holders of sentiment are different, and the methods used to gather and measure sentiment from them are also different, however the conclusions regarding the energy futures markets are remarkably similar, namely that sentiment does have an influence in professionally traded oil and emissions markets both in terms of asset returns and also in terms of asset volatility.

After identifying the topic and the holder of the sentiment, the third stage is the measurement of sentiment itself. The principal component analysis (PCA) method is used for the financial proxies so that a common signal across the selection of proxies may be extracted. This method is widely supported in the literature, for example Brown and Cliff (2004); Baker and Wurgler (2006); Lemmon and Portniaguina (2006); Baker and Wurgler (2007); Tetlock (2007); Festić et al. (2010); Papapostolou et al. (2014). The method of calculating a sentiment score from a set of written sources, such as tweets, is more complex. In this investigation DataSift is used as the source of the tweets and as the processor delivering sentiment scores for each of these tweets. There are several papers in the literature supporting the use of DataSift as a source of accurate sentiment information, for example Parameswaran et al. (2013); Siapera et al. (2015); Corea and Cervellati (2015); Quinn et al. (2016); Jull et al. (2016) and Corea (2016), and an entire body of literature and a new industry, supporting the use of social media as a source of sentiment information.

Thus there is considerable support for both methods used in this thesis regarding their topic, subject and sentiment accuracy. As well as examining the sources of our sentiment information to determine their veracity, we examine the behaviour of the sentiment signals. We note that the financial proxies which are used for the market sentiment indices for oil in Chapter 2 have very low correlations with fundamental data (Table 2.3). This supports our position that these proxies are not effective due to fundamental effects, but rather are effective due to their ability to measure sentiment. In Chapter 3 we use a simple high/low sentiment measure with a small sample size, so it is not reliable to use a correlation measure in this case to establish that the sentiment is not representing fundamental data. In Chapter 4 we use DataSift which specifically extracts sentiment information from the tweets. We find that sentiment extracted from tweets is useful at explaining price changes and volatility. In terms of price we see that the sentiment measures of Chapter 4 display the negativity effect mentioned by Soroka (2006), Chevalier and Mayzlin (2006), Sprenger, Sandner, Tumasjan and Welpe (2014) and, Akhtar et al. (2013) in which negative sentiment has a larger effect on prices than positive sentiment. In terms of volatility, we see in Chapter 3 where we use a binary indicator of sentiment (negative or positive), that negative sentiment is associated with high volatility. In Chapter 4 we see that strong (weak) levels of sentiment are associated with higher (lower) levels of volatility. These behaviours underline the assertion that it is indeed sentiment which has been measured. Finally we note that the sizes of the coefficients and the significance levels for VAR and Granger-causality tests for association between changes emissions market sentiment and EUA returns in Chapter 4, show that the negative emissions market sentiment measures Sum Neg and Count Neg, are more useful than the count of tweets, indicating that the sentiment measuring process has improved the fundamental model more than the traffic intensity measure. Given this reasoning we can have confidence that it is sentiment which has been measured from both the oil markets and the emissions market. We then must ask why sentiment would influence the energy and emissions markets?

The effect of sentiment in the equity markets has been explained as the result of the activity of noise traders (de Long et al.; 1990; Brown; 1999; Lemmon and Portniaguina; 2006; Tetlock; 2007; Kaufmann; 2011), lack of attention Barber and Odean (2008); Hirshleifer et al. (2009); Vozlyublennaia (2014) and information asymmetry Forgas (1995); Medina et al. (2014), so that sentiment essentially fills a gap due to the lack of reliable fundamental information. This effect persists due to limits on arbitrage caused by the difficulty of taking a short position, market frictions and the cost of capital de Long et al. (1990); Shleifer and Vishny (1997); Lemmon and Portniaguina (2006). While this explanation is certainly applicable in the equity markets, it is a much less convincing explanation of the findings of the previous three chapters examining the oil and emissions markets. The energy commodity futures markets are professionally traded and apart from the information private to supplier firms, there is a great deal of public information available, though of course much this information needs to be purchased. The difficulty of taking a short position is much less severe in the energy futures markets than in the equity markets; in the futures markets limits are imposed by portfolio managers not by the availability of shares. The oil markets in particular, and to a lesser extent the emissions market, have quite high levels of liquidity, hence market frictions would be of less importance. The cost of capital for energy commodity traders in the large oil and energy companies should be reasonably low as they are able to access the corporate bond markets. In a survey of the Moody credit ratings[1] of the world's largest energy, oil and non-energy non-oil companies by revenue, we find that the top ten non-oil non-energy companies have 9A ratings and one B; the top ten oil companies have 8 As and two Bs and the top ten energy companies have 4As and 6 Bs. While this survey is not rigorous, it does suggest that oil and energy companies have access to relatively cheap borrowing in the corporate bond market. Hence the borrowing costs while waiting for arbitrage to take effect in energy commodity markets, should be fairly small, and not act as a barrier to arbitrage.

Thus we are left with information asymmetry, inattention in the case of the EU emissions market, and position limits as the remaining mechanisms to explain the effect of sentiment. It is certainly the case that oil companies have a much better estimate of reserves and production levels than others in the oil market, so there is information asymmetry. As for the EU ETS, the future availability of allowances in the short term is known but regulatory risk is a major concern in this market and certainly produces information uncertainty. There would also seem to be a degree of inattention in the EU emissions markets as is seen from Chapter 3 when the market's response to European Parliament decisions is larger when the market is surprised. That is, when there is little media attention and the decisions are instigated from non-party political sources, the market reaction is larger. From the point of view of the limits imposed by portfolio managers on traders, we can assume that there is a likelihood that these limits will

[1] This used https://www.moodys.com/ for the ratings and http://www.forbes.com/forbes/welcome/ and https://en.wikipedia.org/wiki/List_of_largest_companies_by_revenue

reduce the efficiency of arbitrage as suggested by Acharya et al. (2013). This is likely to be the case also in the EU ETS which is much smaller and slower than the oil markets. We therefore conclude that information asymmetry, inattention in the EU emissions market, and position limits are sufficient factors to explain the influence of sentiment in the oil and emissions markets. This suggests that sentiment will always be part of the energy markets as it is not conceivable that energy companies will allow free access to their private information or that portfolio managers will allow traders to take arbitrarily large positions. What we have demonstrated is that the lack of noise traders and the preponderance of professional traders does not prevent sentiment influencing the oil and emissions markets.

5.3 Limitations

We examine the limitations of this research in terms of data availability, event date choice, missing variables, model accuracy and the accuracy of the sentiment analysis.

5.3.1 Data Availability

In adapting the method of Baker and Wurgler (2006) we use similar variables from the energy commodity market as Baker and Wurgler (2006) use from the equity market. These variables are carefully chosen in Sections 2.2.1 and 3.2.3. Unfortunately there are limitations as to data availability, the principle limitation for Chapter 2 was for the speculation indicator which used the CFTC Commitment of Trader data. This data records whether a futures position is held for hedging a real position in the oil market, or whether it is held for speculative purposes. This data is not available before April 2008 for Brent, so we use the WTI figures for both oils, however since the price of the two oils was very similar during that period, this substitution is not a major concern. In Chapter 2 we deal with data covering 144 months, and so it will be unconvincing to attempt to examine long-run relationships or changes in PCA weights. This is because the literature proposes several possible years for structural breaks in the development of the oil price; Hamilton (2009b) proposes 2005, Elder et al. (2014) propose 2008 and Chen, Huang and Yi (2015) propose 2010. There would be a very small sample size to work with if these breaks were to be incorporated, though of course if data were available a long-run relationship model would be an interesting topic for further research. In Chapter 3 we needed to compromise between the length of the estimation windows and the number of events available for analysis. The decision to use a 5 day post-event window is reasonable because the EU ETS futures market has on average 2,000 trades per day (during 2013). The data suggests that the effect of decisions lasts as long as 5 days, however the aim of the tests is to discover whether there is an effect due to sentiment, rather than to test how long the effect endures. This would be an interesting extension to the work but is not realistic for the data available.

5.3.2 Event Date Choice

A more important limitation for Chapter 3 is that the date chosen for the event study is taken from the European Parliament Legislative Observatory's record of the "Decision by Parliament". While this is the obvious choice for the study, it is possible that the outcome of some decisions of the EP are anticipated clearly at an earlier time.

5.3.3 Missing Variables

A common comment about a proposed sentiment effect, is that the observed effect is actually due to missing variables. It is impossible to prove that there are no missing variables. All that can be done is to show that the literature supports the models, which it does. This is of course a limitation to the thesis.

5.3.4 Model Accuracy

Our testing method throughout this thesis is to compare a model of price or volatility before and after adding a sentiment component. When proposing that sentiment has an effect on price or volatility we must ask whether the new information adds to the existing models. This raises the problem of deciding which of the existing models to choose for the comparison. It would be interesting for further research to be conducted into the interactions between volatility and sentiment, perhaps by using a different selection of GARCH models; in this investigation GARCH (1,1) and Threshold GARCH (1,1) are used for the EUA volatility analysis. A GARCH in the mean model, where the conditional variance is added as a regressor in the mean equation of a standard GARCH model, is one of many options. A further development of the research on the interaction of sentiment and volatility in the EU ETS might be to use a fractionally integrated generalized auto-regressive conditional heteroscedasticity (FIGARCH) model which has been found to have some success in modelling equities and currencies, see Baillie et al. (1996) and Bentes (2014). The focus of this research is to examine the effect of sentiment in professionally traded futures markets rather than examining the volatility itself as a phenomenon. The question of the long memory of volatility, or volatility persistence, would be an interesting extension of this work. As a measure of model fit, the sum of the GARCH coefficients was close to one for the GARCH analyses in Chapters 3 and 4, and a little less for the Threshold GARCH analysis in Chapter 4 indicating a better fit for the Threshold GARCH model.

Naturally we cannot exhaustively check every model which attempts to throw light on price and volatility in the oil and carbon markets; there are simply too many. All that we can hope for is that we compare the addition of sentiment information to an existing model which is firmly based in the literature, and that we test it taking account of the likelihood that the inevitable improvement in goodness of fit, is more than would be expected by random chance. Nazifi and Milunovich (2010) and Chen et al. (2017) fail to find evidence for long-run relationships in the carbon market, so the omission of a VECM model which takes long-run relationships into account, is not such a restriction to the present work. The assumption of constancy for the PCA weights may be a of the limitation of the research, however we follow Baker and Wurgler (2006), who do assume constancy of weights.

5.3.5 Sentiment Analysis Accuracy

The measurement of sentiment is perhaps the largest limitation in this thesis. We use two methods to evaluate sentiment, an index, based on Baker and Wurgler (2006) amongst others, and the sentiment analysis of DataSift, a leading social media analysis company. The use of financial data to produce a sentiment signal in Chapters 2 and 3 following Baker and Wurgler (2006) amongst many others, has become an established practice. In this financial data method, we are limited by the extent to which the data available in the futures market, is substitutable for the sentiment proxies used in the equities market. For example there is no futures market equivalent of the closed end fund discount, however the other proxies are very close to their equivalent in equity research.

The use of language processing and sentiment engines to measure sentiment expressed in text in Chapter 4 is relatively new and unfamiliar to many. The use of social media itself has a short history compared with the timescale over which we have access to financial data in the markets. Thus a limitation of the present work is the sentiment analysis of Twitter. We can expect that this analysis will improve as more work is carried out and the technology improves. This is a limitation of the thesis but given the consistency of results from DataSift we find no reason to doubt their accuracy. It would be interesting to repeat the analysis using some other platform such as Facebook or LinkedIn.

5.4 Contribution

The first contribution of this thesis is that it demonstrates the influence of sentiment in professionally traded markets, thus violating the Efficient Market Hypothesis. Sentiment is seen to have an important effect on prices and volatility of oil and emission allowances. A second contribution is in Chapter 3 where we see that the EU emissions market reaction to European Parliament decisions depends on the origin of the decision, market sentiment and news exposure. The EU emissions market is, according to Mizrach and Otsubo (2014) and Griffin et al. (2015), a professionally traded market. A third contribution of this work is that it is one of only a few studies of sentiment in the energy commodity markets[2]. A fourth contribution is that it is the first study of the

[2]Maslyuk et al. (2013) uses the cumulative sentiment index from Thomson Reuters News Analytics to examine price discontinuities in energy spot and futures and Borovkova (2011) uses the same source to examine the shape of the forward

effect of energy and equity market influence on emissions at intra-day frequency. While there have been intra-day studies of EUA prices, for example Daskalakis and Markellos (2009), Bredin et al. (2014), Mizrach and Otsubo (2014), Chevallier and Sevi (2014) and Ibikunle et al. (2016), this is the first study using intra-day data for oil, coal, gas, FTSE, sentiment and EUAs. Finally it is also one of very few studies to use a multiple hypothesis testing (MHT) framework to take account of the multiple comparisons problem.

This contribution of this thesis is recognized in the first two publications which flow from this work, Deeney, Cummins, Dowling and Bermingham (2015) and Deeney et al. (2016a). The first publication has been cited in Chen, He and Yu (2015), Maslyuk-Escobedo et al. (2016), Lee and Ko (2016), Yin and Yang (2016), Batten et al. (2017), Hung (2017) and Byrne et al. (2017). The second publication has been cited in Zhu et al. (2015), Chang et al. (2017) and Lou et al. (2017).

5.5 Implications for Practitioners Including Technical Insights for Researchers Trying to Replicate these Measures

The methods used in Chapters 2 and 3 are replicable using publicly available data, the methods used to process the data are given in these chapters. A limitation for both is that they are not predictive and so they may be of little use to practitioners. There is evidence in Chapter 4 that Twitter sentiment predicts EUA volatility and price level, so this might be of interest to practitioners. The use of Twitter in Chapter 4 relies on methods which are not available outside the DataSift company; we discuss this in detail.

Our reliance on DataSift, a data analysis company based in California, is a strength of this research in that it provides highly reliable, commercially valuable information for our analysis of the emissions market (see Section 4.2.3). The use of a commercial firm to provide this analysis is a method which may be followed by emissions traders, practitioners and other researchers. There are many companies which provide such

curve for oil futures prices, and Lechthaler and Leinert (2012) uses this source for oil markets.

information from many social media sources, for example OptiRisk and RavenPack. DataSift itself was one of the three companies who had access to the whole Twitter "fire hose", meaning the entire set of all tweets. [3] Since 13th August 2015 only Gnip had access to the Twitter fire hose. Twitter which had an IPO earlier, had bought Gnip for this purpose. DataSift has continued as an analysis company and has an exclusive deal with Facebook. DataSift continues to analyse tweets but cannot supply them, thus to repeat the analysis done in Chapter 4 first one would need to purchase the tweets from Gnip and then pay DataSift to analyse them. If a developer wanted to analyse Twitter sentiment in the future, rather than historical data, it is possible to use an Application Programming Interface (API) to request that Twitter pushes selected tweets to particular developers. This method was considered for Chapter 4 but the Twitter API typically supplies between 1% and 40%[4] of the fire hose and furthermore, the problem of sentiment analysis would have remained. Therefore an API would not provide the same information as was available from DataSift, but it might be a cost-effective way for practitioners to gain insight into the emission allowance market.

The second large data set used in Chapter 4 was the tick data from the futures markets provided by the Intercontinental Exchange (ICE). This data is available for purchase from the exchange. Due to licensing agreements with both DataSift and ICE it is not possible to publish either the DataSift or ICE data sets, however they are both available from their vendors.

5.6 Future Research

Baker and Wurgler (2007) define sentiment as beliefs about future cash flows and investment risks which are not justified by the facts at hand. Baker and Wurgler (2006), and Lemmon and Portniaguina (2006) use an orthogonalization technique to express their belief that sentiment indices should not be associated with fundamental economic data, though this is criticized by Hu and Chi (2012). Sentiment has been considered as

[3] Nippon Telegraph and Telephone (NTT) and Gnip being the other two with access to the whole fire hose.

[4] https://brightplanet.com/2013/06/twitter-firehose-vs-twitter-api-whats-the-difference-and-why-should-you-care/ accessed on 24th April 2017

an error term and defined as randomly held beliefs by Tetlock (2007).

This outlook on sentiment has been changing. Simon and Wiggins III (2001) use the VIX, the put-call ratio and the trading index[5] as proxies of sentiment with which to predict the S&P 500 futures. Schmeling (2009) uses consumer confidence as a proxy for individual investor sentiment and finds it forecasts stock returns negatively. Lechthaler and Leinert (2012) use the sentiment measure from Thomson Reuters News Analytics similarly and apply it to the oil market. Thomson Reuters News Analytics is used by Smales (2014) who shows negative news has greater impact than positive news. In Koch et al. (2014) the economic outlook is used to examine EU emissions prices, where economic outlook is proxied by the monthly Eurostat Economic Sentiment Index. Sentiment is found to have an effect in equity markets by Harding and He (2016). We therefore detect that an acceptance of the use of sentiment is growing.

In this thesis we add the emissions markets to the areas affected by sentiment and we confirm the effect of sentiment in the oil markets. This is been done by measuring sentiment using proxies from within the market and using sentiment derived from tweets. In both cases we find that there is an important association between asset prices and volatility, and sentiment. It is of great importance that these two very different methods come to the same conclusions.

Future questions remain regarding the methods by which sentiment influences the energy futures markets. Is it the case that the preponderance of professional traders promotes herd behaviour? Is it possible that sentiment contains a mixture of fundamental information and noise? Is this possibly a reason it is rational to use sentiment as a source of information when other sources are unavailable or unreliable? Much is still to be tested and there are good reasons to do such testing.

Oil is the world's most traded commodity and any insight into its behaviour is important. Concerning the emissions market, the world's second largest economy, China, is about to form a national emissions trading scheme from the pilot schemes which have been running since 2013. What has been learned from the EU ETS is being used to

[5] The trading index, or "TRIN", is the number of advancing stocks scaled by volume divided by the number of declining stocks scaled by volume. It is reported by the NYSE.

form this new trading scheme, for example China's ETS is not planning to set limits as far into the future as the EU ETS did, and the limits are set in terms of carbon intensity rather than the absolute quantity of CO_2 (Zhang et al.; 2014). It is not beyond the bounds of possibility that emissions will become a globally traded commodity, much like oil; at present the prices in the Chinese pilots and the EU ETS are not incompatible with each other[6]. In both areas of oil and emissions trading, the research in this thesis has made a contribution showing that sentiment at monthly, daily and intra-day frequency adds to the existing understanding of professionally traded commodity futures markets.

[6]The price of an EUA December 2017 futures contract on 24th April 2017 is €4.68 while the average price of the equivalent tonne of CO_2 in the Chinese pilots is approximately 40 yuan or €5.35.

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Appendix A

Multiple Hypothesis Testing

A.1 Multiple Hypothesis Testing

A type I error is the false rejection of a true null hypothesis in a single test. If many true null hypotheses are tested simultaneously, with a conventional p-value of say 0.05, then it is likely that there will be approximately 5% of these tests rejected. These false rejections are the result of performing hundreds of simultaneous hypothesis tests while using the p-value calculated for a single test. In Chapters 2, 3 and 4 we perform 120, 468 and 5,388 tests respectively. To correct for this, a multiple hypothesis testing (MHT) method is used in this thesis. Under consideration are four MHT testing methods, Bonferroni, Holm, Generalized Bonferroni and Generalized Holm, see Holm (1979) and Cummins (2013b,a). We now explain the method to calculate the individual thresholds for each hypothesis tested.

The family-wise error rate, (FWER), is the probability that at least one true null hypothesis, $H_{0,i}$ in a "family" of tests will be rejected, namely

$$FWER = P\left[reject\ at\ least\ one\ null\ hypothesis\ H_{0,i},\ which\ is\ true\right]$$

where $H_{0,i},\ i = 1,..s$, is the set of null hypotheses in the "family". A significance level α is chosen so that $FWER \leq \alpha$.

The Bonferroni test rejects the hypothesis $H_{0,i}$ iff $p_i \leq \frac{\alpha}{s}$, where p_i is the p-value of the i^{th} test, and s is the number of hypotheses tested. This is a very conservative measure because it is a single step procedure and takes no account of the distribution of the hypothesis test results ($\frac{\alpha}{s}$ does not change with i).

Holm's method requires that the hypothesis test results, p_i are arranged in sequence starting with the lowest value, re-labelling the hypotheses $H_{0,i}$ as required. Holm's method is step-wise, in that the test rejects H_{0i} iff $p_i \leq \frac{\alpha}{s-i+1}$ for $i = 1, .., s$. This is a more powerful test than the Bonferroni test because the threshold value for significance p_i increases with i. It is still a conservative test because it tolerates only one falsely rejected null hypothesis.

There is a generalization of $FWER$, where we are prepared to accept k or more false discoveries. This is particularly important if we have to work with hundreds of simultaneous hypothesis tests, in which case, the possibility of one or two false discoveries will not obscure the overall conclusion of the investigation. $kFWER$ is defined as follows,

$$kFWER = P\left[reject\ at\ least\ k\ null\ hypotheses,\ H_{0,i}\ which\ are\ true\right].$$

As before the significance level α is set so that $kFWER \leqq \alpha$, the two methods Generalized Bonferonni and Generalized Holm produce p-values for the hypothesis tests which achieve this. In the generalized Bonferonni test $H_{0,i}$ is rejected iff $p_i \leq \frac{k\alpha}{s}$ where k is the number of false positives tolerated, α is the confidence level, and s is the number of hypotheses under consideration. This is robust to the dependence structure of the hypotheses tested but is still a single step procedure and as such is not very powerful Romano et al. (2010).

Generalized Holm is a similar extension to Holm's method. Again the p_i are arranged in sequence and $H_{0,i}$ is rejected if $p_i \leq \frac{k\alpha}{s}$ if $i \leq k$, or $H_{0,i}$ is rejected if $p_i \leq \frac{k\alpha}{s+k-i}$, if $i > k$. The increase of i will cause p_i to increase sequentially, hence the increase in this method's power. This test is also robust to the dependence structure of the hypothesis tests. (Note that it is entirely possible that the p_i will increase in steps smaller than the

Chapter	No of Tests	p-value *
2	120	0.00753
3	468	0.00606
4	5,388	0.00544

The table presents the threshold p-values for the Generalized Holm MHT procedure for Chapters 2, 3 and 4. *Note that, as is frequently the case with real data, there is a unique p-value which acts as a threshold for all of the tests.

Table A.1: Threshold values using Generalized Holm MHT for Chapters 2, 3 and 4

increase in the threshold, thus it is possible that a null hypothesis $H_{0,r}$ with a p-value of p_r would not be rejected but $H_{0,r+1}$ with a larger p-value of p_{r+1} would be rejected. This is not seen in practice very often as the gaps between the p_i are usually larger than the gaps between successive threshold values.)

Using the hypothesis tests in each chapter as three families of hypotheses, the MHT procedures are carried out using the most powerful of the MHT procedures, the Generalized Holm procedure. The results for the Generalized Holm procedure are given in Table A.1. The application of the Generalized Holm procedure used a confidence level of $\alpha = 0.1$ that there are fewer than 5% false hypotheses rejected among the hypotheses tested. This considerably reduces the number of claimed discoveries and yields results which are much more reliable.

Appendix B

VAR Results for Emissions Market Sentiment

B.1 Introduction to VAR Results

The following tables for emissions market sentiment present the results of the VAR analysis, results for climate change sentiment are found in Appendix D. In this appendix, which deals with emissions market sentiment, for each combination of including/excluding outliers and for each of the five sentiment measures there are three tables making a total of thirty tables. This large number of tables is because there are 11 lags considered for each of the VAR results. For each combination of sentiment measure and choice of including or excluding outliers the first table has the results of the VAR test for that sentiment measure and for Brent oil, the next table concerns Coal and the FTSE and finally the third table concerns Gas and EUA. The energy variables and the FTSE are log returns, the sentiment is first-differenced and standardized. In the sample shown in Table B.1 the first equation is,

$$\Delta Brent_t = -0.001 - 0.118 SumPos_{t-1} - 0.114 SumPos_{t-2} - ..... + 0.010 SumPos_{t-11}$$

$$-0.016 Brent_{t-1} + 0.008 Brent_{t-2} - .... + 0.014 Brent_{t-11}$$

$$+0.015Coal_{t-1} - .... + 0.003Coal_{t-11} + 0.043FTSE_{t-1} + ... - 0.017FTSE_{t-11}$$

$$+0.007Gas_{t-1} - .... - 0.033Gas_{t-11} + 0.018EUA_{t-1} + ... + 0.014EUA_{t-11}$$

where the p-value of the Sum Pos first lag coefficient is 0.1904, the p-value of the Sum Pos second lag coefficient is 0.1904 and the p-value of the Count Pos eleventh lag coefficient is 0.0.9153. The value of α is found further down the table along with the R^2 statistic. Note that none of these coefficients in this sample table is significantly different from zero except for FTSE(-1) and Gas(-11).

	Brent	**Coal**	**FTSE**
Sum Pos(-1)	-0.118	0.029	0.068
	0.1904	0.7543	0.4534
Sum Pos(-2)	-0.114	0.006	0.098
	0.1904	0.9457	0.2621
	.	.	.
Sum Pos(-11)	0.010	-0.015	-0.124
	0.9153	0.8682	0.1721
Brent(-1)	-0.016	0.007	0.019
	0.4285	0.7303	0.3558
Brent(-2)	0.008	0.030	0.000
	0.6972	0.1491	0.9973
	.	.	.
Brent(-11)	0.014	0.006	-0.004
	0.5055	0.7578	0.8315
C	-0.001	-0.002	0.000
	0.9574	0.9339	0.9876
Coal(-1)	0.015	-0.011	0.008
	0.4470	0.5838	0.7024
	.	.	.
Coal(-11)	0.003	0.002	-0.010
	0.8869	0.9255	0.6281
FTSE(-1)	0.043	0.016	-0.019
	0.0348	0.4362	0.3462
	.	.	.
FTSE(-11)	-0.017	0.007	-0.023
	0.4229	0.7557	0.2642
Gas(-1)	0.007	0.001	-0.016
	0.7124	0.9574	0.4143
	.	.	.
Gas(-11)	-0.033	0.005	-0.024
	0.0973	0.7993	0.2413
EUA(-1)	0.018	0.003	-0.017
	0.4247	0.8797	0.4498
	.	.	.
EUA(-11)	0.014	0.007	0.001
	0.5335	0.7747	0.9585

The text explains the layout of the following tables of VAR results.

Table B.1: Sample Layout of VAR Result Tables

B.2 VAR Results for Emissions Market Excluding Outliers

B.2.1 No Outliers Emissions Market Sum Positive

	Brent	Coal	FTSE	Gas	EUA	Sum Pos
Sum Pos(-1)	-0.118	0.029	0.068	0.097	-0.025	0.165
	0.1904	0.7543	0.4534	0.2879	0.7594	0.0000
Sum Pos(-2)	-0.114	0.006	0.098	-0.061	0.125	-0.017
	0.1904	0.9457	0.2621	0.4894	0.1107	0.3717
Sum Pos(-3)	-0.055	-0.026	-0.148	-0.043	-0.089	-0.074
	0.5194	0.7611	0.0827	0.6186	0.2487	0.0001
Sum Pos(-4)	-0.237	0.076	0.235	0.129	0.011	-0.063
	0.0055	0.3792	0.0059	0.1351	0.8883	0.0008
Sum Pos(-5)	0.039	-0.012	0.191	0.011	-0.075	0.026
	0.6467	0.8898	0.0263	0.8964	0.3287	0.1639
Sum Pos(-6)	0.026	0.031	-0.019	-0.028	-0.057	0.047
	0.7645	0.7189	0.8219	0.7430	0.4553	0.0133
Sum Pos(-7)	0.329	0.006	0.128	0.017	-0.118	-0.068
	0.0001	0.9468	0.1352	0.8466	0.1247	0.0003
Sum Pos(-8)	-0.115	0.000	0.119	0.119	0.055	-0.042
	0.1799	0.9958	0.1648	0.1695	0.4769	0.0273
Sum Pos(-9)	-0.095	0.048	0.105	-0.111	0.128	-0.185
	0.2645	0.5783	0.2209	0.1983	0.0963	0.0000
Sum Pos(-10)	0.056	-0.011	0.045	0.037	-0.144	0.324
	0.5239	0.9048	0.6076	0.6752	0.0670	0.0000
Sum Pos(-11)	0.010	-0.015	-0.124	-0.091	0.082	-0.143
	0.9153	0.8682	0.1721	0.3205	0.3147	0.0000
Brent(-1)	-0.016	0.007	0.019	0.010	0.010	-0.006
	0.4285	0.7303	0.3558	0.6302	0.5980	0.2044
Brent(-2)	0.008	0.030	0.000	-0.007	0.029	0.015
	0.6972	0.1491	0.9973	0.7333	0.1241	0.0012
Brent(-3)	-0.043	0.005	-0.006	-0.044	-0.023	0.000
	0.0386	0.8099	0.7672	0.0351	0.2199	0.9592
Brent(-4)	0.004	0.014	0.011	0.005	0.005	0.004
	0.8590	0.5148	0.6031	0.8161	0.8019	0.3631
Brent(-5)	0.003	0.011	-0.038	0.012	-0.006	0.000
	0.8858	0.5967	0.0679	0.5805	0.7480	0.9915
Brent(-6)	0.019	0.009	0.007	-0.010	0.026	-0.010
	0.3550	0.6677	0.7345	0.6151	0.1587	0.0295
Brent(-7)	0.011	0.004	0.027	-0.028	-0.001	0.000
	0.5939	0.8539	0.1948	0.1844	0.9709	0.9389
Brent(-8)	-0.014	-0.008	-0.007	-0.021	-0.017	0.000
	0.4817	0.6975	0.7163	0.3100	0.3549	0.9554
Brent(-9)	0.038	-0.020	-0.018	0.004	-0.006	-0.007
	0.0636	0.3507	0.3822	0.8303	0.7653	0.1328
Brent(-10)	0.030	-0.011	-0.021	-0.018	0.007	0.000
	0.1429	0.6043	0.3023	0.3937	0.6934	0.9610
Brent(-11)	0.014	0.006	-0.004	0.006	-0.008	-0.003
	0.5055	0.7578	0.8315	0.7803	0.6734	0.5466
C	-0.001	-0.002	0.000	0.002	0.007	0.000
	0.9574	0.9339	0.9876	0.9295	0.6962	0.9983
R^2	0.0462	0.0120	0.0318	0.0280	0.0388	0.1895

Table B.2: Results of VAR for Emissions Market Sentiment Sum Positive No Outliers - Sum Pos and Brent

	Brent	Coal	FTSE	Gas	EUA	Sum Pos
Coal(-1)	0.015	-0.011	0.008	0.011	0.008	-0.007
	0.4470	0.5838	0.7024	0.5823	0.6554	0.1009
Coal(-2)	-0.022	-0.003	0.010	-0.017	0.006	0.000
	0.2770	0.9007	0.6030	0.4033	0.7447	0.9973
Coal(-3)	-0.047	0.012	0.006	-0.006	0.001	0.000
	0.0181	0.5541	0.7604	0.7636	0.9471	0.9877
Coal(-4)	0.010	-0.009	-0.007	-0.030	-0.023	0.001
	0.6078	0.6506	0.7158	0.1320	0.1982	0.8495
Coal(-5)	-0.090	-0.006	0.028	-0.019	0.020	0.001
	0.0000	0.7495	0.1562	0.3315	0.2520	0.7462
Coal(-6)	-0.011	-0.003	-0.012	-0.016	0.003	0.002
	0.5875	0.8926	0.5629	0.4350	0.8880	0.6526
Coal(-7)	-0.001	0.013	0.027	-0.026	0.000	0.001
	0.9435	0.5255	0.1815	0.1909	0.9983	0.8442
Coal(-8)	-0.001	-0.002	0.002	-0.016	-0.002	-0.001
	0.9496	0.9378	0.9088	0.4278	0.8945	0.7803
Coal(-9)	0.027	0.009	0.017	-0.002	-0.002	0.000
	0.1780	0.6449	0.3891	0.9034	0.9177	0.9402
Coal(-10)	-0.008	0.012	0.008	-0.016	-0.008	0.000
	0.6795	0.5466	0.6796	0.4313	0.6466	0.9636
Coal(-11)	0.003	0.002	-0.010	-0.013	0.005	0.000
	0.8869	0.9255	0.6281	0.5274	0.7912	0.9343
FTSE(-1)	0.043	0.016	-0.019	-0.004	-0.011	0.003
	0.0348	0.4362	0.3462	0.8597	0.5673	0.5052
FTSE(-2)	0.038	0.017	-0.022	-0.018	-0.006	0.004
	0.0664	0.4159	0.2959	0.3955	0.7638	0.3928
FTSE(-3)	0.016	0.045	0.006	-0.001	0.005	0.002
	0.4472	0.0325	0.7566	0.9731	0.7966	0.6867
FTSE(-4)	0.011	-0.028	-0.014	0.005	0.021	-0.007
	0.5920	0.1780	0.4943	0.8267	0.2633	0.1130
FTSE(-5)	0.023	-0.011	0.010	0.024	-0.007	-0.010
	0.2711	0.5952	0.6133	0.2427	0.6934	0.0225
FTSE(-6)	0.008	0.041	-0.011	0.006	-0.007	0.001
	0.7111	0.0536	0.5823	0.7675	0.6969	0.8337
FTSE(-7)	-0.036	-0.012	-0.014	0.049	-0.005	-0.004
	0.0839	0.5636	0.4916	0.0186	0.7785	0.4287
FTSE(-8)	0.038	-0.009	-0.055	0.028	0.018	-0.005
	0.0652	0.6572	0.0077	0.1822	0.3265	0.2342
FTSE(-9)	-0.051	0.001	0.002	0.060	-0.019	0.009
	0.0133	0.9539	0.9352	0.0039	0.2977	0.0454
FTSE(-10)	0.015	-0.001	-0.035	0.028	0.020	0.003
	0.4605	0.9630	0.0862	0.1726	0.2819	0.5108
FTSE(-11)	-0.017	0.007	-0.023	0.038	0.015	-0.002
	0.4229	0.7557	0.2642	0.0671	0.4199	0.7072

Table B.3: Results of VAR for Emissions Market Sentiment Sum Positive No Outliers - Coal and FTSE

	Brent	**Coal**	**FTSE**	**Gas**	**EUA**	**Sum Pos**
Gas(-1)	0.007	0.001	-0.016	-0.017	0.020	-0.002
	0.7124	0.9574	0.4143	0.4151	0.2728	0.7238
Gas(-2)	-0.027	0.000	-0.050	-0.012	-0.004	0.004
	0.1869	0.9901	0.0127	0.5461	0.8157	0.3775
Gas(-3)	0.023	-0.005	-0.016	-0.003	-0.003	0.000
	0.2540	0.7907	0.4145	0.8764	0.8864	0.9537
Gas(-4)	-0.009	0.001	-0.043	-0.022	0.015	-0.002
	0.6546	0.9528	0.0342	0.2781	0.3962	0.6263
Gas(-5)	0.020	0.005	0.031	0.000	0.041	0.002
	0.3195	0.8104	0.1258	0.9867	0.0224	0.6186
Gas(-6)	-0.004	-0.001	0.012	0.013	-0.017	0.000
	0.8414	0.9484	0.5636	0.5073	0.3362	0.9219
Gas(-7)	-0.022	-0.003	-0.026	0.064	-0.007	0.001
	0.2678	0.8708	0.1936	0.0015	0.6936	0.7575
Gas(-8)	-0.001	-0.007	0.011	-0.006	0.003	-0.005
	0.9578	0.7231	0.5893	0.7851	0.8691	0.2862
Gas(-9)	-0.026	0.022	-0.012	0.006	-0.002	-0.002
	0.1976	0.2740	0.5534	0.7824	0.8917	0.6539
Gas(-10)	0.002	0.040	0.016	-0.062	-0.028	-0.010
	0.9216	0.0510	0.4250	0.0021	0.1186	0.0321
Gas(-11)	-0.033	0.005	-0.024	0.016	-0.002	0.008
	0.0973	0.7993	0.2413	0.4379	0.8934	0.0693
EUA(-1)	0.018	0.003	-0.017	0.025	-0.013	0.002
	0.4247	0.8797	0.4498	0.2672	0.5182	0.7414
EUA(-2)	0.023	0.007	0.002	-0.013	0.032	-0.010
	0.3075	0.7643	0.9406	0.5568	0.1096	0.0403
EUA(-3)	0.004	-0.008	-0.011	-0.005	-0.002	-0.003
	0.8655	0.7270	0.6355	0.8332	0.9397	0.5081
EUA(-4)	-0.025	-0.004	0.003	-0.031	0.019	-0.006
	0.2716	0.8781	0.8799	0.1716	0.3568	0.2605
EUA(-5)	0.004	0.024	-0.017	0.019	0.093	-0.007
	0.8446	0.2898	0.4371	0.3944	0.0000	0.1700
EUA(-6)	-0.021	0.014	-0.027	0.023	0.052	0.004
	0.3414	0.5315	0.2323	0.3199	0.0108	0.4664
EUA(-7)	-0.014	0.017	-0.007	-0.014	0.033	0.009
	0.5365	0.4603	0.7408	0.5353	0.1062	0.0864
EUA(-8)	0.035	0.015	0.003	0.006	0.019	0.013
	0.1189	0.5228	0.9100	0.7850	0.3473	0.0067
EUA(-9)	0.030	-0.003	0.013	-0.002	-0.008	0.001
	0.1830	0.8993	0.5494	0.9251	0.7006	0.7989
EUA(-10)	-0.014	-0.016	-0.039	0.008	-0.088	0.004
	0.5270	0.4708	0.0852	0.7227	0.0000	0.4687
EUA(-11)	0.014	0.007	0.001	0.001	-0.028	0.004
	0.5335	0.7747	0.9585	0.9819	0.1671	0.3996

Table B.4: Results of VAR for Emissions Market Sentiment Sum Positive No Outliers - Gas and EUA

B.2.2 No Outliers Emissions Market Sum of Negative

	Brent	Coal	FTSE	Gas	EUA	Sum Neg
Sum Neg(-1)	-0.119	-0.019	-0.181	-0.005	-0.148	-0.275
	0.1625	0.8278	0.0341	0.9541	0.0805	0.0000
Sum Neg(-2)	0.080	-0.019	-0.060	0.014	-0.193	0.047
	0.3257	0.8169	0.4662	0.8656	0.0174	0.0134
Sum Neg(-3)	0.169	0.034	0.107	0.020	0.126	0.047
	0.0386	0.6799	0.1916	0.8059	0.1191	0.0138
Sum Neg(-4)	0.060	0.006	-0.133	-0.016	-0.109	-0.040
	0.4624	0.9400	0.1035	0.8406	0.1793	0.0348
Sum Neg(-5)	-0.007	-0.004	-0.016	-0.035	0.252	0.078
	0.9345	0.9639	0.8477	0.6663	0.0018	0.0000
Sum Neg(-6)	0.027	-0.058	0.170	-0.001	0.043	0.189
	0.7307	0.4691	0.0319	0.9926	0.5882	0.0000
Sum Neg(-7)	-0.128	-0.004	0.026	-0.055	0.028	-0.098
	0.1092	0.9593	0.7420	0.4917	0.7251	0.0000
Sum Neg(-8)	0.028	-0.003	-0.184	-0.147	0.023	0.041
	0.7314	0.9703	0.0228	0.0682	0.7736	0.0298
Sum Neg(-9)	0.170	-0.019	0.070	0.028	0.203	0.071
	0.0347	0.8170	0.3882	0.7288	0.0112	0.0002
Sum Neg(-10)	-0.005	0.007	0.018	-0.004	0.341	-0.410
	0.9529	0.9302	0.8218	0.9620	0.0000	0.0000
Sum Neg(-11)	0.029	-0.023	0.028	-0.077	-0.047	0.244
	0.7313	0.7904	0.7368	0.3608	0.5717	0.0000
Brent(-1)	-0.017	0.007	0.017	0.011	0.002	-0.001
	0.4082	0.7459	0.4034	0.5976	0.9329	0.8956
Brent(-2)	0.010	0.031	0.001	-0.010	0.018	0.008
	0.6178	0.1431	0.9779	0.6411	0.3717	0.1068
Brent(-3)	-0.043	0.005	-0.015	-0.041	-0.021	0.005
	0.0350	0.8265	0.4695	0.0470	0.2933	0.3077
Brent(-4)	0.001	0.013	0.002	0.004	0.014	-0.002
	0.9450	0.5322	0.9176	0.8618	0.4834	0.6632
Brent(-5)	-0.003	0.009	-0.044	0.011	-0.019	0.009
	0.9005	0.6730	0.0323	0.5969	0.3464	0.0662
Brent(-6)	0.014	0.010	-0.002	-0.010	0.039	-0.008
	0.5015	0.6360	0.9092	0.6267	0.0574	0.0936
Brent(-7)	0.009	0.005	0.034	-0.027	0.023	-0.014
	0.6757	0.8098	0.0988	0.1958	0.2527	0.0025
Brent(-8)	-0.015	-0.008	-0.003	-0.020	-0.017	0.002
	0.4727	0.7121	0.8837	0.3274	0.4098	0.6283
Brent(-9)	0.042	-0.019	-0.018	0.005	-0.006	0.002
	0.0394	0.3681	0.3686	0.8074	0.7581	0.6057
Brent(-10)	0.029	-0.011	-0.020	-0.022	0.002	0.007
	0.1581	0.5824	0.3297	0.2932	0.9357	0.1258
Brent(-11)	0.012	0.005	-0.004	0.003	-0.008	-0.008
	0.5738	0.8008	0.8521	0.8863	0.6970	0.1108
C	0.000	-0.001	0.001	0.001	0.000	0.000
	0.9900	0.9439	0.9795	0.9524	0.9977	0.9915
R^2	0.03867	0.011512	0.033311	0.026845	0.049684	0.306667

Table B.5: Results of VAR for Emissions Market Sentiment Sum Negative No Outliers - Sum Neg and Brent

	Brent	Coal	FTSE	Gas	EUA	Sum Neg
Coal(-1)	0.016	-0.011	0.008	0.011	0.009	0.000
	0.4147	0.5881	0.7060	0.5881	0.6431	0.9698
Coal(-2)	-0.020	-0.003	0.007	-0.017	0.007	0.002
	0.3030	0.8977	0.7340	0.3836	0.7053	0.6324
Coal(-3)	-0.043	0.012	0.005	-0.006	-0.002	-0.001
	0.0293	0.5595	0.7876	0.7575	0.9351	0.7531
Coal(-4)	0.011	-0.009	-0.005	-0.030	-0.023	-0.001
	0.5853	0.6409	0.7836	0.1299	0.2390	0.8728
Coal(-5)	-0.089	-0.007	0.028	-0.020	0.018	-0.001
	0.0000	0.7345	0.1665	0.3063	0.3664	0.8929
Coal(-6)	-0.011	-0.003	-0.012	-0.016	0.003	0.000
	0.5970	0.8781	0.5622	0.4341	0.8677	0.9953
Coal(-7)	-0.002	0.013	0.025	-0.027	0.000	0.002
	0.9297	0.5232	0.2144	0.1858	0.9818	0.6310
Coal(-8)	-0.004	-0.002	0.000	-0.015	0.001	-0.002
	0.8488	0.9359	0.9835	0.4508	0.9442	0.7312
Coal(-9)	0.025	0.009	0.014	-0.003	-0.006	0.003
	0.2015	0.6566	0.4697	0.8625	0.7483	0.5480
Coal(-10)	-0.009	0.012	0.010	-0.015	-0.010	0.002
	0.6393	0.5401	0.6288	0.4604	0.6318	0.6641
Coal(-11)	0.004	0.002	-0.007	-0.013	0.004	-0.003
	0.8532	0.9227	0.7304	0.5196	0.8332	0.5558
FTSE(-1)	0.044	0.015	-0.013	-0.004	-0.017	-0.003
	0.0317	0.4688	0.5154	0.8517	0.3958	0.5779
FTSE(-2)	0.036	0.018	-0.015	-0.015	0.013	0.000
	0.0752	0.3972	0.4579	0.4691	0.5307	0.9833
FTSE(-3)	0.011	0.044	0.016	-0.004	-0.007	-0.009
	0.5861	0.0328	0.4344	0.8417	0.7176	0.0498
FTSE(-4)	0.000	-0.029	-0.013	0.000	0.015	-0.006
	0.9966	0.1629	0.5247	0.9921	0.4646	0.2218
FTSE(-5)	0.027	-0.010	0.028	0.024	0.006	-0.005
	0.1888	0.6157	0.1710	0.2477	0.7806	0.3180
FTSE(-6)	0.010	0.040	0.006	0.007	-0.013	0.001
	0.6354	0.0571	0.7846	0.7337	0.5286	0.7693
FTSE(-7)	-0.036	-0.010	-0.011	0.044	-0.005	0.007
	0.0761	0.6148	0.5991	0.0309	0.8120	0.1410
FTSE(-8)	0.044	-0.008	-0.063	0.025	0.012	0.010
	0.0323	0.7011	0.0023	0.2187	0.5688	0.0348
FTSE(-9)	-0.053	0.000	-0.019	0.060	-0.026	0.004
	0.0102	0.9940	0.3512	0.0040	0.2050	0.4484
FTSE(-10)	0.012	0.000	-0.034	0.031	0.017	-0.003
	0.5584	0.9969	0.0958	0.1391	0.3960	0.4727
FTSE(-11)	-0.010	0.006	-0.025	0.038	0.017	-0.001
	0.6320	0.7694	0.2269	0.0678	0.3972	0.7784

Table B.6: Results of VAR for Emissions Market Sentiment Sum Negative No Outliers - Coal and FTSE

	Brent	**Coal**	**FTSE**	**Gas**	**EUA**	**Sum Neg**
Gas(-1)	0.009	0.000	-0.019	-0.019	0.025	-0.001
	0.6693	0.9974	0.3524	0.3607	0.2211	0.8035
Gas(-2)	-0.026	0.000	-0.049	-0.013	-0.004	0.006
	0.2038	0.9949	0.0161	0.5143	0.8435	0.1929
Gas(-3)	0.025	-0.005	-0.016	-0.003	-0.006	0.001
	0.2199	0.7928	0.4260	0.8768	0.7765	0.8960
Gas(-4)	-0.010	0.001	-0.042	-0.022	0.025	-0.003
	0.6105	0.9570	0.0370	0.2756	0.2169	0.5539
Gas(-5)	0.022	0.006	0.028	-0.002	0.043	0.002
	0.2758	0.7846	0.1700	0.9354	0.0326	0.6166
Gas(-6)	-0.003	-0.001	0.008	0.015	-0.020	0.002
	0.8633	0.9611	0.7008	0.4596	0.3056	0.7428
Gas(-7)	-0.026	-0.003	-0.025	0.064	-0.007	0.003
	0.2023	0.8765	0.2076	0.0017	0.7281	0.4957
Gas(-8)	-0.005	-0.008	0.010	-0.008	0.001	0.000
	0.8198	0.7018	0.6094	0.6853	0.9431	0.9168
Gas(-9)	-0.022	0.023	-0.010	0.004	0.000	0.000
	0.2676	0.2685	0.6103	0.8306	0.9976	0.9924
Gas(-10)	0.002	0.040	0.011	-0.061	-0.026	-0.012
	0.9159	0.0487	0.5728	0.0026	0.1883	0.0108
Gas(-11)	-0.031	0.005	-0.018	0.012	-0.004	0.004
	0.1254	0.7989	0.3879	0.5463	0.8291	0.3823
EUA(-1)	0.013	0.008	-0.013	0.022	-0.015	-0.030
	0.5401	0.7130	0.5447	0.3028	0.4771	0.0000
EUA(-2)	0.024	0.009	-0.004	-0.015	0.037	0.003
	0.2466	0.6663	0.8388	0.4771	0.0776	0.6031
EUA(-3)	-0.002	-0.006	-0.011	-0.002	-0.010	-0.006
	0.9171	0.7621	0.6035	0.9127	0.6458	0.2410
EUA(-4)	-0.021	-0.010	0.022	-0.024	0.027	-0.001
	0.3192	0.6373	0.3031	0.2467	0.1978	0.8103
EUA(-5)	0.001	0.019	0.003	0.021	0.067	-0.006
	0.9476	0.3783	0.8812	0.3169	0.0013	0.2503
EUA(-6)	-0.017	0.013	-0.043	0.017	0.048	0.021
	0.4033	0.5317	0.0419	0.4305	0.0209	0.0000
EUA(-7)	-0.008	0.015	0.015	-0.014	0.026	-0.004
	0.6938	0.4904	0.4625	0.4897	0.2164	0.3929
EUA(-8)	0.042	0.011	0.010	0.020	0.008	0.001
	0.0426	0.5974	0.6387	0.3330	0.7019	0.8038
EUA(-9)	0.030	-0.001	0.015	0.004	0.006	0.000
	0.1487	0.9766	0.4714	0.8340	0.7599	0.9283
EUA(-10)	-0.016	-0.015	-0.035	0.007	-0.077	0.010
	0.4414	0.4648	0.0951	0.7278	0.0002	0.0360
EUA(-11)	0.015	0.007	0.011	0.007	-0.034	0.010
	0.4708	0.7296	0.5992	0.7273	0.1024	0.0373

Table B.7: Results of VAR for Emissions Market Sentiment Sum Negative No Outliers - Gas and EUA

B.2.3 No Outliers Emissions Market Count Positive

	Brent	Coal	FTSE	Gas	EUA	Count Pos)
Count Pos(-1)	-0.116	0.024	0.053	0.099	-0.040	0.177
	0.2126	0.7992	0.5716	0.2944	0.6359	0.0000
Count Pos(-2)	-0.128	0.035	0.106	-0.069	0.151	-0.016
	0.1504	0.6996	0.2346	0.4406	0.0595	0.4054
Count Pos(-3)	-0.093	-0.039	-0.123	-0.031	-0.075	-0.046
	0.2874	0.6593	0.1571	0.7216	0.3355	0.0145
Count Pos(-4)	-0.207	0.088	0.243	0.131	0.042	-0.026
	0.0173	0.3224	0.0053	0.1353	0.5931	0.1615
Count Pos(-5)	0.024	-0.008	0.175	-0.006	-0.078	0.012
	0.7814	0.9303	0.0450	0.9446	0.3173	0.5197
Count Pos(-6)	0.055	0.030	-0.066	-0.045	-0.050	0.005
	0.5302	0.7329	0.4497	0.6105	0.5231	0.8073
Count Pos(-7)	0.297	0.007	0.135	0.007	-0.097	-0.069
	0.0006	0.9355	0.1211	0.9345	0.2129	0.0002
Count Pos(-8)	-0.114	-0.005	0.175	0.118	0.088	-0.028
	0.1903	0.9575	0.0451	0.1815	0.2610	0.1418
Count Pos(-9)	-0.113	0.047	0.083	-0.108	0.113	-0.203
	0.1949	0.5984	0.3411	0.2195	0.1494	0.0000
Count Pos(-10)	0.022	-0.002	0.043	0.046	-0.169	0.343
	0.8080	0.9788	0.6342	0.6117	0.0359	0.0000
Count Pos(-11)	0.025	-0.011	-0.060	-0.084	0.122	-0.141
	0.7889	0.9040	0.5192	0.3749	0.1480	0.0000
Brent(-1)	-0.018	0.008	0.018	0.010	0.010	-0.007
	0.3757	0.7143	0.3852	0.6231	0.5978	0.1386
Brent(-2)	0.009	0.031	0.000	-0.008	0.029	0.016
	0.6772	0.1454	0.9892	0.7169	0.1163	0.0003
Brent(-3)	-0.043	0.005	-0.006	-0.044	-0.022	0.001
	0.0378	0.8019	0.7859	0.0334	0.2482	0.7976
Brent(-4)	0.004	0.013	0.010	0.004	0.005	0.003
	0.8454	0.5292	0.6316	0.8533	0.7895	0.5507
Brent(-5)	0.004	0.011	-0.038	0.012	-0.007	0.001
	0.8541	0.6011	0.0675	0.5657	0.7231	0.8902
Brent(-6)	0.019	0.009	0.007	-0.011	0.026	-0.010
	0.3694	0.6697	0.7483	0.5983	0.1604	0.0219
Brent(-7)	0.011	0.004	0.027	-0.027	-0.001	-0.002
	0.5838	0.8604	0.1877	0.1865	0.9651	0.6521
Brent(-8)	-0.015	-0.008	-0.006	-0.021	-0.017	-0.001
	0.4587	0.7128	0.7527	0.3208	0.3576	0.8800
Brent(-9)	0.037	-0.020	-0.016	0.005	-0.005	-0.006
	0.0744	0.3497	0.4320	0.8112	0.7994	0.1780
Brent(-10)	0.031	-0.011	-0.022	-0.018	0.007	0.001
	0.1355	0.6041	0.2890	0.3886	0.6931	0.8166
Brent(-11)	0.013	0.007	-0.005	0.006	-0.008	-0.002
	0.5193	0.7449	0.8099	0.7779	0.6584	0.7161
C	-0.001	-0.002	0.000	0.002	0.007	0.000
	0.9578	0.9337	0.9864	0.9298	0.6965	0.9726
R^2	0.0446	0.0121	0.0315	0.0279	0.0393	0.1926

Table B.8: Results of VAR for Emissions Market Sentiment Count Positive No Outliers - Sent and Brent

	Brent	Coal	FTSE	Gas	EUA	Count Pos
Coal(-1)	0.015	-0.011	0.008	0.011	0.008	-0.007
	0.4399	0.5860	0.6901	0.5749	0.6479	0.1009
Coal(-2)	-0.022	-0.003	0.010	-0.017	0.006	0.001
	0.2794	0.8947	0.6195	0.3989	0.7579	0.8383
Coal(-3)	-0.047	0.012	0.006	-0.006	0.001	0.000
	0.0181	0.5483	0.7786	0.7585	0.9363	0.9931
Coal(-4)	0.010	-0.009	-0.007	-0.030	-0.023	0.001
	0.6087	0.6473	0.7112	0.1337	0.1955	0.8453
Coal(-5)	-0.090	-0.006	0.028	-0.019	0.021	0.003
	0.0000	0.7523	0.1539	0.3349	0.2392	0.5547
Coal(-6)	-0.011	-0.003	-0.012	-0.016	0.003	0.001
	0.5887	0.8921	0.5450	0.4193	0.8775	0.7762
Coal(-7)	-0.001	0.013	0.026	-0.026	-0.001	0.002
	0.9587	0.5282	0.1970	0.1914	0.9753	0.7246
Coal(-8)	-0.001	-0.002	0.002	-0.016	-0.002	-0.002
	0.9420	0.9342	0.9054	0.4232	0.9189	0.6261
Coal(-9)	0.027	0.009	0.017	-0.003	-0.002	-0.001
	0.1773	0.6465	0.3869	0.8999	0.9201	0.8945
Coal(-10)	-0.009	0.012	0.008	-0.016	-0.008	0.000
	0.6672	0.5471	0.6825	0.4321	0.6407	0.9681
Coal(-11)	0.003	0.002	-0.010	-0.013	0.005	-0.002
	0.8967	0.9259	0.6290	0.5321	0.7978	0.6776
FTSE(-1)	0.046	0.016	-0.019	-0.003	-0.011	0.001
	0.0270	0.4414	0.3484	0.8774	0.5387	0.8106
FTSE(-2)	0.037	0.017	-0.021	-0.017	-0.005	0.002
	0.0707	0.4191	0.3095	0.4110	0.7718	0.5876
FTSE(-3)	0.016	0.045	0.006	-0.001	0.004	0.000
	0.4458	0.0324	0.7746	0.9758	0.8166	0.9800
FTSE(-4)	0.009	-0.028	-0.015	0.005	0.020	-0.004
	0.6480	0.1780	0.4726	0.8152	0.2898	0.3607
FTSE(-5)	0.023	-0.011	0.011	0.024	-0.007	-0.008
	0.2649	0.5971	0.5814	0.2479	0.7120	0.0717
FTSE(-6)	0.008	0.040	-0.012	0.006	-0.008	0.001
	0.6844	0.0539	0.5559	0.7695	0.6494	0.8521
FTSE(-7)	-0.035	-0.012	-0.014	0.049	-0.006	-0.001
	0.0855	0.5757	0.4880	0.0179	0.7519	0.7403
FTSE(-8)	0.040	-0.010	-0.054	0.028	0.018	-0.006
	0.0503	0.6468	0.0087	0.1793	0.3285	0.1765
FTSE(-9)	-0.050	0.001	0.000	0.060	-0.019	0.009
	0.0155	0.9468	0.9826	0.0040	0.2958	0.0402
FTSE(-10)	0.015	-0.001	-0.035	0.028	0.021	0.000
	0.4784	0.9743	0.0871	0.1782	0.2568	0.9329
FTSE(-11)	-0.017	0.006	-0.024	0.038	0.015	-0.002
	0.4137	0.7720	0.2471	0.0681	0.4111	0.7234

Table B.9: Results of VAR for Emissions Market Sentiment Count Positive No Outliers - Coal and FTSE

	Brent	**Coal**	**FTSE**	**Gas**	**EUA**	**Count Pos**
Gas(-1)	0.008	0.001	-0.016	-0.017	0.020	-0.001
	0.6992	0.9621	0.4203	0.4170	0.2749	0.8020
Gas(-2)	-0.026	0.000	-0.049	-0.012	-0.004	0.004
	0.1888	0.9942	0.0143	0.5516	0.8279	0.3921
Gas(-3)	0.023	-0.005	-0.016	-0.003	-0.003	0.001
	0.2598	0.7951	0.4135	0.8785	0.8762	0.7606
Gas(-4)	-0.009	0.001	-0.043	-0.022	0.015	-0.002
	0.6528	0.9599	0.0327	0.2750	0.3996	0.6757
Gas(-5)	0.021	0.005	0.030	0.000	0.041	0.003
	0.2988	0.8096	0.1296	0.9943	0.0228	0.4541
Gas(-6)	-0.004	-0.001	0.012	0.013	-0.017	-0.001
	0.8500	0.9464	0.5651	0.5096	0.3390	0.7593
Gas(-7)	-0.022	-0.004	-0.027	0.064	-0.007	0.002
	0.2717	0.8632	0.1786	0.0015	0.6808	0.7004
Gas(-8)	-0.001	-0.007	0.011	-0.006	0.003	-0.004
	0.9514	0.7262	0.5854	0.7832	0.8594	0.4112
Gas(-9)	-0.025	0.022	-0.012	0.005	-0.003	-0.001
	0.2113	0.2790	0.5460	0.7868	0.8854	0.8856
Gas(-10)	0.002	0.040	0.015	-0.062	-0.028	-0.008
	0.9294	0.0504	0.4563	0.0021	0.1169	0.0713
Gas(-11)	-0.033	0.005	-0.024	0.016	-0.002	0.007
	0.0998	0.8042	0.2379	0.4451	0.8924	0.1128
EUA(-1)	0.019	0.003	-0.017	0.025	-0.012	0.000
	0.3993	0.8819	0.4411	0.2715	0.5428	0.9292
EUA(-2)	0.022	0.007	0.001	-0.014	0.033	-0.012
	0.3244	0.7703	0.9719	0.5485	0.1068	0.0127
EUA(-3)	0.003	-0.008	-0.011	-0.005	-0.002	-0.006
	0.9074	0.7186	0.6160	0.8390	0.9370	0.2390
EUA(-4)	-0.026	-0.003	0.004	-0.031	0.019	-0.005
	0.2447	0.8944	0.8580	0.1774	0.3557	0.3066
EUA(-5)	0.003	0.024	-0.016	0.020	0.093	-0.005
	0.8975	0.2852	0.4774	0.3812	0.0000	0.2777
EUA(-6)	-0.022	0.015	-0.027	0.023	0.052	0.004
	0.3337	0.5271	0.2375	0.3173	0.0108	0.3883
EUA(-7)	-0.014	0.018	-0.006	-0.014	0.032	0.009
	0.5282	0.4418	0.7924	0.5476	0.1078	0.0533
EUA(-8)	0.036	0.014	0.004	0.006	0.019	0.013
	0.1052	0.5271	0.8609	0.7801	0.3432	0.0069
EUA(-9)	0.031	-0.003	0.013	-0.002	-0.008	0.001
	0.1716	0.9028	0.5653	0.9132	0.7017	0.8764
EUA(-10)	-0.013	-0.017	-0.038	0.008	-0.088	0.002
	0.5501	0.4618	0.0879	0.7363	0.0000	0.6791
EUA(-11)	0.015	0.006	0.001	0.000	-0.028	0.001
	0.5187	0.7776	0.9601	0.9825	0.1678	0.8587
C	-0.001	-0.002	0.000	0.002	0.007	0.000
	0.9578	0.9337	0.9864	0.9298	0.6965	0.9726
$\mathbf{R}^2$	0.0446	0.0121	0.0315	0.0279	0.0393	0.1926

Table B.10: Results of VAR for Emissions Market Sentiment Count Positive No Outliers - Gas and EUA

B.2.4 No Outliers Emissions Market Count of Negative

	Brent	**Coal**	**FTSE**	**Gas**	**EUA**	**Count Neg**
Count Neg(-1)	-0.200	0.020	0.012	-0.018	0.015	0.065
	0.042	0.844	0.900	0.854	0.863	0.001
Count Neg(-2)	-0.181	0.038	-0.044	0.008	0.017	0.022
	0.053	0.688	0.641	0.937	0.842	0.261
Count Neg(-3)	-0.225	-0.012	-0.025	-0.027	-0.148	0.010
	0.013	0.899	0.785	0.772	0.069	0.592
Count Neg(-4)	-0.199	0.040	0.132	0.016	-0.006	0.026
	0.028	0.667	0.146	0.861	0.939	0.152
Count Neg(-5)	0.052	0.000	0.104	0.024	-0.231	-0.018
	0.564	0.997	0.253	0.793	0.004	0.338
Count Neg(-6)	0.084	0.050	-0.111	-0.105	0.008	-0.046
	0.352	0.585	0.224	0.252	0.921	0.013
Count Neg(-7)	0.064	0.033	-0.115	-0.067	-0.011	-0.008
	0.477	0.717	0.209	0.465	0.891	0.668
Count Neg(-8)	-0.097	0.008	0.171	0.120	0.108	-0.073
	0.283	0.930	0.060	0.191	0.183	0.000
Count Neg(-9)	-0.188	0.044	0.057	-0.010	0.145	-0.257
	0.039	0.634	0.535	0.914	0.076	0.000
Count Neg(-10)	-0.012	0.029	-0.047	0.026	-0.330	0.304
	0.903	0.761	0.624	0.785	0.000	0.000
Count Neg(-11)	0.259	0.019	-0.084	0.058	0.144	-0.099
	0.009	0.853	0.396	0.560	0.105	0.000
Brent(-1)	-0.022	0.008	0.019	0.012	0.005	-0.005
	0.293	0.714	0.365	0.553	0.806	0.224
Brent(-2)	0.009	0.031	0.000	-0.010	0.028	0.011
	0.672	0.138	0.984	0.621	0.127	0.008
Brent(-3)	-0.043	0.006	-0.010	-0.044	-0.024	0.001
	0.036	0.776	0.629	0.037	0.195	0.751
Brent(-4)	0.003	0.014	0.008	0.001	0.007	-0.005
	0.883	0.507	0.716	0.978	0.695	0.274
Brent(-5)	0.000	0.011	-0.042	0.011	-0.003	0.005
	0.999	0.606	0.043	0.613	0.882	0.210
Brent(-6)	0.015	0.010	0.005	-0.009	0.026	-0.005
	0.473	0.636	0.802	0.669	0.157	0.240
Brent(-7)	0.011	0.005	0.029	-0.026	0.000	-0.005
	0.582	0.826	0.164	0.215	0.981	0.253
Brent(-8)	-0.014	-0.007	-0.010	-0.019	-0.020	0.003
	0.488	0.738	0.634	0.371	0.285	0.475
Brent(-9)	0.044	-0.019	-0.014	0.008	-0.008	-0.005
	0.030	0.368	0.492	0.708	0.673	0.280
Brent(-10)	0.036	-0.012	-0.023	-0.019	0.009	0.004
	0.081	0.573	0.260	0.362	0.609	0.374
Brent(-11)	0.014	0.007	-0.006	0.006	-0.011	-0.005
	0.506	0.750	0.763	0.759	0.565	0.225
C	-0.001	-0.002	0.000	0.002	0.007	0.000
	0.960	0.933	0.991	0.929	0.695	0.955
R^2	0.046	0.012	0.027	0.027	0.048	0.193

Table B.11: Results of VAR for Emissions Market Sentiment Count Negative No Outliers - Sent and Brent

	Brent	Coal	FTSE	Gas	EUA	Count Neg
Coal(-1)	0.016	-0.011	0.009	0.011	0.008	-0.001
	0.430	0.574	0.662	0.587	0.640	0.886
Coal(-2)	-0.021	-0.003	0.009	-0.018	0.005	0.001
	0.288	0.889	0.647	0.377	0.765	0.873
Coal(-3)	-0.045	0.012	0.006	-0.006	0.000	0.000
	0.023	0.560	0.757	0.775	0.995	0.939
Coal(-4)	0.009	-0.009	-0.006	-0.030	-0.022	0.000
	0.639	0.650	0.765	0.138	0.209	0.986
Coal(-5)	-0.089	-0.007	0.028	-0.021	0.020	0.001
	0.000	0.738	0.164	0.301	0.254	0.713
Coal(-6)	-0.011	-0.003	-0.013	-0.016	0.003	0.001
	0.576	0.893	0.513	0.432	0.883	0.824
Coal(-7)	-0.002	0.013	0.026	-0.027	0.000	0.002
	0.913	0.532	0.199	0.180	1.000	0.544
Coal(-8)	-0.004	-0.002	0.002	-0.016	0.000	-0.003
	0.859	0.940	0.911	0.431	0.982	0.511
Coal(-9)	0.027	0.009	0.016	-0.004	-0.002	0.000
	0.177	0.649	0.428	0.855	0.909	0.940
Coal(-10)	-0.008	0.012	0.007	-0.015	-0.009	0.001
	0.682	0.541	0.714	0.461	0.624	0.755
Coal(-11)	0.003	0.002	-0.010	-0.013	0.005	0.000
	0.869	0.928	0.606	0.534	0.775	0.908
FTSE(-1)	0.043	0.016	-0.017	-0.004	-0.010	-0.004
	0.036	0.447	0.399	0.847	0.597	0.372
FTSE(-2)	0.033	0.018	-0.016	-0.016	-0.002	-0.002
	0.110	0.381	0.425	0.428	0.913	0.709
FTSE(-3)	0.012	0.044	0.011	0.000	-0.001	-0.002
	0.553	0.034	0.609	0.989	0.957	0.683
FTSE(-4)	0.004	-0.027	-0.012	0.005	0.020	-0.001
	0.852	0.196	0.571	0.818	0.270	0.872
FTSE(-5)	0.025	-0.011	0.016	0.023	-0.009	0.000
	0.217	0.612	0.442	0.270	0.613	0.944
FTSE(-6)	0.010	0.040	-0.012	0.005	-0.011	0.003
	0.637	0.054	0.568	0.802	0.563	0.496
FTSE(-7)	-0.034	-0.011	-0.015	0.046	-0.006	0.002
	0.098	0.597	0.453	0.027	0.737	0.617
FTSE(-8)	0.043	-0.010	-0.051	0.028	0.018	-0.001
	0.038	0.638	0.014	0.172	0.325	0.764
FTSE(-9)	-0.049	0.001	-0.001	0.058	-0.016	-0.004
	0.018	0.965	0.949	0.005	0.389	0.383
FTSE(-10)	0.013	0.000	-0.036	0.030	0.018	-0.001
	0.534	0.983	0.081	0.155	0.340	0.862
FTSE(-11)	-0.017	0.006	-0.025	0.038	0.019	0.003
	0.414	0.762	0.226	0.071	0.310	0.484

Table B.12: Results of VAR for Emissions Market Sentiment Count Negative No Outliers - Coal and FTSE

	Brent	**Coal**	**FTSE**	**Gas**	**EUA**	**Count Neg**
Gas(-1)	0.008	0.001	-0.015	-0.018	0.021	-0.003
	0.701	0.959	0.455	0.384	0.249	0.502
Gas(-2)	-0.027	0.000	-0.049	-0.012	-0.003	0.003
	0.182	0.982	0.015	0.554	0.850	0.464
Gas(-3)	0.023	-0.005	-0.015	-0.002	-0.004	0.004
	0.253	0.812	0.448	0.912	0.817	0.294
Gas(-4)	-0.008	0.001	-0.041	-0.021	0.015	-0.002
	0.699	0.965	0.041	0.290	0.413	0.578
Gas(-5)	0.022	0.005	0.029	-0.001	0.044	0.002
	0.279	0.811	0.146	0.953	0.015	0.596
Gas(-6)	-0.003	-0.001	0.013	0.015	-0.019	0.000
	0.894	0.953	0.525	0.459	0.294	0.937
Gas(-7)	-0.023	-0.004	-0.026	0.064	-0.006	0.004
	0.262	0.849	0.195	0.002	0.742	0.365
Gas(-8)	-0.002	-0.007	0.009	-0.007	0.004	0.000
	0.930	0.727	0.644	0.746	0.810	0.917
Gas(-9)	-0.022	0.022	-0.010	0.006	-0.005	0.004
	0.274	0.290	0.612	0.760	0.787	0.328
Gas(-10)	0.003	0.040	0.015	-0.062	-0.026	-0.012
	0.874	0.053	0.471	0.002	0.142	0.005
Gas(-11)	-0.034	0.005	-0.025	0.013	-0.003	0.011
	0.091	0.796	0.227	0.513	0.871	0.006
EUA(-1)	0.023	0.004	-0.020	0.024	-0.008	-0.009
	0.318	0.872	0.379	0.301	0.676	0.041
EUA(-2)	0.018	0.008	0.000	-0.014	0.031	-0.005
	0.430	0.743	0.995	0.540	0.120	0.265
EUA(-3)	0.001	-0.008	-0.011	-0.006	-0.001	-0.007
	0.958	0.723	0.627	0.778	0.945	0.125
EUA(-4)	-0.031	-0.002	0.000	-0.032	0.020	-0.005
	0.173	0.916	0.995	0.162	0.314	0.251
EUA(-5)	0.002	0.025	-0.012	0.023	0.086	0.001
	0.945	0.268	0.586	0.318	0.000	0.825
EUA(-6)	-0.020	0.015	-0.025	0.024	0.052	0.000
	0.383	0.528	0.274	0.283	0.010	0.939
EUA(-7)	-0.014	0.018	-0.011	-0.016	0.028	0.009
	0.541	0.419	0.621	0.491	0.164	0.039
EUA(-8)	0.042	0.015	0.004	0.008	0.017	0.013
	0.060	0.521	0.845	0.724	0.398	0.004
EUA(-9)	0.030	-0.003	0.012	-0.002	-0.002	-0.004
	0.187	0.884	0.583	0.920	0.938	0.352
EUA(-10)	-0.018	-0.016	-0.039	0.005	-0.087	-0.010
	0.421	0.484	0.087	0.810	0.000	0.033
EUA(-11)	0.014	0.007	-0.001	0.002	-0.027	0.001
	0.535	0.769	0.979	0.942	0.186	0.873

Table B.13: Results of VAR for Emissions Market Sentiment Count Negative No Outliers - Gas and EUA

B.2.5 No Outliers Emissions Market Count All Tweets

	Brent	Coal	FTSE	Gas	EUA	Count All
Count All(-1)	-0.204	-0.005	0.166	0.033	-0.105	0.087
	0.0739	0.9681	0.1469	0.7772	0.3063	0.0000
Count All(-2)	-0.174	0.029	0.140	-0.080	0.169	0.008
	0.0833	0.7778	0.1630	0.4324	0.0599	0.6627
Count All(-3)	-0.120	-0.017	-0.076	-0.007	-0.038	0.025
	0.2245	0.8691	0.4417	0.9448	0.6677	0.1503
Count All(-4)	-0.347	0.121	0.160	0.053	0.000	-0.024
	0.0004	0.2260	0.1056	0.5914	0.9969	0.1743
Count All(-5)	0.007	0.012	-0.056	0.034	-0.167	0.012
	0.9440	0.9059	0.5669	0.7351	0.0590	0.4806
Count All(-6)	0.102	0.038	-0.172	-0.026	-0.049	-0.018
	0.2992	0.7004	0.0812	0.7956	0.5776	0.2962
Count All(-7)	0.185	0.012	0.007	0.018	-0.107	-0.069
	0.0595	0.9035	0.9417	0.8576	0.2251	0.0001
Count All(-8)	-0.058	0.018	0.283	0.179	0.046	-0.060
	0.5549	0.8562	0.0042	0.0720	0.5991	0.0005
Count All(-9)	-0.218	0.038	0.101	-0.102	0.145	-0.163
	0.0271	0.7055	0.3068	0.3047	0.1010	0.0000
Count All(-10)	-0.073	0.016	0.101	0.058	-0.288	0.483
	0.4682	0.8787	0.3159	0.5640	0.0014	0.0000
Count All(-11)	0.139	0.037	0.067	-0.032	0.282	-0.116
	0.2243	0.7525	0.5563	0.7807	0.0061	0.0000
Brent(-1)	-0.020	0.008	0.015	0.011	0.008	0.001
	0.3368	0.7128	0.4592	0.5900	0.6505	0.8236
Brent(-2)	0.009	0.032	-0.003	-0.009	0.032	0.014
	0.6666	0.1319	0.8926	0.6536	0.0892	0.0001
Brent(-3)	-0.042	0.006	-0.012	-0.043	-0.023	0.002
	0.0423	0.7788	0.5627	0.0407	0.2222	0.5913
Brent(-4)	0.006	0.013	0.006	0.005	0.005	0.000
	0.7685	0.5252	0.7772	0.7956	0.7948	0.9601
Brent(-5)	0.002	0.011	-0.042	0.011	-0.007	0.002
	0.9177	0.6154	0.0410	0.6074	0.7122	0.6746
Brent(-6)	0.019	0.009	0.005	-0.009	0.023	-0.005
	0.3565	0.6810	0.8014	0.6662	0.2111	0.1748
Brent(-7)	0.012	0.004	0.034	-0.027	0.003	-0.003
	0.5461	0.8643	0.1023	0.2018	0.8707	0.4480
Brent(-8)	-0.018	-0.008	-0.003	-0.021	-0.017	0.004
	0.3779	0.6999	0.8969	0.3144	0.3685	0.2798
Brent(-9)	0.040	-0.019	-0.012	0.005	-0.004	-0.001
	0.0525	0.3564	0.5603	0.7914	0.8200	0.8659
Brent(-10)	0.032	-0.011	-0.022	-0.020	0.009	0.001
	0.1181	0.5955	0.2956	0.3361	0.6377	0.7462
Brent(-11)	0.014	0.007	-0.008	0.006	-0.010	-0.002
	0.4866	0.7514	0.7010	0.7784	0.6054	0.6137
C	-0.001	-0.002	0.000	0.002	0.007	0.000
	0.9618	0.9319	0.9851	0.9309	0.6950	0.9644
R^2	0.0452	0.0122	0.0302	0.0275	0.0451	0.3000

Table B.14: Results of VAR for Emissions Market Sentiment Count All Tweets No Outliers - Sent and Brent

	Brent	Coal	FTSE	Gas	EUA	Count All
Coal(-1)	0.016	-0.011	0.009	0.011	0.008	-0.002
	0.4311	0.5779	0.6586	0.5890	0.6361	0.5671
Coal(-2)	-0.022	-0.003	0.010	-0.018	0.006	-0.001
	0.2755	0.8839	0.6196	0.3786	0.7470	0.7230
Coal(-3)	-0.046	0.012	0.006	-0.006	0.001	-0.001
	0.0199	0.5574	0.7551	0.7736	0.9775	0.8400
Coal(-4)	0.009	-0.009	-0.007	-0.031	-0.023	0.001
	0.6342	0.6533	0.7118	0.1288	0.2068	0.7094
Coal(-5)	-0.089	-0.007	0.027	-0.020	0.020	0.000
	0.0000	0.7441	0.1796	0.3143	0.2531	0.9500
Coal(-6)	-0.011	-0.003	-0.014	-0.016	0.004	-0.002
	0.5723	0.8938	0.4877	0.4317	0.8429	0.6326
Coal(-7)	-0.003	0.013	0.025	-0.026	-0.001	0.003
	0.8835	0.5289	0.2069	0.1924	0.9612	0.3598
Coal(-8)	-0.003	-0.001	0.001	-0.016	-0.001	-0.002
	0.8672	0.9428	0.9582	0.4244	0.9503	0.6382
Coal(-9)	0.027	0.009	0.016	-0.003	-0.003	0.000
	0.1729	0.6459	0.4225	0.8850	0.8663	0.9312
Coal(-10)	-0.008	0.012	0.009	-0.015	-0.009	0.000
	0.6800	0.5465	0.6638	0.4593	0.6334	0.9043
Coal(-11)	0.003	0.002	-0.009	-0.013	0.005	-0.001
	0.8706	0.9332	0.6381	0.5315	0.7922	0.7620
FTSE(-1)	0.048	0.016	-0.018	-0.003	-0.014	-0.004
	0.0190	0.4455	0.3724	0.8889	0.4334	0.2157
FTSE(-2)	0.040	0.017	-0.016	-0.017	-0.005	-0.003
	0.0514	0.4069	0.4261	0.4191	0.7890	0.4606
FTSE(-3)	0.017	0.044	0.010	-0.001	0.004	-0.004
	0.4211	0.0372	0.6167	0.9808	0.8425	0.2205
FTSE(-4)	0.003	-0.028	-0.011	0.004	0.021	-0.005
	0.8826	0.1872	0.6039	0.8526	0.2472	0.1576
FTSE(-5)	0.021	-0.010	0.019	0.023	-0.007	-0.002
	0.2990	0.6257	0.3588	0.2580	0.6969	0.5816
FTSE(-6)	0.008	0.040	-0.012	0.004	-0.006	0.002
	0.7111	0.0569	0.5514	0.8387	0.7469	0.6129
FTSE(-7)	-0.035	-0.011	-0.017	0.047	-0.008	0.004
	0.0881	0.5864	0.4056	0.0223	0.6781	0.2861
FTSE(-8)	0.043	-0.009	-0.054	0.029	0.017	-0.002
	0.0357	0.6625	0.0082	0.1675	0.3623	0.4946
FTSE(-9)	-0.048	0.001	-0.004	0.059	-0.020	0.003
	0.0193	0.9576	0.8423	0.0050	0.2806	0.3939
FTSE(-10)	0.017	-0.001	-0.039	0.030	0.019	-0.002
	0.4182	0.9769	0.0602	0.1560	0.3175	0.5906
FTSE(-11)	-0.016	0.006	-0.023	0.039	0.015	0.003
	0.4333	0.7780	0.2670	0.0634	0.4091	0.3827

Table B.15: Results of VAR for Emissions Market Sentiment Count All Tweets No Outliers - Coal and FTSE

	Brent	Coal	FTSE	Gas	EUA	Count All
Gas(-1)	0.008	0.001	-0.015	-0.017	0.019	-0.001
	0.7040	0.9735	0.4491	0.4053	0.3019	0.8368
Gas(-2)	-0.027	0.000	-0.050	-0.013	-0.003	0.005
	0.1866	0.9950	0.0141	0.5368	0.8552	0.1784
Gas(-3)	0.024	-0.005	-0.017	-0.003	-0.004	0.003
	0.2334	0.7996	0.3980	0.8871	0.8305	0.4095
Gas(-4)	-0.008	0.001	-0.044	-0.021	0.015	-0.003
	0.7030	0.9686	0.0309	0.2923	0.4041	0.3689
Gas(-5)	0.021	0.005	0.030	-0.001	0.041	0.001
	0.3003	0.8001	0.1318	0.9611	0.0220	0.7445
Gas(-6)	-0.001	-0.002	0.012	0.014	-0.018	0.004
	0.9452	0.9256	0.5480	0.4772	0.3188	0.2196
Gas(-7)	-0.022	-0.004	-0.027	0.064	-0.005	0.001
	0.2769	0.8460	0.1794	0.0017	0.7886	0.7026
Gas(-8)	-0.002	-0.007	0.010	-0.006	0.002	-0.002
	0.9015	0.7331	0.6036	0.7700	0.8996	0.6669
Gas(-9)	-0.023	0.022	-0.011	0.006	-0.003	0.003
	0.2588	0.2821	0.5911	0.7674	0.8644	0.4146
Gas(-10)	0.004	0.039	0.012	-0.064	-0.027	-0.012
	0.8460	0.0563	0.5603	0.0017	0.1357	0.0008
Gas(-11)	-0.033	0.005	-0.023	0.015	-0.004	0.006
	0.1022	0.8202	0.2555	0.4510	0.8048	0.0755
EUA(-1)	0.020	0.004	-0.017	0.025	-0.009	-0.010
	0.3707	0.8595	0.4537	0.2779	0.6492	0.0170
EUA(-2)	0.020	0.007	0.000	-0.013	0.031	-0.009
	0.3846	0.7763	0.9890	0.5562	0.1298	0.0249
EUA(-3)	0.002	-0.009	-0.008	-0.005	-0.002	-0.007
	0.9352	0.6992	0.7311	0.8295	0.9185	0.0809
EUA(-4)	-0.032	-0.002	0.008	-0.031	0.020	-0.008
	0.1543	0.9157	0.7355	0.1680	0.3189	0.0449
EUA(-5)	0.000	0.025	-0.011	0.021	0.090	0.001
	0.9987	0.2671	0.6281	0.3575	0.0000	0.8819
EUA(-6)	-0.022	0.015	-0.026	0.022	0.053	0.003
	0.3223	0.5123	0.2494	0.3408	0.0090	0.3968
EUA(-7)	-0.014	0.019	-0.010	-0.014	0.031	0.008
	0.5266	0.4155	0.6698	0.5338	0.1262	0.0552
EUA(-8)	0.039	0.016	0.004	0.009	0.019	0.013
	0.0853	0.4926	0.8604	0.6908	0.3395	0.0007
EUA(-9)	0.029	-0.002	0.007	-0.003	-0.006	-0.002
	0.1979	0.9187	0.7572	0.9117	0.7606	0.5814
EUA(-10)	-0.014	-0.016	-0.041	0.009	-0.092	0.003
	0.5220	0.4789	0.0684	0.6977	0.0000	0.4229
EUA(-11)	0.017	0.006	0.004	0.002	-0.027	0.001
	0.4641	0.7787	0.8670	0.9324	0.1817	0.7831

Table B.16: Results of VAR for Emissions Market Sentiment Count All Tweets No Outliers - Gas and EUAs

B.3 VAR Results for Emissions Market Sentiment With Outliers

B.3.1 With Outliers Emissions Market Sum Positive

	Brent	Coal	FTSE	Gas	EUA	Sum Pos
Sum Pos(-1)	0.102	0.054	0.048	0.077	-0.047	0.197
	0.1929	0.4974	0.5353	0.3291	0.553	0
Sum Pos(-2)	-0.022	0.019	0.156	-0.056	0.15	0.024
	0.7616	0.801	0.0343	0.4469	0.0424	0.2096
Sum Pos(-3)	-0.051	-0.026	-0.125	-0.018	-0.073	-0.033
	0.4894	0.7258	0.089	0.8123	0.3254	0.0752
Sum Pos(-4)	-0.101	0.02	0.237	0.104	0.126	0.043
	0.168	0.786	0.0013	0.1619	0.0881	0.0216
Sum Pos(-5)	0.041	-0.025	-0.014	-0.027	-0.155	-0.062
	0.5812	0.7433	0.8472	0.7209	0.0362	0.0009
Sum Pos(-6)	-0.045	0.025	-0.232	-0.006	-0.073	-0.189
	0.5353	0.7348	0.0013	0.9324	0.3115	0
Sum Pos(-7)	0.278	0	0.214	0.064	-0.084	-0.063
	0.0002	0.9961	0.0037	0.386	0.2549	0.0008
Sum Pos(-8)	-0.095	0.007	0.12	0.119	0.009	-0.009
	0.1968	0.9299	0.1024	0.1097	0.9061	0.6487
Sum Pos(-9)	-0.127	0.045	0.073	-0.068	0.038	-0.066
	0.0856	0.5499	0.3191	0.3576	0.6029	0.0005
Sum Pos(-10)	0.032	-0.018	0.104	0.078	-0.064	0.388
	0.6682	0.8062	0.1583	0.2939	0.3881	0
Sum Pos(-11)	-0.074	-0.021	0.064	-0.061	0.009	-0.154
	0.3465	0.79	0.4135	0.4414	0.9061	0
Brent(-1)	-0.014	0.007	0.02	0.009	0.007	-0.001
	0.498	0.7542	0.34	0.6504	0.7378	0.882
Brent(-2)	0.009	0.029	-0.003	-0.01	0.018	0.006
	0.6658	0.1584	0.8762	0.643	0.3878	0.2186
Brent(-3)	-0.042	0.003	-0.012	-0.044	-0.022	0.003
	0.0417	0.8674	0.5568	0.0324	0.2833	0.5452
Brent(-4)	0.001	0.012	0.003	0.004	0.017	0.004
	0.9713	0.552	0.8959	0.8501	0.3987	0.4464
Brent(-5)	-0.006	0.009	-0.045	0.01	-0.018	-0.005
	0.7593	0.6575	0.0281	0.6331	0.3892	0.3538
Brent(-6)	0.015	0.01	-0.001	-0.009	0.043	-0.011
	0.4704	0.6286	0.9442	0.6473	0.0352	0.041
Brent(-7)	0.009	0.005	0.032	-0.027	0.025	-0.006
	0.6447	0.794	0.1131	0.1872	0.2324	0.2821
Brent(-8)	-0.015	-0.007	-0.004	-0.02	-0.02	0.001
	0.4505	0.7298	0.8606	0.33	0.3233	0.8676
Brent(-9)	0.042	-0.019	-0.02	0.006	-0.01	0.003
	0.0408	0.372	0.3354	0.788	0.6131	0.5176
Brent(-10)	0.028	-0.011	-0.019	-0.019	-0.001	0.003
	0.1645	0.6127	0.3659	0.3472	0.9725	0.5258
Brent(-11)	0.013	0.006	-0.005	0.004	-0.009	-0.005
	0.5252	0.7738	0.8031	0.8404	0.6438	0.3326
C	0	-0.001	0	0.001	0	0
	0.9908	0.944	0.9808	0.9516	0.9948	0.9844
R^2	0.0414	0.0116	0.0399	0.0277	0.0336	0.2646

Table B.17: Results of VAR for Emissions Market Sentiment Sum Pos With Outliers - Sent and Brent

	Brent	Coal	FTSE	Gas	EUA	Sum Pos
Coal(-1)	0.016	-0.011	0.006	0.011	0.009	-0.007
	0.4308	0.5914	0.7576	0.582	0.6682	0.1933
Coal(-2)	-0.019	-0.002	0.008	-0.016	0.007	0.005
	0.3349	0.9076	0.699	0.4101	0.7331	0.3118
Coal(-3)	-0.044	0.012	0.006	-0.007	-0.001	-0.002
	0.0266	0.561	0.7672	0.7367	0.9663	0.7669
Coal(-4)	0.011	-0.009	-0.007	-0.031	-0.025	0
	0.5934	0.6412	0.7353	0.1264	0.2129	0.9498
Coal(-5)	-0.09	-0.007	0.028	-0.02	0.019	-0.001
	0	0.7339	0.1538	0.3242	0.3483	0.8266
Coal(-6)	-0.01	-0.003	-0.012	-0.016	0.003	0.003
	0.6238	0.8689	0.5459	0.4137	0.8847	0.5406
Coal(-7)	-0.002	0.013	0.024	-0.027	0	-0.001
	0.9017	0.5188	0.2311	0.1853	0.9865	0.8701
Coal(-8)	-0.002	-0.002	0.001	-0.015	-0.001	0
	0.9347	0.9275	0.9788	0.4476	0.9652	0.9478
Coal(-9)	0.024	0.009	0.015	-0.002	-0.005	-0.001
	0.2323	0.6499	0.4575	0.9025	0.7982	0.9053
Coal(-10)	-0.009	0.012	0.01	-0.016	-0.01	-0.001
	0.6492	0.5374	0.6246	0.4373	0.6255	0.9009
Coal(-11)	0.003	0.002	-0.006	-0.012	0.005	-0.001
	0.869	0.9185	0.7609	0.5448	0.8137	0.7784
FTSE(-1)	0.045	0.016	-0.014	-0.004	-0.018	-0.004
	0.0281	0.443	0.492	0.8422	0.3738	0.3923
FTSE(-2)	0.038	0.017	-0.019	-0.015	0.007	0.005
	0.0636	0.4213	0.3508	0.466	0.7302	0.3808
FTSE(-3)	0.008	0.046	0.014	-0.004	0	-0.013
	0.7029	0.0289	0.5095	0.8506	0.9993	0.0122
FTSE(-4)	0.004	-0.028	-0.011	0.002	0.013	-0.016
	0.8332	0.175	0.6082	0.9061	0.5167	0.0016
FTSE(-5)	0.026	-0.01	0.024	0.025	-0.002	-0.011
	0.1988	0.6435	0.2464	0.2275	0.9058	0.0341
FTSE(-6)	0.013	0.041	0.006	0.005	-0.013	0.004
	0.5111	0.0502	0.7734	0.8047	0.5327	0.4618
FTSE(-7)	-0.034	-0.011	-0.006	0.048	-0.004	0.007
	0.0974	0.607	0.7699	0.0205	0.8619	0.1603
FTSE(-8)	0.039	-0.008	-0.06	0.025	0.013	0.003
	0.0554	0.7099	0.0032	0.2228	0.5398	0.5347
FTSE(-9)	-0.054	0	-0.018	0.059	-0.026	0.01
	0.0093	0.9836	0.3901	0.0042	0.2057	0.0586
FTSE(-10)	0.013	-0.001	-0.035	0.029	0.023	-0.006
	0.5133	0.9528	0.0875	0.1573	0.2666	0.2787
FTSE(-11)	-0.009	0.005	-0.026	0.038	0.017	-0.013
	0.6684	0.7944	0.2155	0.0666	0.4219	0.0123

Table B.18: Results of VAR for Emissions Market Sentiment Sum Pos With Outliers - Coal and FTSE

	Brent	**Coal**	**FTSE**	**Gas**	**EUA**	**Sum Pos**
Gas(-1)	0.009	0	-0.02	-0.017	0.022	-0.002
	0.653	0.9892	0.3177	0.4028	0.2732	0.6908
Gas(-2)	-0.026	0.001	-0.047	-0.013	-0.006	0.006
	0.2011	0.9744	0.0186	0.5288	0.7555	0.2141
Gas(-3)	0.023	-0.005	-0.017	-0.003	-0.005	-0.002
	0.2538	0.7951	0.3922	0.873	0.8169	0.6761
Gas(-4)	-0.011	0.001	-0.044	-0.022	0.025	0.001
	0.5832	0.9527	0.0284	0.2793	0.2124	0.8206
Gas(-5)	0.022	0.005	0.03	-0.001	0.041	0.001
	0.2838	0.7911	0.1368	0.9783	0.0429	0.8419
Gas(-6)	-0.004	-0.001	0.005	0.014	-0.022	-0.003
	0.8557	0.9666	0.7881	0.4781	0.2795	0.5845
Gas(-7)	-0.025	-0.002	-0.026	0.065	-0.006	-0.002
	0.2061	0.918	0.2027	0.0014	0.7749	0.6752
Gas(-8)	-0.002	-0.008	0.013	-0.007	0.001	-0.003
	0.9145	0.7076	0.509	0.7462	0.9625	0.4958
Gas(-9)	-0.026	0.023	-0.012	0.005	0	0
	0.1998	0.2614	0.5662	0.8156	0.9852	0.9677
Gas(-10)	0.002	0.04	0.014	-0.061	-0.029	-0.009
	0.9196	0.0482	0.4941	0.0024	0.1501	0.095
Gas(-11)	-0.033	0.005	-0.02	0.014	-0.009	0.004
	0.1027	0.7955	0.3117	0.4771	0.6514	0.3818
EUA(-1)	0.003	0.005	-0.018	0.018	-0.015	-0.014
	0.8878	0.8019	0.3737	0.365	0.4667	0.0057
EUA(-2)	0.024	0.007	-0.015	-0.016	0.019	-0.01
	0.2428	0.7441	0.4636	0.4376	0.3524	0.0558
EUA(-3)	0.008	-0.004	-0.004	0	-0.008	0.001
	0.6861	0.8363	0.8305	0.9965	0.7036	0.7822
EUA(-4)	-0.006	-0.008	0.021	-0.026	0.025	-0.013
	0.7613	0.7001	0.2984	0.1935	0.2229	0.0124
EUA(-5)	0.002	0.021	-0.007	0.021	0.08	-0.003
	0.9163	0.3166	0.7462	0.2977	0.0001	0.5382
EUA(-6)	-0.013	0.01	-0.027	0.015	0.058	0.005
	0.5172	0.6167	0.18	0.4551	0.0042	0.3164
EUA(-7)	-0.014	0.012	0.028	-0.015	0.032	0.009
	0.4915	0.5434	0.1644	0.4499	0.1166	0.0662
EUA(-8)	0.035	0.012	0.002	0.008	0.011	0.004
	0.0858	0.5689	0.9097	0.6987	0.575	0.4058
EUA(-9)	0.035	-0.004	0.009	0.003	0.008	0.005
	0.0792	0.852	0.6683	0.8765	0.6874	0.3395
EUA(-10)	-0.014	-0.016	-0.03	0.008	-0.046	-0.005
	0.4791	0.4368	0.1367	0.6858	0.0227	0.3422
EUA(-11)	0.017	0.006	0.014	0.005	-0.032	0.009
	0.394	0.7536	0.4856	0.7982	0.1119	0.0674

Table B.19: Results of VAR for Emissions Market Sentiment Sum Pos With Outliers - Gas and EUAs

B.3.2 With Outliers Emissions Market Sum of Negative

	Brent	Coal	FTSE	Gas	EUA	Sum Neg
Sum Neg(-1)	-0.1192	-0.0188	-0.1813	-0.0049	-0.1483	-0.2753
	0.1625	0.8278	0.0341	0.9541	0.0805	0
Sum Neg(-2)	0.0803	-0.0192	-0.0597	0.0139	-0.1933	0.0472
	0.3257	0.8169	0.4662	0.8656	0.0174	0.0134
Sum Neg(-3)	0.1687	0.0341	0.1067	0.0201	0.1263	0.0469
	0.0386	0.6799	0.1916	0.8059	0.1191	0.0138
Sum Neg(-4)	0.06	0.0062	-0.1331	-0.0165	-0.1089	-0.0402
	0.4624	0.94	0.1035	0.8406	0.1793	0.0348
Sum Neg(-5)	-0.0067	-0.0037	-0.0156	-0.0352	0.2521	0.0781
	0.9345	0.9639	0.8477	0.6663	0.0018	0
Sum Neg(-6)	0.0272	-0.058	0.1701	-0.0007	0.0426	0.1889
	0.7307	0.4691	0.0319	0.9926	0.5882	0
Sum Neg(-7)	-0.1285	-0.0041	0.0264	-0.0554	0.028	-0.098
	0.1092	0.9593	0.742	0.4917	0.7251	0
Sum Neg(-8)	0.0276	-0.003	-0.1837	-0.1474	0.023	0.0408
	0.7314	0.9703	0.0228	0.0682	0.7736	0.0298
Sum Neg(-9)	0.1701	-0.0189	0.0696	0.028	0.2032	0.0706
	0.0347	0.817	0.3882	0.7288	0.0112	0.0002
Sum Neg(-10)	-0.0048	0.0072	0.0182	-0.0039	0.3411	-0.4101
	0.9529	0.9302	0.8218	0.962	0	0
Sum Neg(-11)	0.0288	-0.0225	0.0282	-0.0769	-0.0471	0.2441
	0.7313	0.7904	0.7368	0.3608	0.5717	0
Brent(-1)	-0.017	0.0068	0.0173	0.0109	0.0017	-0.0006
	0.4082	0.7459	0.4034	0.5976	0.9329	0.8956
Brent(-2)	0.0103	0.0306	0.0006	-0.0096	0.0183	0.0078
	0.6178	0.1431	0.9779	0.6411	0.3717	0.1068
Brent(-3)	-0.0434	0.0046	-0.0149	-0.041	-0.0215	0.0049
	0.035	0.8265	0.4695	0.047	0.2933	0.3077
Brent(-4)	0.0014	0.013	0.0021	0.0036	0.0143	-0.0021
	0.945	0.5322	0.9176	0.8618	0.4834	0.6632
Brent(-5)	-0.0026	0.0088	-0.0441	0.0109	-0.0192	0.0088
	0.9005	0.673	0.0323	0.5969	0.3464	0.0662
Brent(-6)	0.0138	0.0099	-0.0024	-0.01	0.0389	-0.0081
	0.5015	0.636	0.9092	0.6267	0.0574	0.0936
Brent(-7)	0.0086	0.005	0.0339	-0.0266	0.0233	-0.0145
	0.6757	0.8098	0.0988	0.1958	0.2527	0.0025
Brent(-8)	-0.0148	-0.0077	-0.003	-0.0202	-0.0168	0.0023
	0.4727	0.7121	0.8837	0.3274	0.4098	0.6283
Brent(-9)	0.0423	-0.0187	-0.0185	0.005	-0.0063	0.0025
	0.0394	0.3681	0.3686	0.8074	0.7581	0.6057
Brent(-10)	0.0289	-0.0114	-0.02	-0.0217	0.0016	0.0073
	0.1581	0.5824	0.3297	0.2932	0.9357	0.1258
Brent(-11)	0.0115	0.0052	-0.0038	0.0029	-0.0079	-0.0076
	0.5738	0.8008	0.8521	0.8863	0.697	0.1108
	0.4708	0.7296	0.5992	0.7273	0.1024	0.0373
C	0.0002	-0.0014	0.0005	0.0012	-0.0001	0
	0.99	0.9439	0.9795	0.9524	0.9977	0.9915
R^2	0.0387	0.0115	0.0333	0.0268	0.0497	0.3067

Table B.20: Results of VAR for Emissions Market Sentiment Sum Neg With Outliers - Sent and Brent

	Brent	Coal	FTSE	Gas	EUA	Sum Neg
Coal(-1)	0.0162	-0.0109	0.0075	0.0108	0.0092	-0.0002
	0.4147	0.5881	0.706	0.5881	0.6431	0.9698
Coal(-2)	-0.0205	-0.0026	0.0068	-0.0174	0.0075	0.0022
	0.303	0.8977	0.734	0.3836	0.7053	0.6324
Coal(-3)	-0.0434	0.0118	0.0054	-0.0062	-0.0016	-0.0015
	0.0293	0.5595	0.7876	0.7575	0.9351	0.7531
Coal(-4)	0.0109	-0.0094	-0.0055	-0.0303	-0.0233	-0.0007
	0.5853	0.6409	0.7836	0.1299	0.239	0.8728
Coal(-5)	-0.0887	-0.0068	0.0276	-0.0204	0.0179	-0.0006
	0	0.7345	0.1665	0.3063	0.3664	0.8929
Coal(-6)	-0.0106	-0.0031	-0.0116	-0.0157	0.0033	0
	0.597	0.8781	0.5622	0.4341	0.8677	0.9953
Coal(-7)	-0.0018	0.0129	0.0249	-0.0266	-0.0005	0.0022
	0.9297	0.5232	0.2144	0.1858	0.9818	0.631
Coal(-8)	-0.0038	-0.0016	0.0004	-0.0151	0.0014	-0.0016
	0.8488	0.9359	0.9835	0.4508	0.9442	0.7312
Coal(-9)	0.0255	0.009	0.0145	-0.0035	-0.0064	0.0028
	0.2015	0.6566	0.4697	0.8625	0.7483	0.548
Coal(-10)	-0.0094	0.0124	0.0097	-0.0148	-0.0095	0.002
	0.6393	0.5401	0.6288	0.4604	0.6318	0.6641
Coal(-11)	0.0037	0.002	-0.0069	-0.0129	0.0042	-0.0027
	0.8532	0.9227	0.7304	0.5196	0.8332	0.5558
FTSE(-1)	0.044	0.015	-0.0134	-0.0038	-0.0173	-0.0027
	0.0317	0.4688	0.5154	0.8517	0.3958	0.5779
FTSE(-2)	0.0365	0.0176	-0.0152	-0.0149	0.0128	0.0001
	0.0752	0.3972	0.4579	0.4691	0.5307	0.9833
FTSE(-3)	0.0112	0.0444	0.0161	-0.0041	-0.0074	-0.0094
	0.5861	0.0328	0.4344	0.8417	0.7176	0.0498
FTSE(-4)	0.0001	-0.029	-0.0131	-0.0002	0.0149	-0.0058
	0.9966	0.1629	0.5247	0.9921	0.4646	0.2218
FTSE(-5)	0.0269	-0.0104	0.0281	0.0238	0.0057	-0.0048
	0.1888	0.6157	0.171	0.2477	0.7806	0.318
FTSE(-6)	0.0097	0.0395	0.0056	0.007	-0.0128	0.0014
	0.6354	0.0571	0.7846	0.7337	0.5286	0.7693
FTSE(-7)	-0.0363	-0.0104	-0.0108	0.0444	-0.0048	0.007
	0.0761	0.6148	0.5991	0.0309	0.812	0.141
FTSE(-8)	0.0439	-0.008	-0.0626	0.0253	0.0116	0.0101
	0.0323	0.7011	0.0023	0.2187	0.5688	0.0348
FTSE(-9)	-0.0529	0.0002	-0.0192	0.0596	-0.0259	0.0036
	0.0102	0.994	0.3512	0.004	0.205	0.4484
FTSE(-10)	0.0121	-0.0001	-0.0344	0.0306	0.0174	-0.0035
	0.5584	0.9969	0.0958	0.1391	0.396	0.4727
FTSE(-11)	-0.0099	0.0061	-0.0249	0.0378	0.0173	-0.0014
	0.632	0.7694	0.2269	0.0678	0.3972	0.7784

Table B.21: Results of VAR for Emissions Market Sentiment Sum Neg With Outliers - Coal and FTSE

	Brent	Coal	FTSE	Gas	EUA	Sum Neg
Gas(-1)	0.0086	0.0001	-0.0188	-0.0185	0.0245	-0.0012
	0.6693	0.9974	0.3524	0.3607	0.2211	0.8035
Gas(-2)	-0.0256	0.0001	-0.0486	-0.0132	-0.004	0.0061
	0.2038	0.9949	0.0161	0.5143	0.8435	0.1929
Gas(-3)	0.0247	-0.0054	-0.0161	-0.0031	-0.0057	0.0006
	0.2199	0.7928	0.426	0.8768	0.7765	0.896
Gas(-4)	-0.0103	0.0011	-0.0421	-0.022	0.0247	-0.0028
	0.6105	0.957	0.037	0.2756	0.2169	0.5539
Gas(-5)	0.0219	0.0056	0.0276	-0.0016	0.0427	0.0024
	0.2758	0.7846	0.17	0.9354	0.0326	0.6166
Gas(-6)	-0.0035	-0.001	0.0077	0.0149	-0.0205	0.0015
	0.8633	0.9611	0.7008	0.4596	0.3056	0.7428
Gas(-7)	-0.0257	-0.0032	-0.0254	0.0635	-0.007	0.0032
	0.2023	0.8765	0.2076	0.0017	0.7281	0.4957
Gas(-8)	-0.0046	-0.0078	0.0103	-0.0082	0.0014	-0.0005
	0.8198	0.7018	0.6094	0.6853	0.9431	0.9168
Gas(-9)	-0.0223	0.0226	-0.0103	0.0043	0.0001	0
	0.2676	0.2685	0.6103	0.8306	0.9976	0.9924
Gas(-10)	0.0021	0.0402	0.0114	-0.061	-0.0263	-0.012
	0.9159	0.0487	0.5728	0.0026	0.1883	0.0108
Gas(-11)	-0.031	0.0052	-0.0175	0.0123	-0.0043	0.0041
	0.1254	0.7989	0.3879	0.5463	0.8291	0.3823
EUA(-1)	0.0127	0.0077	-0.0126	0.0215	-0.0147	-0.0302
	0.5401	0.713	0.5447	0.3028	0.4771	0
EUA(-2)	0.0242	0.0091	-0.0043	-0.0149	0.0367	0.0025
	0.2466	0.6663	0.8388	0.4771	0.0776	0.6031
EUA(-3)	-0.0022	-0.0064	-0.0109	-0.0023	-0.0096	-0.0057
	0.9171	0.7621	0.6035	0.9127	0.6458	0.241
EUA(-4)	-0.0208	-0.01	0.0216	-0.0243	0.0268	-0.0012
	0.3192	0.6373	0.3031	0.2467	0.1978	0.8103
EUA(-5)	0.0014	0.0187	0.0031	0.021	0.0671	-0.0056
	0.9476	0.3783	0.8812	0.3169	0.0013	0.2503
EUA(-6)	-0.0175	0.0132	-0.0426	0.0165	0.048	0.0208
	0.4033	0.5317	0.0419	0.4305	0.0209	0
EUA(-7)	-0.0082	0.0146	0.0154	-0.0145	0.0257	-0.0042
	0.6938	0.4904	0.4625	0.4897	0.2164	0.3929
EUA(-8)	0.0423	0.0112	0.0098	0.0203	0.0079	0.0012
	0.0426	0.5974	0.6387	0.333	0.7019	0.8038
EUA(-9)	0.0301	-0.0006	0.0151	0.0044	0.0063	0.0004
	0.1487	0.9766	0.4714	0.834	0.7599	0.9283
EUA(-10)	-0.016	-0.0154	-0.0348	0.0073	-0.0771	0.0102
	0.4414	0.4648	0.0951	0.7278	0.0002	0.036
EUA(-11)	0.015	0.0073	0.011	0.0073	-0.0338	0.0101
	0.4708	0.7296	0.5992	0.7273	0.1024	0.0373

Table B.22: Results of VAR for Emissions Market Sentiment Sum Neg With Outliers - Gas and EUAs

B.3.3 With Outliers Emissions Market Count Positive

	Brent	Coal	FTSE	Gas	EUA	Count Pos
Count Pos(-1)	0.102	0.051	0.029	0.068	-0.048	0.228
	0.1984	0.5284	0.7156	0.3930	0.5446	0.0000
Count Pos(-2)	-0.026	0.037	0.167	-0.062	0.167	0.026
	0.7303	0.6235	0.0251	0.4117	0.0259	0.1631
Count Pos(-3)	-0.069	-0.044	-0.108	-0.001	-0.081	-0.023
	0.3544	0.5582	0.1492	0.9944	0.2818	0.2212
Count Pos(-4)	-0.079	0.028	0.244	0.107	0.159	0.058
	0.2895	0.7110	0.0011	0.1554	0.0334	0.0017
Count Pos(-5)	0.022	-0.022	-0.017	-0.038	-0.170	-0.089
	0.7723	0.7752	0.8227	0.6174	0.0241	0.0000
Count Pos(-6)	-0.025	0.024	-0.258	-0.014	-0.070	-0.194
	0.7390	0.7513	0.0005	0.8546	0.3399	0.0000
Count Pos(-7)	0.252	0.003	0.211	0.055	-0.075	-0.027
	0.0008	0.9656	0.0047	0.4692	0.3206	0.1439
Count Pos(-8)	-0.095	0.006	0.164	0.117	0.041	-0.003
	0.2032	0.9382	0.0283	0.1194	0.5855	0.8516
Count Pos(-9)	-0.132	0.039	0.054	-0.057	0.023	-0.073
	0.0775	0.6069	0.4682	0.4522	0.7560	0.0001
Count Pos(-10)	0.025	-0.013	0.099	0.080	-0.086	0.401
	0.7440	0.8643	0.1848	0.2874	0.2530	0.0000
Count Pos(-11)	-0.062	-0.021	0.108	-0.062	0.022	-0.191
	0.4336	0.7950	0.1752	0.4377	0.7844	0.0000
Brent(-1)	-0.015	0.007	0.019	0.010	0.006	-0.002
	0.4596	0.7511	0.3491	0.6310	0.7552	0.6638
Brent(-2)	0.010	0.030	-0.002	-0.010	0.018	0.008
	0.6418	0.1567	0.9186	0.6322	0.3889	0.0992
Brent(-3)	-0.043	0.003	-0.012	-0.044	-0.022	0.004
	0.0384	0.8668	0.5584	0.0315	0.2910	0.4230
Brent(-4)	0.000	0.012	0.002	0.003	0.017	0.003
	0.9860	0.5610	0.9134	0.8654	0.4065	0.6006
Brent(-5)	-0.005	0.009	-0.045	0.011	-0.018	-0.004
	0.7923	0.6650	0.0285	0.6065	0.3849	0.4660
Brent(-6)	0.015	0.010	-0.002	-0.010	0.043	-0.011
	0.4759	0.6238	0.9146	0.6306	0.0378	0.0382
Brent(-7)	0.009	0.005	0.032	-0.027	0.024	-0.007
	0.6476	0.7944	0.1176	0.1841	0.2355	0.1817
Brent(-8)	-0.015	-0.007	-0.003	-0.020	-0.020	0.001
	0.4541	0.7360	0.8857	0.3369	0.3223	0.8475
Brent(-9)	0.041	-0.019	-0.018	0.006	-0.010	0.004
	0.0438	0.3718	0.3669	0.7763	0.6364	0.4759
Brent(-10)	0.029	-0.011	-0.019	-0.020	0.000	0.005
	0.1570	0.6110	0.3612	0.3431	0.9848	0.3748
Brent(-11)	0.013	0.006	-0.006	0.004	-0.010	-0.005
	0.5296	0.7747	0.7790	0.8409	0.6427	0.2872
C	0.000	-0.001	0.000	0.001	0.000	0.000
	0.9911	0.9439	0.9806	0.9516	0.9948	0.9719
$\mathbf{R}^2$	0.0398	0.0117	0.0420	0.0276	0.0347	0.2758

Table B.23: Results of VAR for Emissions Market Sentiment Count Pos With Outliers - Sent and Brent

	Brent	Coal	FTSE	Gas	EUA	Count Pos
Coal(-1)	0.016	-0.011	0.007	0.011	0.009	-0.006
	0.4242	0.5930	0.7385	0.5771	0.6504	0.2049
Coal(-2)	-0.019	-0.002	0.007	-0.017	0.006	0.006
	0.3337	0.9052	0.7242	0.4008	0.7503	0.2368
Coal(-3)	-0.044	0.012	0.006	-0.007	-0.001	-0.002
	0.0261	0.5575	0.7793	0.7344	0.9763	0.7382
Coal(-4)	0.011	-0.010	-0.006	-0.030	-0.025	0.000
	0.5857	0.6317	0.7470	0.1294	0.2076	0.9705
Coal(-5)	-0.090	-0.007	0.028	-0.020	0.019	0.000
	0.0000	0.7408	0.1521	0.3251	0.3353	0.9613
Coal(-6)	-0.010	-0.003	-0.012	-0.017	0.003	0.002
	0.6104	0.8667	0.5342	0.4023	0.8936	0.6571
Coal(-7)	-0.002	0.013	0.023	-0.026	0.000	0.000
	0.9197	0.5195	0.2397	0.1891	0.9964	0.9746
Coal(-8)	-0.002	-0.002	0.001	-0.015	-0.001	0.000
	0.9209	0.9240	0.9600	0.4433	0.9778	0.9958
Coal(-9)	0.024	0.009	0.015	-0.003	-0.005	0.000
	0.2277	0.6483	0.4654	0.8970	0.8060	0.9720
Coal(-10)	-0.009	0.012	0.009	-0.016	-0.010	-0.001
	0.6407	0.5395	0.6452	0.4366	0.6167	0.8447
Coal(-11)	0.004	0.002	-0.006	-0.012	0.005	-0.003
	0.8560	0.9187	0.7585	0.5466	0.8207	0.5273
FTSE(-1)	0.047	0.016	-0.015	-0.004	-0.019	-0.006
	0.0235	0.4435	0.4517	0.8407	0.3692	0.2661
FTSE(-2)	0.038	0.017	-0.018	-0.015	0.008	0.004
	0.0671	0.4128	0.3783	0.4622	0.6890	0.4927
FTSE(-3)	0.008	0.045	0.013	-0.004	0.000	-0.013
	0.6853	0.0292	0.5112	0.8628	0.9825	0.0104
FTSE(-4)	0.003	-0.028	-0.012	0.003	0.013	-0.013
	0.8801	0.1743	0.5604	0.8932	0.5431	0.0124
FTSE(-5)	0.026	-0.009	0.026	0.024	-0.001	-0.009
	0.1996	0.6501	0.2111	0.2380	0.9544	0.0955
FTSE(-6)	0.013	0.041	0.005	0.005	-0.013	0.003
	0.5267	0.0510	0.8068	0.8166	0.5204	0.6163
FTSE(-7)	-0.034	-0.011	-0.007	0.048	-0.004	0.006
	0.0958	0.6088	0.7275	0.0195	0.8453	0.2045
FTSE(-8)	0.041	-0.008	-0.059	0.026	0.013	0.002
	0.0464	0.7060	0.0040	0.2108	0.5245	0.7227
FTSE(-9)	-0.053	0.000	-0.018	0.059	-0.026	0.010
	0.0099	0.9976	0.3762	0.0043	0.2073	0.0569
FTSE(-10)	0.013	-0.001	-0.035	0.029	0.023	-0.006
	0.5374	0.9613	0.0871	0.1607	0.2623	0.2697
FTSE(-11)	-0.009	0.005	-0.025	0.038	0.017	-0.011
	0.6488	0.8067	0.2242	0.0671	0.4194	0.0307

Table B.24: Results of VAR for Emissions Market Sentiment Count Pos With Outliers - Coal and FTSE

	Brent	Coal	FTSE	Gas	EUA	Count Pos)
Gas(-1)	0.009	0.000	-0.020	-0.017	0.022	-0.002
	0.6451	0.9916	0.3099	0.4011	0.2769	0.6937
Gas(-2)	-0.026	0.001	-0.047	-0.013	-0.006	0.007
	0.2035	0.9726	0.0197	0.5340	0.7746	0.1918
Gas(-3)	0.023	-0.005	-0.017	-0.003	-0.005	-0.001
	0.2572	0.7989	0.4001	0.8789	0.8166	0.8601
Gas(-4)	-0.011	0.001	-0.045	-0.022	0.025	0.001
	0.5692	0.9633	0.0261	0.2768	0.2172	0.8125
Gas(-5)	0.022	0.006	0.029	-0.001	0.041	0.002
	0.2791	0.7855	0.1418	0.9691	0.0427	0.6779
Gas(-6)	-0.004	-0.001	0.006	0.014	-0.022	-0.003
	0.8496	0.9604	0.7640	0.4791	0.2820	0.4912
Gas(-7)	-0.025	-0.002	-0.027	0.065	-0.006	-0.001
	0.2114	0.9152	0.1866	0.0014	0.7651	0.8639
Gas(-8)	-0.003	-0.008	0.013	-0.007	0.001	-0.003
	0.8913	0.7107	0.5138	0.7404	0.9581	0.5819
Gas(-9)	-0.025	0.023	-0.011	0.005	0.000	0.001
	0.2102	0.2648	0.5751	0.8175	0.9831	0.8325
Gas(-10)	0.002	0.040	0.013	-0.061	-0.029	-0.007
	0.9362	0.0479	0.5120	0.0024	0.1514	0.1621
Gas(-11)	-0.033	0.005	-0.021	0.014	-0.009	0.003
	0.1030	0.8022	0.3033	0.4884	0.6459	0.4980
EUA(-1)	0.004	0.006	-0.017	0.019	-0.014	-0.014
	0.8488	0.7867	0.3875	0.3588	0.4931	0.0071
EUA(-2)	0.023	0.006	-0.014	-0.016	0.019	-0.011
	0.2574	0.7565	0.4859	0.4207	0.3449	0.0328
EUA(-3)	0.008	-0.004	-0.006	0.000	-0.007	-0.001
	0.6782	0.8448	0.7822	0.9911	0.7138	0.9126
EUA(-4)	-0.007	-0.008	0.022	-0.026	0.025	-0.012
	0.7341	0.7080	0.2713	0.2042	0.2244	0.0138
EUA(-5)	0.003	0.020	-0.006	0.021	0.080	-0.002
	0.8924	0.3205	0.7814	0.2933	0.0001	0.6874
EUA(-6)	-0.014	0.011	-0.028	0.015	0.058	0.007
	0.4938	0.6081	0.1638	0.4638	0.0041	0.1891
EUA(-7)	-0.013	0.012	0.029	-0.015	0.032	0.009
	0.5193	0.5438	0.1470	0.4652	0.1184	0.0707
EUA(-8)	0.035	0.011	0.002	0.009	0.011	0.001
	0.0863	0.5799	0.9167	0.6730	0.5937	0.8526
EUA(-9)	0.035	-0.003	0.009	0.003	0.008	0.005
	0.0790	0.8777	0.6705	0.8919	0.6747	0.3111
EUA(-10)	-0.013	-0.016	-0.029	0.008	-0.046	-0.004
	0.5059	0.4309	0.1425	0.6925	0.0216	0.4011
EUA(-11)	0.016	0.006	0.014	0.005	-0.032	0.006
	0.4185	0.7542	0.4969	0.7989	0.1134	0.2192

Table B.25: Results of VAR for Emissions Market Sentiment Count Pos With Outliers - Gas and EUAs

B.3.4 With Outliers Emissions Market Count of Negative

	Brent	Coal	FTSE	Gas	EUA	Count Neg
Count Neg (-1)	0.118	0.027	0.158	0.001	0.125	0.268
	0.1709	0.7613	0.0677	0.9947	0.1480	0.0000
Count Neg (-2)	-0.073	0.019	0.076	0.000	0.185	-0.029
	0.3733	0.8227	0.3527	0.9987	0.0228	0.1236
Count Neg (-3)	-0.180	-0.049	-0.097	-0.011	-0.090	-0.041
	0.0275	0.5547	0.2339	0.8939	0.2684	0.0282
Count Neg (-4)	-0.089	0.019	0.122	0.016	0.110	0.049
	0.2730	0.8193	0.1359	0.8497	0.1740	0.0091
Count Neg (-5)	0.033	0.006	0.023	0.033	-0.228	-0.091
	0.6865	0.9408	0.7761	0.6886	0.0049	0.0000
Count Neg (-6)	-0.034	0.051	-0.177	0.008	-0.033	-0.204
	0.6679	0.5216	0.0255	0.9199	0.6721	0.0000
Count Neg (-7)	0.140	0.010	-0.018	0.055	-0.048	0.097
	0.0799	0.9003	0.8196	0.4919	0.5472	0.0000
Count Neg (-8)	-0.027	-0.003	0.193	0.163	-0.020	-0.031
	0.7366	0.9665	0.0169	0.0431	0.8066	0.0978
Count Neg (-9)	-0.187	0.015	-0.051	-0.040	-0.182	-0.064
	0.0200	0.8582	0.5278	0.6166	0.0228	0.0005
Count Neg (-10)	-0.014	0.004	-0.007	0.022	-0.326	0.424
	0.8654	0.9620	0.9287	0.7819	0.0001	0.0000
Count Neg (-11)	-0.024	0.017	-0.009	0.056	0.038	-0.251
	0.7746	0.8463	0.9165	0.5099	0.6496	0.0000
Brent(-1)	-0.017	0.007	0.018	0.011	0.002	0.000
	0.4000	0.7386	0.3872	0.5948	0.9043	0.9486
Brent(-2)	0.010	0.031	0.000	-0.010	0.019	0.007
	0.6247	0.1398	0.9926	0.6366	0.3666	0.1257
Brent(-3)	-0.043	0.005	-0.015	-0.041	-0.022	0.005
	0.0378	0.8286	0.4550	0.0449	0.2871	0.3006
Brent(-4)	0.002	0.013	0.002	0.004	0.014	-0.001
	0.9182	0.5454	0.9073	0.8440	0.4854	0.8726
Brent(-5)	-0.003	0.009	-0.044	0.011	-0.020	0.007
	0.8837	0.6705	0.0312	0.5980	0.3365	0.1561
Brent(-6)	0.014	0.010	-0.002	-0.010	0.038	-0.007
	0.4876	0.6359	0.9261	0.6236	0.0620	0.1198
Brent(-7)	0.009	0.005	0.034	-0.027	0.023	-0.016
	0.6739	0.8162	0.0967	0.1945	0.2538	0.0010
Brent(-8)	-0.015	-0.008	-0.003	-0.020	-0.018	0.002
	0.4678	0.7188	0.8819	0.3233	0.3861	0.6549
Brent(-9)	0.042	-0.019	-0.018	0.005	-0.006	0.003
	0.0396	0.3636	0.3841	0.8042	0.7701	0.4671
Brent(-10)	0.028	-0.012	-0.020	-0.022	0.002	0.007
	0.1702	0.5744	0.3283	0.2881	0.9249	0.1591
Brent(-11)	0.011	0.006	-0.004	0.003	-0.007	-0.007
	0.5867	0.7852	0.8435	0.8873	0.7230	0.1220
C	0.000	-0.001	0.000	0.001	0.000	0.000
	0.9900	0.9438	0.9800	0.9525	0.9972	0.9846
R^2	0.0395	0.0115	0.0329	0.0270	0.0466	0.3214

Table B.26: Results of VAR for Emissions Market Sentiment Count Neg With Outliers - Sent and Brent

	Brent	Coal	FTSE	Gas	EUA	Count Neg
Coal(-1)	0.016	-0.011	0.007	0.011	0.009	0.000
	0.4183	0.5897	0.7112	0.5936	0.6361	0.9320
Coal(-2)	-0.020	-0.003	0.007	-0.017	0.007	0.003
	0.3085	0.8960	0.7193	0.3860	0.7083	0.5532
Coal(-3)	-0.044	0.012	0.005	-0.006	-0.001	-0.002
	0.0283	0.5610	0.7925	0.7562	0.9414	0.7253
Coal(-4)	0.011	-0.009	-0.006	-0.031	-0.024	0.000
	0.5836	0.6418	0.7640	0.1263	0.2341	0.9289
Coal(-5)	-0.088	-0.007	0.028	-0.020	0.018	-0.001
	0.0000	0.7365	0.1650	0.3093	0.3577	0.8977
Coal(-6)	-0.011	-0.003	-0.011	-0.016	0.004	-0.001
	0.5986	0.8735	0.5667	0.4320	0.8540	0.9112
Coal(-7)	-0.002	0.013	0.025	-0.027	-0.001	0.003
	0.9266	0.5235	0.2160	0.1853	0.9716	0.5685
Coal(-8)	-0.004	-0.002	0.000	-0.015	0.001	-0.002
	0.8542	0.9382	0.9859	0.4480	0.9422	0.7308
Coal(-9)	0.026	0.009	0.014	-0.003	-0.006	0.003
	0.1990	0.6578	0.4709	0.8626	0.7524	0.5570
Coal(-10)	-0.009	0.012	0.010	-0.015	-0.009	0.001
	0.6378	0.5414	0.6290	0.4602	0.6354	0.7503
Coal(-11)	0.004	0.002	-0.007	-0.013	0.004	-0.003
	0.8485	0.9252	0.7346	0.5186	0.8396	0.4536
FTSE(-1)	0.044	0.015	-0.014	-0.004	-0.017	-0.003
	0.0302	0.4604	0.5079	0.8443	0.3915	0.5828
FTSE(-2)	0.037	0.017	-0.015	-0.015	0.012	0.000
	0.0718	0.3994	0.4516	0.4613	0.5489	0.9870
FTSE(-3)	0.011	0.044	0.016	-0.004	-0.007	-0.009
	0.5977	0.0346	0.4227	0.8548	0.7458	0.0553
FTSE(-4)	-0.001	-0.029	-0.013	0.000	0.015	-0.006
	0.9709	0.1660	0.5348	0.9980	0.4750	0.2310
FTSE(-5)	0.027	-0.010	0.028	0.023	0.005	-0.006
	0.1882	0.6307	0.1754	0.2550	0.8229	0.1949
FTSE(-6)	0.010	0.039	0.006	0.007	-0.012	0.001
	0.6230	0.0586	0.7888	0.7301	0.5518	0.7884
FTSE(-7)	-0.037	-0.010	-0.010	0.045	-0.004	0.007
	0.0726	0.6196	0.6114	0.0286	0.8493	0.1276
FTSE(-8)	0.043	-0.008	-0.063	0.025	0.012	0.010
	0.0338	0.7109	0.0023	0.2158	0.5622	0.0415
FTSE(-9)	-0.053	0.000	-0.019	0.059	-0.026	0.003
	0.0100	0.9957	0.3469	0.0041	0.2056	0.5543
FTSE(-10)	0.012	0.000	-0.034	0.031	0.018	-0.003
	0.5519	0.9984	0.0995	0.1343	0.3831	0.5810
FTSE(-11)	-0.010	0.006	-0.025	0.038	0.017	-0.001
	0.6267	0.7630	0.2209	0.0662	0.4174	0.8326

Table B.27: Results of VAR for Emissions Market Sentiment Count Pos With Outliers - Coal and FTSE

	Brent	Coal	FTSE	Gas	EUA	Count Neg
Gas(-1)	0.009	0.000	-0.019	-0.019	0.024	-0.002
	0.6556	0.9971	0.3485	0.3611	0.2233	0.7041
Gas(-2)	-0.025	0.000	-0.049	-0.013	-0.004	0.005
	0.2085	0.9951	0.0151	0.5050	0.8579	0.2785
Gas(-3)	0.025	-0.005	-0.016	-0.003	-0.005	0.002
	0.2135	0.7940	0.4336	0.8802	0.8030	0.7417
Gas(-4)	-0.010	0.001	-0.042	-0.022	0.025	-0.005
	0.6026	0.9650	0.0365	0.2753	0.2156	0.3249
Gas(-5)	0.022	0.006	0.027	-0.002	0.042	0.003
	0.2780	0.7804	0.1734	0.9270	0.0358	0.5031
Gas(-6)	-0.003	-0.001	0.008	0.015	-0.021	0.002
	0.8811	0.9543	0.6890	0.4555	0.3032	0.6895
Gas(-7)	-0.026	-0.003	-0.026	0.064	-0.007	0.003
	0.1936	0.8722	0.2022	0.0016	0.7273	0.5330
Gas(-8)	-0.005	-0.008	0.010	-0.008	0.001	-0.001
	0.8127	0.7124	0.6109	0.6802	0.9417	0.8848
Gas(-9)	-0.022	0.023	-0.010	0.004	-0.001	0.000
	0.2756	0.2703	0.6154	0.8245	0.9764	0.9171
Gas(-10)	0.002	0.040	0.011	-0.061	-0.027	-0.012
	0.9272	0.0484	0.5847	0.0025	0.1834	0.0103
Gas(-11)	-0.031	0.005	-0.018	0.012	-0.005	0.004
	0.1275	0.7952	0.3661	0.5448	0.7885	0.3357
EUA(-1)	0.012	0.008	-0.013	0.021	-0.016	-0.027
	0.5650	0.6989	0.5364	0.3166	0.4515	0.0000
EUA(-2)	0.024	0.009	-0.004	-0.015	0.034	0.004
	0.2545	0.6667	0.8380	0.4672	0.1010	0.4366
EUA(-3)	-0.003	-0.008	-0.010	-0.001	-0.009	-0.005
	0.8964	0.7071	0.6496	0.9494	0.6576	0.3365
EUA(-4)	-0.023	-0.009	0.022	-0.024	0.029	-0.002
	0.2795	0.6696	0.2875	0.2445	0.1632	0.7077
EUA(-5)	0.002	0.020	0.003	0.021	0.070	-0.008
	0.9176	0.3410	0.9045	0.3237	0.0008	0.0961
EUA(-6)	-0.016	0.013	-0.043	0.016	0.051	0.020
	0.4377	0.5386	0.0416	0.4410	0.0134	0.0000
EUA(-7)	-0.008	0.014	0.017	-0.014	0.027	-0.005
	0.7094	0.4971	0.4076	0.5156	0.1897	0.3146
EUA(-8)	0.042	0.011	0.010	0.020	0.007	0.006
	0.0450	0.6101	0.6318	0.3298	0.7338	0.2451
EUA(-9)	0.029	0.000	0.014	0.004	0.005	0.001
	0.1680	0.9846	0.5012	0.8646	0.8140	0.8927
EUA(-10)	-0.015	-0.016	-0.034	0.008	-0.076	0.009
	0.4624	0.4492	0.1040	0.6906	0.0002	0.0517
EUA(-11)	0.015	0.008	0.012	0.007	-0.033	0.007
	0.4786	0.7201	0.5528	0.7251	0.1067	0.1594

Table B.28: Results of VAR for Emissions Market Sentiment Count Pos With Outliers - Gas and EUA

B.3.5 With Outliers Emissions Market Count All Tweets

	Brent	Coal	FTSE	Gas	EUA	Count All
Count All(-1)	0.196	0.029	0.170	0.045	0.017	0.250
	0.0353	0.7578	0.0680	0.6293	0.8527	0.0000
Count All(-2)	-0.032	0.022	0.176	-0.057	0.162	-0.020
	0.6922	0.7867	0.0296	0.4793	0.0441	0.2362
Count All(-3)	-0.067	-0.049	-0.0788	0.0288	-0.2143	0.0428
	0.4044	0.548	0.3272	0.7217	0.0077	0.0111
Count All(-4)	-0.156	0.0584	0.1531	0.0518	0.2545	0
	0.0527	0.4743	0.0572	0.5217	0.0016	0.9997
Count All(-5)	-0.005	-0.0199	-0.0548	-0.0019	-0.2165	-0.1007
	0.9518	0.8082	0.4972	0.9811	0.0073	0
Count All(-6)	0.008	0.0262	-0.2422	0.0299	-0.1588	-0.1444
	0.9183	0.7454	0.0024	0.7085	0.0458	0
Count All(-7)	0.223	-0.0051	0.0945	0.0613	-0.0783	-0.0004
	0.0054	0.9499	0.2382	0.4467	0.328	0.98
Count All(-8)	-0.030	0.0246	0.2582	0.179	-0.1297	0.0362
	0.7055	0.7614	0.0013	0.0261	0.1048	0.0307
Count All(-9)	-0.183	0.0247	-0.029	-0.0495	-0.0114	-0.0755
	0.0230	0.7618	0.7183	0.5398	0.8871	0
Count All(-10)	-0.002	0.0053	-0.0468	0.0738	-0.1357	0.5443
	0.9853	0.9483	0.561	0.3617	0.0915	0
Count All(-11)	-0.112	0.0097	0.047	-0.0017	-0.0162	-0.2672
	0.2250	0.9176	0.6116	0.9852	0.8605	0
Brent(-1)	-0.018	0.0066	0.0138	0.0099	0.0065	0.001
	0.3901	0.753	0.5027	0.6314	0.7539	0.8209
Brent(-2)	0.009	0.0304	-0.0033	-0.0099	0.0187	0.0101
	0.6549	0.1461	0.874	0.631	0.3622	0.019
Brent(-3)	-0.043	0.0032	-0.0139	-0.0432	-0.022	0.0007
	0.0355	0.8773	0.4976	0.0365	0.2849	0.8726
Brent(-4)	0.002	0.0121	0.0026	0.0043	0.0132	0.0008
	0.9296	0.5603	0.898	0.8342	0.5192	0.854
Brent(-5)	-0.004	0.0093	-0.0456	0.0098	-0.0166	0
	0.8342	0.6563	0.0264	0.6338	0.419	0.9951
Brent(-6)	0.015	0.0099	-0.0026	-0.0105	0.0433	-0.0082
	0.4595	0.6342	0.8992	0.6124	0.0348	0.0558
Brent(-7)	0.010	0.0048	0.0357	-0.0271	0.0261	-0.0085
	0.6224	0.816	0.0809	0.1882	0.2019	0.0488
Brent(-8)	-0.015	-0.0078	-0.0014	-0.0212	-0.0172	0.0027
	0.4602	0.7088	0.9463	0.3051	0.4014	0.5343
Brent(-9)	0.041	-0.0187	-0.0175	0.0043	-0.0091	0.0038
	0.0438	0.3679	0.394	0.8335	0.6573	0.3764
Brent(-10)	0.029	-0.0107	-0.0196	-0.0217	0.002	0.0029
	0.1635	0.6072	0.338	0.2915	0.9234	0.5052
Brent(-11)	0.012	0.0058	-0.007	0.0032	-0.0065	-0.0068
	0.5561	0.7788	0.7308	0.8753	0.7509	0.1136
C	0.000	-0.0014	0.0005	0.0012	-0.0001	0.0001
	0.9904	0.944	0.9808	0.952	0.9963	0.9868
R^2	0.0403	0.0117	0.04	0.028	0.0433	0.4107

Table B.29: Results of VAR for Emissions Market Sentiment Count All Tweets With Outliers - Sent and Brent

	Brent	Coal	FTSE	Gas	EUA	Count All
Coal(-1)	0.016	-0.0107	0.007	0.0112	0.0097	-0.0018
	0.4163	0.597	0.7258	0.5759	0.6252	0.6697
Coal(-2)	-0.020	-0.0027	0.0081	-0.0172	0.0079	0.0022
	0.3176	0.8915	0.6843	0.389	0.6921	0.6023
Coal(-3)	-0.044	0.0117	0.0051	-0.0062	-0.0023	-0.0015
	0.0268	0.5627	0.7987	0.7553	0.9089	0.722
Coal(-4)	0.011	-0.0094	-0.0067	-0.0308	-0.024	0.0003
	0.5866	0.641	0.7345	0.1233	0.2271	0.9399
Coal(-5)	-0.089	-0.0067	0.028	-0.0202	0.0187	-0.0024
	0.0000	0.7407	0.1595	0.3126	0.3457	0.5661
Coal(-6)	-0.010	-0.0035	-0.0111	-0.0162	0.0036	-0.0011
	0.6098	0.8634	0.5767	0.4196	0.8563	0.7878
Coal(-7)	-0.002	0.0131	0.0244	-0.0266	0.0004	0.0039
	0.9357	0.5191	0.2208	0.185	0.9853	0.346
Coal(-8)	-0.004	-0.0018	0	-0.0156	0.0004	-0.0013
	0.8463	0.93	0.9995	0.4365	0.9833	0.7573
Coal(-9)	0.025	0.0092	0.0146	-0.0031	-0.0056	0.0012
	0.2122	0.6508	0.4639	0.8777	0.7765	0.7692
Coal(-10)	-0.009	0.0121	0.0096	-0.0152	-0.0092	-0.0003
	0.6412	0.5489	0.6305	0.449	0.6442	0.9461
Coal(-11)	0.004	0.0019	-0.0071	-0.0125	0.0031	-0.0037
	0.8407	0.924	0.7206	0.5312	0.8751	0.3722
FTSE(-1)	0.047	0.0156	-0.0146	-0.0031	-0.019	-0.0077
	0.0233	0.4545	0.476	0.8798	0.3552	0.0749
FTSE(-2)	0.040	0.0176	-0.0116	-0.0152	0.009	-0.0022
	0.0544	0.3975	0.5734	0.4626	0.6622	0.6069
FTSE(-3)	0.013	0.0441	0.0167	-0.0037	-0.0043	-0.0097
	0.5445	0.0345	0.4157	0.8587	0.8327	0.0241
FTSE(-4)	0.001	-0.0285	-0.0121	0.0013	0.0166	-0.006
	0.9518	0.1709	0.5557	0.9488	0.4181	0.1609
FTSE(-5)	0.025	-0.0091	0.0322	0.0233	0.0043	-0.0049
	0.2171	0.6635	0.1164	0.2593	0.8339	0.2579
FTSE(-6)	0.010	0.0391	0.0056	0.0047	-0.0136	0.0024
	0.6164	0.0602	0.7846	0.8183	0.5056	0.5806
FTSE(-7)	-0.035	-0.011	-0.0117	0.0457	-0.0047	0.0081
	0.0907	0.5975	0.5674	0.0264	0.8188	0.0591
FTSE(-8)	0.042	-0.0073	-0.062	0.026	0.0117	0.0025
	0.0403	0.7253	0.0025	0.2075	0.5666	0.5554
FTSE(-9)	-0.054	0.0003	-0.0202	0.059	-0.0264	0.0025
	0.0091	0.9869	0.3251	0.0043	0.1988	0.5666
FTSE(-10)	0.014	-0.001	-0.0388	0.0314	0.0201	-0.0054
	0.5127	0.9607	0.0601	0.1293	0.3287	0.2097
FTSE(-11)	-0.008	0.0058	-0.0252	0.04	0.0139	0.0012
	0.6945	0.7832	0.2215	0.0537	0.4986	0.7898

Table B.30: Results of VAR for Emissions Market Sentiment Count All Tweets With Outliers -Coal and FTSE

	Brent	Coal	FTSE	Gas	EUA	Count All
Gas(-1)	0.010	-0.0002	-0.02	-0.0182	0.0221	-0.001
	0.6311	0.9913	0.3211	0.3678	0.2713	0.8107
Gas(-2)	-0.026	0.0005	-0.0478	-0.0138	-0.0039	0.0048
	0.2006	0.9816	0.0175	0.4954	0.8476	0.2512
Gas(-3)	0.024	-0.0056	-0.0165	-0.0034	-0.0044	-0.0006
	0.2295	0.7847	0.4126	0.8681	0.8259	0.8855
Gas(-4)	-0.011	0.0007	-0.0445	-0.0216	0.0239	-0.0032
	0.5907	0.9733	0.027	0.2845	0.2338	0.4485
Gas(-5)	0.022	0.0059	0.0283	-0.0017	0.0428	0.0017
	0.2701	0.7728	0.1589	0.9324	0.0327	0.684
Gas(-6)	-0.002	-0.0013	0.0084	0.0149	-0.0228	0.0038
	0.9074	0.9494	0.6746	0.4594	0.2553	0.3661
Gas(-7)	-0.027	-0.0027	-0.0267	0.0637	-0.0055	-0.0004
	0.1846	0.8934	0.1845	0.0016	0.7857	0.9318
Gas(-8)	-0.004	-0.0076	0.0109	-0.0074	0.0035	-0.0002
	0.8253	0.711	0.5869	0.7145	0.862	0.9669
Gas(-9)	-0.024	0.0228	-0.0099	0.0044	-0.0006	0.002
	0.2322	0.2636	0.6228	0.8276	0.9769	0.642
Gas(-10)	0.002	0.0397	0.0094	-0.0625	-0.0285	-0.0144
	0.9384	0.052	0.6409	0.002	0.1559	0.0007
Gas(-11)	-0.029	0.0053	-0.0183	0.0139	-0.0081	0.0048
	0.1518	0.7971	0.3655	0.4929	0.687	0.2544
EUA(-1)	0.008	0.008	-0.0133	0.022	-0.014	-0.0215
	0.7024	0.6992	0.5122	0.2823	0.4907	0
EUA(-2)	0.026	0.0074	-0.0027	-0.015	0.0211	0.004
	0.2046	0.7217	0.8928	0.4647	0.3006	0.3436
EUA(-3)	0.004	-0.0052	-0.0056	-0.0011	-0.0148	-0.0018
	0.8320	0.8005	0.7854	0.9586	0.4687	0.6701
EUA(-4)	-0.013	-0.0074	0.023	-0.0233	0.0293	-0.0059
	0.5259	0.7209	0.2598	0.2554	0.1503	0.1677
EUA(-5)	0.001	0.021	0.0009	0.0224	0.0775	-0.0032
	0.9593	0.3086	0.9648	0.2733	0.0001	0.45
EUA(-6)	-0.018	0.0104	-0.0393	0.0134	0.053	0.0147
	0.3802	0.6131	0.0535	0.5116	0.0092	0.0006
EUA(-7)	-0.009	0.012	0.0227	-0.0142	0.0253	0.0042
	0.6477	0.5625	0.2647	0.4868	0.2128	0.3215
EUA(-8)	0.037	0.0115	0.0065	0.0163	0.003	0.0062
	0.0696	0.5772	0.7494	0.4267	0.8808	0.1446
EUA(-9)	0.028	-0.0006	0.0097	0.0016	0.0127	-0.0017
	0.1624	0.9754	0.6348	0.9384	0.5325	0.695
EUA(-10)	-0.011	-0.0173	-0.0366	0.0097	-0.0593	0.0116
	0.5922	0.4005	0.0722	0.6339	0.0035	0.0066
EUA(-11)	0.015	0.0073	0.0146	0.0066	-0.0291	0.0108
	0.4736	0.7251	0.4743	0.7456	0.1528	0.0116

Table B.31: Results of VAR for Emissions Market Sentiment Count All Tweets With Outliers - Gas and EUAs

Appendix C

Granger Causality Results for Emissions Market Sentiment

C.1 Introduction to Granger Causality Results

The results of the Granger causality tests excluding the outliers are given in the main text of the thesis in Tables 4.14 on page 123 and 4.15 on page 124. This introduction applies to the Granger causality test results for the emissions market and for climate change sentiment in Appendix E.

The following table (C.1) indicates the χ^2 statistic from the Granger causality test and the associated p-value. For example the first entry indicates that the χ^2 statistic for the null hypothesis that Brent returns do not Granger-cause EUA returns is 10.989 with an associated p-value of 0.4442. This indicates that there is no evidence that changes in the price of Brent crude oil Granger-causes EU emission allowance (EUA) returns. Next we see the χ^2 statistic for the null hypothesis that coal does not Granger-cause EUAs is 3.115 and that the associated p-value is 0.9891, indicating that there is no evidence that coal returns Granger causes EUA returns. Similarly at the bottom of that section of the table we see that there is only weak evidence with a p-value of 0.1017, that the Sum of Positive emissions market sentiment measure Granger-causes EUA returns.

C.2 Emissions Market Sentiment Measures With Outliers

	Sum Pos				**Count Pos**		
	EUAs		**FTSE**		**EUAs**		**FTSE**
Brent	10.989	**Brent**	10.384	**Brent**	10.762	**Brent**	10.175
	0.4442		0.4962		0.4634		0.5147
Coal	3.115	**Coal**	5.137	**Coal**	3.205	**Coal**	5.051
	0.9891		0.9243		0.9877		0.9287
FTSE	5.634	**Gas**	18.382	**FTSE**	5.716	**Gas**	18.497
	0.8966		0.0731		0.8917		0.0707
Gas	10.352	**EUA**	9.338	**Gas**	10.284	**EUA**	9.591
	0.4991		0.5907		0.5050		0.5675
Sum Pos	17.170	**Sum Pos**	38.707	**Count Pos**	20.027	**Count Pos**	44.087
	0.1029		0.0001		0.0450		0.0000
	Brent		**Gas**		**Brent**		**Gas**
Coal	29.390	**Brent**	8.981	**Coal**	29.531	**Brent**	9.133
	0.0020		0.6237		0.0019		0.6096
FTSE	25.278	**Coal**	8.229	**FTSE**	25.679	**Coal**	8.239
	0.0083		0.6927		0.0072		0.6917
Gas	11.058	**FTSE**	21.508	**Gas**	10.959	**FTSE**	21.495
	0.4384		0.0285		0.4467		0.0286
EUA	9.958	**EUA**	5.928	**EUA**	9.781	**EUA**	5.900
	0.5342		0.8781		0.5502		0.8800
Sum Pos	21.809	**Sum Pos**	8.140	**Count of Pos**	17.538	**Count Pos**	7.878
	0.0259		0.7007		0.0929		0.7242
	Coal		**Sum Pos**		**Coal**		**Count Pos**
Brent	4.189	**Brent**	10.645	**Brent**	4.185	**Brent**	13.119
	0.9641		0.4734		0.9642		0.2856
FTSE	12.672	**Coal**	3.397	**FTSE**	12.632	**Coal**	3.810
	0.3153		0.9844		0.3181		0.9751
Gas	5.435	**FTSE**	35.312	**Gas**	5.422	**FTSE**	28.232
	0.9083		0.0002		0.9090		0.0030
EUA	3.094	**Gas**	6.816	**EUA**	3.065	**Gas**	5.680
	0.9894		0.8138		0.9898		0.8938
Sum Pos	1.314	**EUA**	27.083	**Count Pos**	1.557	**EUA**	25.043
	0.9998		0.0045		0.9995		0.0090

Table C.1: Results of Granger Causality for Emissions Market Sentiment Sum Positive and Count Positive Including Outliers

	Count Neg				Sum Neg		
	EUA		**Coal**		**EUA**		**Coal**
Count Neg	50.947	**Count Neg**	1.093	**Sum Neg**	59.048	Sum Neg	1.030
	0.0000		0.9999		0.0000		0.9999
Brent	9.403	**Brent**	4.447	**Brent**	9.416	Brent	4.401
	0.5848		0.9550		0.5836		0.9567
Coal	3.043	**EUA**	3.455	**Coal**	2.983	EUA	3.296
	0.9901		0.9833		0.9910		0.9862
FTSE	5.569	**FTSE**	12.218	**FTSE**	5.755	FTSE	12.410
	0.9005		0.3475		0.8892		0.3336
Gas	10.410	**Gas**	5.391	**Gas**	10.536	Gas	5.396
	0.4940		0.9108		0.4829		0.9105
	Brent		**FTSE**		**Brent**		**FTSE**
Count Neg	16.904	**Count Neg**	20.539	**Sum Neg**	14.704	**Sum Neg**	21.693
	0.1108		0.0385		0.1965		0.0269
Coal	29.046	**Coal**	5.053	**Coal**	29.138	**Coal**	5.043
	0.0022		0.9286		0.0022		0.9290
FTSE	26.105	**Brent**	10.510	**FTSE**	25.886	**Brent**	10.371
	0.0063		0.4852		0.0067		0.4974
Gas	10.514	**Gas**	17.179	**Gas**	10.497	**Gas**	16.977
	0.4849		0.1027		0.4863		0.1086
EUA	10.280	**EUA**	10.337	**EUA**	10.597	**EUA**	10.320
	0.5054		0.5003		0.4776		0.5019
Count Neg		**Gas**		**Sum Neg**		**Gas**	
Brent	23.902	**Brent**	8.784	**Brent**	24.547	**Brent**	8.633
	0.0132		0.6418		0.0106		0.6558
Coal	2.003	**Coal**	8.281	**Coal**	1.646	**Coal**	8.248
	0.9985		0.6879		0.9994		0.6909
FTSE	13.785	**FTSE**	21.176	**FTSE**	13.978	**FTSE**	21.055
	0.2451		0.0316		0.2342		0.0328
Gas	11.155	**Count Neg**	6.296	**Gas**	10.447	**EUA**	6.441
	0.4304		0.8529		0.4907		0.8424
EUA	63.918	**EUA**	6.341	**EUA**	72.489	**Sum Neg**	6.015
	0.0000		0.8497		0.0000		0.8724

Table C.2: Results of Granger Causality for Emissions Market Sentiment Sum Negative and Count Negative Including Outliers

	Count of Tweets		
	Brent		**Coal**
Coal	29.259	**Brent**	4.301
	0.0021		0.9603
FTSE	26.444	**FTSE**	12.124
	0.0056		0.3544
Gas	10.600	**Gas**	5.314
	0.4774		0.9150
EUA	9.219	**EUA**	3.308
	0.6017		0.9860
Count of Tweets	18.877	**Count of Tweets**	1.396
	0.0633		0.9997
	EUAs		**FTSE**
FTSE	5.726	**EUA**	11.043
	0.8910		0.4397
Brent	10.499	**Brent**	10.680
	0.4861		0.4704
Coal	3.110	**Coal**	5.127
	0.9892		0.9249
Gas	10.705	**Gas**	17.830
	0.4683		0.0856
Count of Tweets	42.238	**Count of Tweets**	39.093
	0.0000		0.0001
	Count of Tweets		**Gas**
Gas	16.690	**Count of Tweets**	8.971
	0.1174		0.6246
Brent	17.058	**Brent**	9.152
	0.1062		0.6079
Coal	2.893	**Coal**	8.386
	0.9921		0.6784
FTSE	17.608	**FTSE**	21.561
	0.0911		0.0280
EUA	57.603	**EUA**	6.335
	0.0000		0.8501

Table C.3: Results of Granger Causality for Emissions Market Sentiment Count of All Tweets Including Outliers

Appendix D

VAR Results for Climate Change Sentiment

D.1 VAR Results for Climate Change Sentiment No Outliers

D.1.1 No Outliers Climate Change Sum Positive

	Brent	**Coal**	**FTSE**	**Gas**	**EUA**	**Sum Positive**
Brent (-1)	-0.015	0.018	0.013	0.015	0.030	1.531
	0.4686	0.6941	0.4081	0.5789	0.8529	0.8347
Coal (-1)	0.006	-0.009	0.002	0.006	0.033	-2.509
	0.4782	0.6588	0.7992	0.6191	0.6413	0.4307
FTSE (-1)	0.055	0.041	-0.010	-0.014	-0.228	2.846
	0.0368	0.4889	0.6291	0.6894	0.2788	0.7630
Gas (-1)	0.013	-0.002	-0.010	-0.013	0.151	0.487
	0.4043	0.9639	0.3950	0.5117	0.2172	0.9296
EUA (-1)	0.000	0.002	-0.002	0.003	-0.009	1.534
	0.8875	0.6987	0.3687	0.3562	0.6362	0.0884
Sum Positive (-1)	0.000	0.000	0.000	0.000	-0.000	0.326
	0.0387	0.4859	0.3889	0.8523	0.3647	0.0000
Constant	0.000	0.000	0.000	0.000	0.000	0.000
	0.0690	0.5511	0.3537	0.8672	0.5302	0.9801
R^2	0.0040	0.0007	0.0013	0.0008	0.0016	0.1079

Table D.1: Results of VAR for Climate Change Sentiment Sum Positive No Outliers

D.1.2 No Outliers Climate Change Sum Negative

	Brent	Coal	FTSE	Gas	EUA	Sum Negative
Brent (-1)	-0.015	0.017	0.015	0.016	0.030	4.519
	0.4708	0.7085	0.3412	0.5553	0.8568	0.5152
Brent (-2)	0.017	0.067	0.004	-0.007	0.191	1.912
	0.3964	0.1442	0.8242	0.7997	0.2428	0.7828
Coal (-1)	0.006	-0.010	0.002	0.006	0.031	1.609
	0.5263	0.6283	0.7733	0.6074	0.6642	0.5927
Coal (-2)	-0.008	-0.004	0.002	-0.009	0.030	-0.651
	0.3392	0.8412	0.7344	0.4286	0.6727	0.8288
FTSE (-1)	0.054	0.041	-0.012	-0.014	-0.230	6.028
	0.0390	0.4929	0.5547	0.6801	0.2750	0.4994
FTSE (-2)	0.038	0.045	-0.017	-0.026	0.014	6.382
	0.1499	0.4440	0.3914	0.4542	0.9462	0.4749
Gas (-1)	0.012	-0.002	-0.012	-0.012	0.146	-4.403
	0.4438	0.9639	0.3189	0.5471	0.2340	0.3987
Gas (-2)	-0.025	0.001	-0.029	-0.006	-0.041	2.374
	0.0962	0.9878	0.0157	0.7739	0.7375	0.6486
EUA (-1)	0.000	0.002	-0.002	0.003	-0.010	-1.301
	0.8585	0.6830	0.3861	0.3657	0.6191	0.1265
EUA (-2)	0.002	0.002	-0.001	-0.003	0.028	-1.431
	0.3378	0.7341	0.4778	0.3576	0.1685	0.0928
Sum Negative (-1)	0.000	0.000	0.000	0.000	0.001	0.305
	0.8699	0.9691	0.8950	0.7405	0.0801	0.0000
Sum Negative (-2)	0.000	0.000	0.000	0.000	0.000	0.233
	0.6995	0.8056	0.6510	0.3721	0.3025	0.0000
Constant	0.000	0.000	0.000	0.000	0.000	0.001
	0.9279	0.8468	0.8973	0.7696	0.6816	0.9710
R^2	0.0054	0.0019	0.0042	0.0020	0.0040	0.2054

Table D.2: Results of VAR for Climate Change Sentiment Sum Negative No Outliers

D.1.3 No Outliers Climate Change Count Positive

	Brent	Coal	FTSE	Gas	EUA	Count Positive
Brent (-1)	-0.015	0.018	0.013	0.015	0.030	1.377
	0.4687	0.6939	0.4082	0.5794	0.8531	0.8489
Coal (-1)	0.006	-0.009	0.002	0.006	0.033	-1.574
	0.4767	0.6577	0.7984	0.6150	0.6391	0.0020
FTSE (-1)	0.055	0.041	-0.010	-0.014	-0.226	6.182
	0.0356	0.4868	0.6257	0.6910	0.2821	0.0020
Gas (-1)	0.013	-0.001	-0.010	-0.013	0.152	-1.484
	0.4001	0.9678	0.3922	0.5078	0.2166	0.0030
EUA (-1)	0.000	0.002	-0.002	0.003	-0.009	1.439
	0.8752	0.6968	0.3666	0.3536	0.6426	01045
Count Positive (-1)	0.000	0.000	0.000	0.000	-0.000	0.367
	0.1255	0.6967	0.5988	0.8657	0.4419	0.0000
Constant	0.000	0.000	0.000	0.000	0.000	-0.000
	0.1527	0.7113	0.4976	0.9210	0.2968	0.9753
R^2	0.0032	0.0005	0.0011	0.0007	0.0015	0.1357

Table D.3: Results of VAR for Climate Change Sentiment Count Positive No Outliers

D.1.4 No Outliers Climate Change Count Negative

	Brent	**Coal**	**FTSE**	**Gas**	**EUA**	**Count Negative**
Brent (-1)	-0.015	0.017	0.015	0.016	0.029	-5.240
	0.4730	0.7092	0.3405	0.5510	0.8613	0.4440
Brent (-2)	0.017	0.067	0.004	-0.007	0.190	-1.120
	0.3939	0.1443	0.8208	0.8041	0.2444	0.8698
Coal (-1)	0.006	-0.010	0.002	0.006	0.031	-1.849
	0.5265	0.6283	0.7734	0.6076	0.6643	0.5330
Coal (-2)	-0.008	-0.004	0.002	-0.009	0.030	1.103
	0.3392	0.8413	0.7329	0.4301	0.6755	0.7100
FTSE (-1)	0.054	0.041	-0.012	-0.014	-0.230	-5.396
	0.0392	0.4930	0.5528	0.6802	0.2750	0.5396
FTSE (-2)	0.038	0.045	-0.017	-0.026	0.015	-7.543
	0.1497	0.4441	0.3913	0.4555	0.9445	0.3916
Gas (-1)	0.012	-0.002	-0.012	-0.012	0.147	4.387
	0.4439	0.9633	0.3162	0.5463	0.2316	0.3937
Gas (-2)	-0.026	0.000	-0.029	-0.006	-0.041	-3.985
	0.0958	0.9885	0.0154	0.7720	0.7388	0.4378
EUA (-1)	0.000	0.002	-0.002	0.003	-0.010	1.208
	0.8499	0.6838	0.3907	0.3599	0.6155	0.1502
EUA (-2)	0.002	0.002	-0.001	-0.003	0.028	1.504
	0.3331	0.7350	0.4796	0.3582	0.1686	0.0732
Count Negative (-1)	0.000	0.000	0.000	0.000	-0.001	0.327
	0.9121	0.9758	0.7847	0.5958	0.0679	0.0000
Count Negative (-2)	0.000	0.000	0.000	0.000	0.001	0.232
	0.9314	0.8426	0.6259	0.4344	0.2703	0.0000
Constant	0.000	0.000	0.000	0.000	0.000	-0.001
	0.8181	0.8561	0.9867	0.8714	0.6497	0.9663
R^2	0.0053	0.0019	0.0043	0.0019	0.0041	0.2276

Table D.4: Results of VAR for Climate Change Sentiment Count Negative No Outliers

D.1.5 No Outliers Climate Change Count of Tweets

	Brent	Coal	FTSE	Gas	EUA	Count of Tweets
Brent (-1)	-0.014	0.017	0.015	0.016	0.028	-4.884
	0.4807	0.7129	0.3455	0.5505	0.8640	0.4691
Brent (-2)	0.018	0.067	0.003	-0.007	0.191	-1.041
	0.3851	0.1438	0.8273	0.8066	0.2442	0.8772
Coal (-1)	0.006	-0.010	0.002	0.006	0.029	-0.799
	0.5231	0.6262	0.7744	0.6065	0.6740	0.7845
Coal (-2)	-0.008	-0.004	0.002	-0.009	0.031	-0.463
	0.3417	0.8424	0.7340	0.4268	0.6651	0.8741
FTSE (-1)	0.054	0.041	-0.012	-0.014	-0.232	-8.505
	0.0387	0.4927	0.5569	0.6770	0.2706	0.3265
FTSE (-2)	0.038	0.046	-0.017	-0.026	0.012	-9.044
	0.1451	0.4401	0.3947	0.4544	0.9543	0.2972
Gas (-1)	0.011	-0.002	-0.012	-0.012	0.151	-0.384
	0.4603	0.9574	0.3154	0.5423	0.2197	0.9395
Gas (-2)	-0.025	0.0001	-0.029	-0.006	-0.047	-5.108
	0.0963	0.9971	0.0155	0.7758	0.7037	0.3128
EUA (-1)	0.001	0.002	-0.002	0.003	-0.011	2.437
	0.8188	0.6716	0.3882	0.3519	0.5974	0.0033
EUA (-2)	0.002	0.002	-0.001	-0.003	0.029	0.319
	0.364	0.7322	0.4718	0.3670	0.1470	0.7001
Count of Tweets (-1)	0.000	0.000	0.000	0.000	-0.001	0.418
	0.3624	0.8325	0.7790	0.7733	0.0653	0.0000
Count of Tweets (-2)	0.000	0.000	0.000	-0.000	0.001	0.137
	0.5439	0.7459	0.8334	0.8430	0.1714	0.0000
Constant	0.000	-0.0001	-0.000	-0.000	0.000	-0.001
	0.6304	0.6228	0.9096	0.9591	0.6679	0.9723
R^2	0.0056	0.0020	0.0042	0.0017	0.0042	0.2505

Table D.5: Results of VAR for Climate Change Sentiment Count of Tweets No Outliers

D.2 VAR Results for Climate Change Sentiment With Outliers

D.2.1 With Outliers Climate Change Sum Positive

	Brent	Coal	FTSE	Gas	EUA	Sum Positive
Brent (-1)	-0.019	0.021	0.015	0.018	0.041	0.903
	0.3611	0.6470	0.3286	0.4949	0.7982	0.8997
Coal (-1)	0.006	-0.009	0.002	0.005	0.032	-2.305
	0.4909	0.6554	0.7938	0.6514	0.6475	0.4605
FTSE (-1)	0.050	0.041	-0.014	-0.014	-0.227	0.915
	0.0539	0.4902	0.5020	0.6824	0.2752	0.9210
Gas (-1)	0.011	-0.002	-0.012	-0.013	0.145	0.081
	0.4549	0.9490	0.3247	0.5192	0.2326	0.9880
EUA (-1)	0.000	0.002	-0.002	0.003	-0.010	1.668
	0.8836	0.7029	0.3408	0.3607	0.6215	0.0589
Sum Positive (-1)	0.000	0.000	-0.000	0.000	0.000	0.372
	0.0699	0.3660	0.3239	0.9697	0.4188	0.0000
Constant	-0.000	-0.000	0.000	0.000	-0.000	0.011
	0.1022	0.4757	0.3023	0.9662	0.8899	0.979
R^2	0.0033	0.0008	0.0016	0.0008	0.0015	0.1400

Table D.6: Results of VAR for Climate Change Sentiment Sum Positive With Outliers

D.2.2 With Outliers Climate Change Sum Negative

	Brent	Coal	FTSE	Gas	EUA	Sum Negative
Brent (-1)	-0.018	0.021	0.017	0.019	0.044	-0.246
	0.3633	0.6474	0.2766	0.4765	0.7859	0.9678
Brent (-2)	0.016	0.065	0.001	-0.009	0.177	1.026
	0.4246	0.1520	0.9417	0.7234	0.2741	0.8663
Coal (-1)	0.006	-0.010	0.002	0.006	0.030	2.368
	0.5299	0.6182	0.7719	0.6319	0.6678	0.3725
Coal (-2)	-0.008	-0.004	0.004	-0.010	0.031	-0.495
	0.3551	0.8392	0.6931	0.4032	0.6616	0.8520
FTSE (-1)	0.049	0.040	-0.016	-0.014	-0.234	9.128
	0.0593	0.4991	0.4382	0.6745	0.2613	0.2448
FTSE (-2)	0.042	0.045	-0.017	-0.030	0.007	4.342
	0.1120	0.4410	0.40985	0.3753	0.9726	0.5803
Gas (-1)	0.010	-0.002	-0.013	-0.012	0.141	-3.093
	0.4968	0.9467	0.2576	0.5536	0.2493	0.5010
Gas (-2)	-0.024	0.002	-0.030	-0.006	-0.036	1.933
	0.1136	0.9616	0.0112	0.7543	0.7670	0.6735
EUA (-1)	0.000	0.002	-0.002	0.003	-0.010	-1.444
	0.8533	0.6826	0.3522	0.3688	0.6142	0.0547
EUA (-2)	0.002	0.002	-0.001	-0.003	0.028	-1.322
	0.3475	0.7103	0.5079	0.3543	0.1666	0.0786
Sum Negative (-1)	0.000	-0.000	0.000	-0.000	0.001	0.434
	0.8711	0.7839	0.9250	0.4580	0.0902	0.000
Sum Negative (-2)	0.000	-0.000	0.000	0.000	-0.001	0.251
	0.6567	0.6916	0.7289	0.1869	0.1455	0.000
Constant	-0.000	-0.000	0.000	0.000	0.000	0.000
	0.9160	0.7014	0.7486	0.7825	0.8014	0.9804
$\mathbf{R}^2$	0.0052	0.0020	0.0046	0.0025	0.0038	0.3801

Table D.7: Results of VAR for Climate Change Sentiment Sum Negative With Outliers

D.2.3 With Outliers Climate Change Count Positive

	Brent	Coal	FTSE	Gas	EUA	Count Positive
Brent (-1)	-0.018	0.021	0.015	0.018	0.041	0.148
	0.3616	0.6472	0.3288	0.4959	0.7987	0.9831
Coal (-1)	0.006	-0.009	0.002	0.005	0.032	-1.315
	0.4910	0.6565	0.7939	0.6486	0.6457	0.6667
FTSE (-1)	0.050	0.041	-0.014	-0.014	-0.226	4.827
	0.0536	0.4878	0.5009	0.6865	0.2775	0.5925
Gas (-1)	0.012	-0.002	-0.012	-0.013	0.146	-1.795
	0.4477	0.9522	0.3215	0.5157	0.2318	0.7336
EUA (-1)	0.001	0.002	-0.002	0.003	-0.010	1.638
	0.8773	0.6984	0.3388	0.3579	0.6266	0.0579
Count Positive (-1)	0.000	0.000	-0.000	0.000	0.000	0.421
	0.2455	0.4967	0.5315	0.8081	0.4939	0.0000
Constant	-0.000	-0.000	0.000	-0.000	-0.000	-0.001
	0.2451	0.5811	0.4428	0.8600	0.8899	0.9731
R^2	0.0025	0.0007	0.0014	0.0008	0.0014	0.1777

Table D.8: Results of VAR for Climate Change Sentiment Count Positive With Outliers

D.2.4 With Outliers Climate Change Count Negative

	Brent	Coal	FTSE	Gas	EUA	Count Negative
Brent (-1)	-0.018	0.021	0.017	0.019	0.043	0.494
	0.3655	0.6485	0.2770	0.4723	0.7885	0.9310
Brent (-2)	0.016	0.065	0.001	-0.009	0.178	0.392
	0.4233	0.1523	0.9416	0.7242	0.2728	0.9452
Coal (-1)	0.005	-0.010	0.002	0.005	0.030	-2.505
	0.5314	0.6184	0.7722	0.6343	0.6685	0.3127
Coal (-2)	-0.008	-0.004	0.003	-0.010	0.030	0.835
	0.3534	0.8396	0.6930	0.4057	0.6656	0.7365
FTSE (-1)	0.049	0.040	-0.0157	-0.014	-0.235	-8.378
	0.0595	0.4990	0.4382	0.6775	0.2594	0.2534
FTSE (-2)	0.042	0.045	-0.017	-0.030	0.007	-4.113
	0.1115	0.4412	0.4103	0.3783	0.9716	0.5752
Gas (-1)	0.010	-0.002	-0.013	-0.012	0.141	2.022
	0.4960	0.9442	0.2569	0.5528	0.2488	0.6379
Gas (-2)	-0.024	0.002	-0.030	-0.006	-0.037	-3.176
	0.1126	0.9626	0.0111	0.7549	0.7615	0.4590
EUA (-1)	0.000	0.002	-0.002	0.003	-0.010	1.310
	0.8479	0.6839	0.3521	0.3633	0.6133	0.0620
EUA (-2)	0.003	0.002	-0.001	-0.003	0.028	1.284
	0.3439	0.7105	0.5072	0.3528	0.1661	0.0674
Count Negative (-1)	-0.000	0.000	-0.000	0.000	-0.001	0.495
	0.8743	0.7943	0.9498	0.3147	0.0823	0.0000
Count Negative (-2)	-0.000	0.000	0.000	-0.000	0.001	0.239
	0.8638	0.7409	0.7507	0.1923	0.1109	0.0000
Constant	-0.000	-0.000	0.000	0.000	0.000	0.000
	0.8309	0.7017	0.7648	0.8717	0.8307	0.9807
R^2	0.0051	0.0020	0.0046	0.0025	0.0039	0.4584

Table D.9: Results of VAR for Climate Change Sentiment Count Negative With Outliers

D.2.5 With Outliers Climate Change Count of Tweets

	Brent	Coal	FTSE	Gas	EUA	Count Tweets
Brent (-1)	-0.018	0.020	0.017	0.019	0.045	-3.387
	0.3669	0.6553	0.2784	0.4714	0.7830	0.5415
Brent (-2)	0.016	0.065	0.001	-0.009	0.173	2.169
	0.4166	0.1532	0.9411	0.7372	0.2863	0.6956
Coal (-1)	0.006	-0.010	0.002	0.006	0.029	-0.360
	0.5297	0.6174	0.7649	0.6338	0.6807	0.8814
Coal (-2)	-0.008	-0.004	0.003	-0.010	0.033	-0.868
	0.3543	0.8371	0.6876	0.3923	0.6432	0.7192
FTSE (-1)	0.049	0.040	-0.016	-0.014	-0.237	-9.589
	0.0583	0.4944	0.4424	0.6740	0.2564	0.17921
FTSE (-2)	0.042	0.0460	-0.017	-0.030	0.007	-3.796
	0.1087	0.4346	0.4111	0.3767	0.9739	0.5951
Gas (-1)	0.010	-0.003	-0.013	-0.012	0.143	-1.892
	0.5049	0.9393	0.2558	0.5488	0.2408	0.6509
Gas (-2)	-0.024	0.002	-0.030	-0.006	-0.042	-3.185
	0.1139	0.9636	0.0115	0.76416	0.7307	0.4455
EUA (-1)	0.000	0.000	0.000	0.000	-0.000	2.321
	0.6202	0.6948	0.7968	0.5397	0.1727	0.0007
EUA (-2)	-0.000	0.000	-0.000	-0.000	0.000	0.301
	0.5554	0.7747	0.7078	0.5137	0.1861	0.6604
Count Tweets (-1)	0.001	0.002	-0.002	0.003	-0.001	0.586
	0.8319	0.6774	0.3517	0.3546	0.0864	0.0000
Count Tweets (-2)	0.002	0.002	-0.001	-0.003	0.001	0.149
	0.3670	0.7153	0.4845	0.3559	0.1861	0.0000
Constant	-0.000	-0.000	0.000	0.000	0.000	0.000
	0.8146	0.5173	0.6480	0.9729	0.8875	0.9792
R^2	0.0051	0.0021	0.0046	0.0020	0.0039	0.4873

Table D.10: Results of VAR for Climate Change Sentiment Count of Tweets With Outliers

Appendix E

Granger Causality Results for Climate Change Sentiment

E.1 No Outliers Climate Change Sentiment Measures

	Sum Pos				Count Pos		
	EUAs		**FTSE**		**EUAs**		**FTSE**
Brent	0.034	**Brent**	0.685	**Brent**	0.034	**Brent**	0.684
	0.8528		0.408		0.8531		0.4082
Coal	0.217	**Coal**	0.065	**Coal**	0.220	**Coal**	0.065
	0.6412		0.7992		0.6391		0.7984
FTSE	1.174	**Gas**	0.724	**FTSE**	1.157	**Gas**	0.733
	0.2787		0.3949		0.282		0.3921
Gas	1.524	**EUA**	0.808	**Gas**	1.528	**EUA**	0.815
	0.217		0.3686		0.2164		0.3666
Sum Pos	0.822	**Sum Pos**	0.743	**Count Pos**	0.592	**Count Pos**	0.277
	0.3646		0.3888		0.4418		0.5987
	Brent		**Gas**		**Brent**		**Gas**
Coal	0.503	**Brent**	0.308	**Coal**	0.506	**Brent**	0.307
	0.4781		0.5789		0.4767		0.5794
FTSE	4.366	**Coal**	0.247	**FTSE**	4.423	**Coal**	0.253
	0.0367		0.6191		0.0355		0.6150
Gas	0.696	**FTSE**	0.160	**Gas**	0.708	**FTSE**	0.158
	0.4042		0.6894		0.400		0.691
EUA	0.020	**EUA**	0.852	**EUA**	0.025	**EUA**	0.861
	0.8875		0.3561		0.8752		0.3535
Sum Pos	4.278	**Sum Pos**	0.035	**Count of Pos**	2.348	**Count Pos**	0.029
	0.0386		0.8523		0.1254		0.8657
	Coal		**Sum Pos**		**Coal**		**Count Pos**
Brent	0.155	**Brent**	0.044	**Brent**	0.155	**Brent**	0.036
	0.694		0.8347		0.6939		0.8488
FTSE	0.479	**Coal**	0.621	**FTSE**	0.484	**Coal**	0.252
	0.4888		0.4307		0.4867		0.6155
Gas	0.002	**FTSE**	0.091	**Gas**	0.002	**FTSE**	0.443
	0.9639		0.763		0.9678		0.5057
EUA	0.150	**Gas**	0.008	**EUA**	0.152	**Gas**	0.075
	0.6986		0.9295		0.6968		0.7843
Sum Pos	0.486	**EUA**	2.906	**Count Pos**	0.152	**EUA**	2.638
	0.4858		0.0883		0.6966		0.1043

Table E.1: Results of Granger Causality for Climate Change Sentiment Sum Positive and Count Positive No Outliers

	Sum Neg				Count Neg		
	EUAs		**FTSE**		**EUAs**		**FTSE**
Brent	1.390	**Brent**	0.948	**Brent**	1.379	**Brent**	0.952
	0.499		0.6225		0.5018		0.6212
Coal	0.364	**Coal**	0.196	**Coal**	0.360	**Coal**	0.198
	0.8337		0.9065		0.8351		0.9059
FTSE	1.199	**Gas**	6.766	**FTSE**	1.200	**Gas**	6.810
	0.549		0.0339		0.5489		0.0332
Gas	1.543	**EUA**	1.242	**Gas**	1.557	**EUA**	1.224
	0.4624		0.5374		0.4592		0.5424
Sum Neg	3.199	**Sum Neg**	0.320	**Count Neg**	3.465	**Count Neg**	0.520
	0.202		0.8521		0.1768		0.771
	Brent		**Gas**		**Brent**		**Gas**
Coal	1.326	**Brent**	0.418	**Coal**	1.326	**Brent**	0.423
	0.5152		0.8113		0.5153		0.8094
FTSE	6.242	**Coal**	0.898	**FTSE**	6.235	**Coal**	0.894
	0.0441		0.6382		0.0443		0.6396
Gas	3.398	**FTSE**	0.720	**Gas**	3.405	**FTSE**	0.717
	0.1829		0.6976		0.1822		0.6987
EUA	0.947	**EUA**	1.684	**EUA**	0.969	**EUA**	1.702
	0.6227		0.4309		0.616		0.427
Sum Neg	0.268	**Sum Neg**	0.798	**Count Neg**	0.034	**Count Neg**	0.659
	0.8744		0.6711		0.9832		0.7193
	Coal		**Sum Neg**		**Coal**		**Count Neg**
Brent	2.254	**Brent**	0.493	**Brent**	2.252	**Brent**	0.608
	0.324		0.7816		0.3243		0.7378
FTSE	1.039	**Coal**	0.335	**FTSE**	1.039	**Coal**	0.531
	0.5948		0.8457		0.5949		0.7667
Gas	0.002	**FTSE**	0.951	**Gas**	0.002	**FTSE**	1.093
	0.9988		0.6216		0.9988		0.5789
EUA	0.279	**Gas**	0.933	**EUA**	0.278	**Gas**	1.352
	0.8697		0.6272		0.8704		0.5086
Sum Neg	0.065	**EUA**	5.107	**Count Neg**	0.043	**EUA**	5.226
	0.9682		0.0778		0.9787		0.0733

Table E.2: Results of Granger Causality for Climate Change Sentiment Sum Negative and Count Negative No Outliers

	Count of Tweets		
	EUAs		**FTSE**
Brent	1.379	**Brent**	0.930
	0.5018		0.628
Coal	0.361	**Coal**	0.196
	0.8348		0.9067
FTSE	1.220	**Gas**	6.798
	0.5434		0.0334
Gas	1.667	**EUA**	1.251
	0.4345		0.5351
Count of Tweets	3.695	**Count of Tweets**	0.235
	0.1576		0.889
	Brent		**Gas**
Coal	1.323	**Brent**	0.422
	0.516		0.8097
FTSE	6.303	**Coal**	0.905
	0.0428		0.6362
Gas	3.355	**FTSE**	0.723
	0.1869		0.6966
EUA	0.873	**EUA**	1.697
	0.6463		0.4281
Count of Tweets	0.866	**Count of Tweets**	0.087
	0.6485		0.9572
	Coal		**Count of Tweets**
Brent	2.254	**Brent**	0.544
	0.324		0.7618
FTSE	1.050	**Coal**	0.099
	0.5917		0.9516
Gas	0.003	**FTSE**	2.016
	0.9986		0.3649
EUA	0.294	**Gas**	1.023
	0.8632		0.5997
Count of Tweets	0.282	**Count of Tweets**	8.801
	0.8684		0.0123

Table E.3: Results of Granger Causality for Climate Change Sentiment Count of All Tweets No Outliers

E.2 With Outliers Climate Change Sentiment Measures

	Sum Pos				Count Pos		
	EUAs		**FTSE**		**EUAs**		**FTSE**
Brent	0.065	**Brent**	0.955	**Brent**	0.065	**Brent**	0.954
	0.7982		0.3285		0.7987		0.3287
Coal	0.209	**Coal**	0.068	**Coal**	0.211	**Coal**	0.068
	0.6475		0.7938		0.6457		0.7938
FTSE	1.192	**Gas**	0.970	**FTSE**	1.180	**Gas**	0.983
	0.2750		0.3246		0.2774		0.3214
Gas	1.425	**EUA**	0.908	**Gas**	1.430	**EUA**	0.915
	0.2325		0.3407		0.2317		0.3387
Sum Pos	0.654	**Sum Pos**	0.973	**Count Pos**	0.468	**Count Pos**	0.392
	0.4187		0.3238		0.4938		0.5314
	Brent		**Gas**		**Brent**		**Gas**
Coal	0.475	**Brent**	0.466	**Coal**	0.474	**Brent**	0.464
	0.4908		0.4949		0.4909		0.4958
FTSE	3.718	**Coal**	0.204	**FTSE**	3.729	**Coal**	0.208
	0.0538		0.6513		0.0535		0.6485
Gas	0.559	**FTSE**	0.168	**Gas**	0.577	**FTSE**	0.163
	0.4548		0.6823		0.4477		0.6865
EUA	0.021	**EUA**	0.836	**EUA**	0.024	**EUA**	0.846
	0.8836		0.3606		0.8773		0.3578
Sum Pos	3.287	**Sum Pos**	0.001	**Count of Pos**	1.349	**Count Pos**	0.059
	0.0698		0.9697		0.2454		0.8081
	Coal		**Sum Pos**		**Coal**		**Count Pos**
Brent	0.210	**Brent**	0.016	**Brent**	0.210	**Brent**	0.000
	0.6469		0.8997		0.6471		0.9831
FTSE	0.476	**Coal**	0.545	**FTSE**	0.482	**Coal**	0.186
	0.4902		0.4604		0.4877		0.6666
Gas	0.004	**FTSE**	0.010	**Gas**	0.004	**FTSE**	0.287
	0.9490		0.9210		0.9522		0.5925
EUA	0.146	**Gas**	0.000	**EUA**	0.150	**Gas**	0.116
	0.7029		0.9880		0.6984		0.7336
Sum Pos	0.818	**EUA**	3.570	**Count Pos**	0.462	**EUA**	3.601
	0.3659		0.0588		0.4966		0.0578

Table E.4: Results of Granger Causality for Climate Change Sentiment Sum Positive and Count Positive With Outliers

	Sum Neg				Count Neg		
	EUAs		**FTSE**		**EUAs**		**FTSE**
Brent	1.257	**Brent**	1.187	**Brent**	1.262	**Brent**	1.185
	0.5334		0.5525		0.5321		0.553
Coal	0.373	**Coal**	0.238	**Coal**	0.367	**Coal**	0.238
	0.8300		0.8879		0.8324		0.8879
FTSE	1.266	**Gas**	7.639	**FTSE**	1.276	**Gas**	7.652
	0.5311		0.0219		0.5284		0.0218
Gas	1.427	**EUA**	1.291	**Gas**	1.434	**EUA**	1.293
	0.4900		0.5244		0.4882		0.5239
Sum Neg	3.209	**Sum Neg**	0.137	**Count Neg**	3.393	**Count Neg**	0.137
	0.2009		0.9336		0.1833		0.9338
	Brent		**Gas**		**Brent**		**Gas**
Coal	1.263	**Brent**	0.644	**Coal**	1.264	**Brent**	0.653
	0.5319		0.7246		0.5315		0.7213
FTSE	5.972	**Coal**	0.936	**FTSE**	5.972	**Coal**	0.925
	0.0505		0.6263		0.0505		0.6297
Gas	3.011	**FTSE**	0.948	**Gas**	3.018	**FTSE**	0.935
	0.2219		0.6224		0.2211		0.6264
EUA	0.913	**EUA**	1.685	**EUA**	0.929	**EUA**	1.709
	0.6334		0.4307		0.6284		0.4255
Sum Neg	0.464	**Sum Neg**	1.743	**Count Neg**	0.156	**Count Neg**	1.743
	0.7930		0.4182		0.9249		0.4183
	Coal		**Sum Neg**		**Coal**		**Count Neg**
Brent	2.233	**Brent**	0.030	**Brent**	2.229	**Brent**	0.012
	0.3274		0.985		0.328		0.994
FTSE	1.031	**Coal**	0.833	**FTSE**	1.030	**Coal**	1.139
	0.5973		0.6592		0.5974		0.5657
Gas	0.007	**FTSE**	1.634	**Gas**	0.007	**FTSE**	1.595
	0.9966		0.4417		0.9964		0.4505
EUA	0.302	**Gas**	0.639	**EUA**	0.300	**Gas**	0.781
	0.8598		0.7263		0.8606		0.6766
Sum Neg	0.541	**EUA**	6.719	**Count Neg**	0.503	**EUA**	6.759
	0.7629		0.0348		0.7776		0.0341

Table E.5: Results of Granger Causality for Climate Change Sentiment Sum Negative and Count Negative With Outliers

	Count of Tweets		
	EUAs		**FTSE**
Brent	1.200	**Brent**	1.178
	0.5487		0.555
Coal	0.381	**Coal**	0.249
	0.8267		0.8829
FTSE	1.292	**Gas**	7.598
	0.5242		0.0224
Gas	1.508	**EUA**	0.140
	0.4706		0.9322
Count of Tweets	3.415	**Count of Tweets**	1.345
	0.1813		0.5104
	Brent		**Gas**
Coal	1.264	**Brent**	0.643
	0.5315		0.7251
FTSE	6.044	**Coal**	0.967
	0.0487		0.6167
Gas	2.979	**FTSE**	0.944
	0.2255		0.6237
EUA	0.363	**EUA**	0.477
	0.834		0.7876
Count of Tweets	0.856	**Count of Tweets**	1.730
	0.6519		0.421
	Coal		**Sum Pos**
Brent	2.212	**Brent**	0.537
	0.3309		0.7644
FTSE	1.057	**Coal**	0.151
	0.5896		0.9275
Gas	0.008	**FTSE**	2.060
	0.996		0.357
EUA	0.744	**Gas**	0.777
	0.6893		0.6782
Count of Tweets	0.303	**Count of Tweets**	11.706
	0.8592		0.0029

Table E.6: Results of Granger Causality for Climate Change Sentiment Count of Tweets With Outliers