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The Relationship between the EU ETS and Energy Commodities under Extreme Market Conditions

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Abstract

Climate change is becoming a more and more severe problem. Over many years, governments and organizations have introduced and proposed several measures to limit global warming. One of which is the Kyoto Protocol which was introduced by the UN as a measure to limit greenhouse gas emissions by introducing carbon trading. Carbon trading is a concept where those responsible for the emissions pay the price of their negative impact on climate. Fossil fuels, i.e., oil, gas, and coal are commodities that heavily influence the climate negatively. Therefore, this thesis aims to research the relationship between the returns of European Union Allowances and the returns of energy commodities under extreme market conditions. Employing quantile regression method, we study these relationships at different quantile levels. Through our research we found that there is a significant relationship between the variables, but that the relationship varies across different quantile levels. In addition, results differ when conducting the analyses with each commodity separately against carbon returns, then when all energy commodities are included. Overall, our thesis findings contribute to the existing literature regarding the relationship between carbon and energy markets under extreme market conditions.

Keywords: Quantile Regression, Carbon Market, Energy Commodities

JEL Classification: C22, C32, C58, Q02

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1. Introduction

The industrial revolution had a major positive impact on the world economy, but it also increased the need for fossil fuels (Wang & Zhao, 2021). As the consumption of fossil fuels increased, emissions increased with it (Wu et al., 2020). Data show that in 1950, the world emitted around 6 billion tonnes of carbon dioxide (CO_2), and in 1990 the emissions had almost quadrupled, emitting almost 22 billion tonnes. Today, the world emits over 34 billion tonnes of CO_2 each year (Ritchie et al., 2020), accounting for about 65% of the greenhouse effect (Wu et al., 2020). Although the rate of emissions growth has slowed down in recent years, it has not yet peaked (Ritchie et al., 2020).

Global warming is becoming a more and more severe problem. It is seriously endangering the survival of human society, consequently by the rising of sea levels, food shortages, glacier melting, and other extreme climate changes. Because of the severeness of this challenge, several countries agreed to attach great importance to it and act to reduce carbon emissions. As a result, the United Nations Framework Convention on Climate Change created the Paris Agreement, where the central objective is to limit global warming to well below two degrees Celsius compared to pre-industrial levels. To achieve this, global greenhouse gas (GHG) emissions must be cut by 25 to 50 percent below 2019 levels by 2030 (Black et al., 2022).

Prior to the Paris Agreement, the Kyoto Protocol was signed. The Kyoto Protocol came into force on February 16, 2005. Under that framework the United Nations Framework Convention on Climate Change had formed the idea of creating markets on which firms can buy and sell (trade) emission rights. The general idea behind carbon trading was that by setting a price on carbon, it would reduce emissions, which would limit global warming (Wu et al., 2020). As of 2010, emissions trading had become popular and was the most widely supported government policy. Following that, carbon permits rapidly became a significant financial tool in markets with annual revenue of billions of dollars (Spash, 2010). In 2021, the average price of carbon throughout the world was 5$ per tonne, but by 2030 the price must reach 75$ per tonne in order to be able to limit GHG emissions and reach the goals regarding global warming (Black et al., 2022).

Since the Kyoto Protocol, the EU has launched the European Union Emissions Trading System (EU ETS) to carry out its obligations to the protocol. The system is today used as the main tool to manage the reduction of emissions in Europe. The EU ETS has had good results and is today the largest market for carbon trading. The trading system raised their transaction volume by roughly ten times between 2005 and 2013, and accounts for around 90% of the global carbon trading volume (Wu et al., 2020). In 2021, the market covered over 1.2 billion tonnes of CO_2 (L, 2022). The EU ETS includes four phases, and as of 2021 the EU ETS has entered a fourth phase which will last until 2030, where the goal is for the sectors covered by the EU ETS to reduce their emissions by 43% compared to 2005 levels (European Commission, n.d.).

Studying the relationship between carbon emissions markets and energy markets is a topic that has been broadly researched, both by focusing on the relationship between prices, and the volatile spillover between the markets. Our thesis is inspired by the study written by Chen et al. (2022), where the authors studied the spillover effect between carbon markets, traditional energy, clean energy, and the metal market. We want to contribute to the existing literature by further analyzing the relationship between the European carbon market and energy commodities under extreme market conditions. Thus, we have developed the following research question:

Is there any relationship between the carbon market and energy commodities under extreme market conditions?

In our research we want to focus on the relationship between the price of one European Union Allowance (EUA) in the EU ETS, and prices of three different energy commodities; Brent Crude Oil, Natural Gas, and Rotterdam Coal. To answer our research question, we are using Quantile regression. Quantile regression is beneficial for understanding the conditional distribution of a dependent variable when there exist extreme observations. Through the three completed phases of the EU ETS, the second (2008-2012) and third (2013-2020) phase included about 57% of the total amount of allowances. As the first phase (2005-2007) was a trial period, we decided to only consider the second and third phase in our analysis. Our data range from April 8, 2008, to December 31, 2020. The energy commodities included was chosen as they are the ones most used in the EU to produce electricity. In 2011, these made up about 49% of the electricity production, and as of 2021 they covered about 36% (Conte, 2023).

The remainder of the thesis is organized as follows. In the following chapter we will present relevant underlying background information concerning the thesis topic. Chapter 3 provides an overview of the existing literature regarding carbon markets and different energy commodities.

Chapter 4 consists of a detailed description of the data. Further, Chapter 5 covers the chosen methodology, and in Chapter 6 the empirical results are presented. Chapter 7 provides a discussion of the results, limitations and implications to the study. Chapter 8 summarizes the thesis with a conclusion and suggestions for future research.

2. Institutional Background

This chapter presents relevant background information regarding the thesis topic. First, the Paris Agreement will be discussed, before presenting the concept of carbon pricing and carbon markets, and then finishing with the connection between carbon emissions and energy markets.

2.1 The Paris Agreement

In December 2015, the world leaders at the United Nations Framework Convention on Climate Change came to a breakthrough on how to strengthen the global response to climate change. This measure is called the Paris Agreement. The Paris Agreement is in practice the successor to the older Kyoto Protocol, which aimed to limit global warming and having legally binding national commitments to cut emissions. However, as the Kyoto Protocol only required developed countries to comply with the commitments, the emissions of the developing countries grew tremendously, which resulted in the Kyoto Protocol being inadequate to accomplish its task (Horowitz, 2016).

The Paris Agreement yields to tackle the consequences of global climate change and it includes several long-term goals. It was the beginning of the change towards a net-zero emissions world. The agreement depends on a number of reporting requirements and collective stock-taking activities to encourage transparency and political pressure for the engaged countries to ensure performance, but the agreement does not require any legally binding responsibility to achieve any targets that have been stated (Horowitz, 2016).

The Paris Agreement has three stated objectives:

> "(a) Holding the increase in global average temperature to well below 2^{o}C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5^{o}C above pre-industrial levels (…); (b) Increasing the ability to adapt to the adverse impacts of climate change (…); and (c) Making finance flows consistent with a pathway towards low greenhouse gas emissions and climate resilient development" (United Nations, 2015b, p. 3).

For the world to achieve the UNs Sustainable Development Goals, the implementation of the Paris Agreement was essential (United Nations, 2015a). The UN developed 17 goals with 169 target goals in 2015 as an action plan for people, planet, and prosperity. These goals aim to create action in fields which are of critical importance to the planet and humanity. One of these goals, number

13, is to "take urgent action to combat climate change and its impacts" (United Nations, 2015c). Both objective (a) and (b) are directly linked to achieving sustainable and climate-resilient development. While objective (c) highlights the importance of aligning financial activities with the goals of reducing GHG emissions and promoting climate resilience. Carbon trading can play a significant role in achieving these three objectives.

2.2 Carbon Pricing

Carbon pricing is an important tool in climate policy as there is a real-world cost to carbon emissions. It can play a crucial role in meeting the goals of the Paris Agreement as it can be designed in such a way that it can guarantee the achievement of holding the increase in the global temperature to 1.5 – 2^{o}C above pre-industrial levels. This sets carbon pricing apart from other policies. There exist several methods to carbon pricing, and it encourages both short-term cost-effective emission reductions, and long-term cost-reducing innovation. Further, it can support the employment of other policy tools e.g., public investment and regulations (Boyce, 2018).

Since there are several ways to price carbon emissions, there is also disagreement as to which of the methods is most effective in terms of emitting less CO_2. Within carbon pricing, there are two primary pricing instruments: carbon tax and emissions trading systems. A high carbon tax will lead to increased carbon prices, which can result in less CO_2 emissions from institutions. An emissions trading system is a system which is built to trade CO_2 emissions, this results in a carbon market where the market can set the price within certain restrictions. Further, it incentivizes decarbonization by allowing regulatory bodies to generate a baseline price which will increase over time (L, 2022).

2.3 Carbon Markets

As mentioned in Chapter 1, one of the measures that was implemented by the United Nations Framework Convention on Climate Change was the Kyoto Protocol (United Nations, 1997). The Kyoto Protocol was established in 1997 and was a response to the global concern regarding climate change. It set legally binding commitments to reduce GHG emissions for 37 developed countries (Calel, 2013). When agreeing on the protocol the debate was focused on creating a single global market for trading carbon permits. The idea of creating only one global market was due to the fact that one tonne of GHGs emitted in the world has the same consequences to the climate for everyone. Hence the proposal of establishing a single global market was put out to equalize incentives for reducing emissions worldwide (Newell et al., 2013).

A carbon market refers to a system where companies and countries can buy and sell carbon permits that allow them to emit a certain amount of GHGs, including CO_2. This system operates on a supply and demand basis. There are different types of carbon markets: compliance or voluntary. As mentioned in Section 2.2, emissions trading is a specific type of carbon pricing where companies are allocated a certain number of allowances. It is a scheme where the number of allowances is based on the company's historical emissions of GHGs, and their overall environmental ambitions decided by their government (Commission of the European Communities, 2000).

The emission allowances are often referred to as "permits" or "caps". The sum of these permits that are provided to every company that takes part in the scheme, constitutes the program's overall emissions cap. This cap or total limit is what makes the scheme environmentally beneficial. If the company emits less than what it is allocated, it can trade the remaining allowances with other companies. Individual corporations are permitted to emit more than their maximum amount under the terms of the emissions trading system, provided that they can locate another firm willing to grant the transfer of its "spare" credits, given that the firm has emitted less than permitted. With the critical distinction that both purchasing and selling firms profited from the flexibility provided by trade, without harm to the environment, the total environmental outcome is the same as if both companies utilized their allowances perfectly (Commission of the European Communities, 2000).

Today, the world has experience with actual carbon markets unlike back in 1997. In terms of market value and volume, carbon markets are now the largest segment of environmental emissions trading markets worldwide. In 2012 most of carbon markets occurred in five arenas: the European Union Emissions Trading System, the Clean Development Mechanism, Regional Greenhouse Gas Initiative (RGGI), New Zealand Emissions Trading Scheme, and voluntary markets (Newell et al., 2013).

2.3.1 European Union Emissions Trading System

When the EU committed to the Kyoto Protocol in 1997, they agreed to reduce their emissions of GHGs by 8% during 2008 to 2012, compared to their 1990 levels (Commission of the European Communities, 2000). And in 2000, the European Commission introduced ideas of their first design on the EU ETS. Their idea was to have a "cap-and-trade" system, also known as an emissions allowance trading system, which was discussed in Section 2.3. The two main components are to first limit or "cap" the pollution, and the second is that the tradeable allowances given to a specific company equal the amount they are allowed to emit. The EU ETS was finally launched in 2005 and was the world's first international emissions trading system, including all 28 member states, Iceland, Lichtenstein, and Norway (Comission of the European Communities, 2023). As of today, it is the dominating market-based system to reduce global GHG emissions (Wu et al., 2020). Like most regulatory carbon markets, the EU ETS applies a slowly decreasing cap on emissions to force companies to gradually decrease their carbon output (L, 2022).

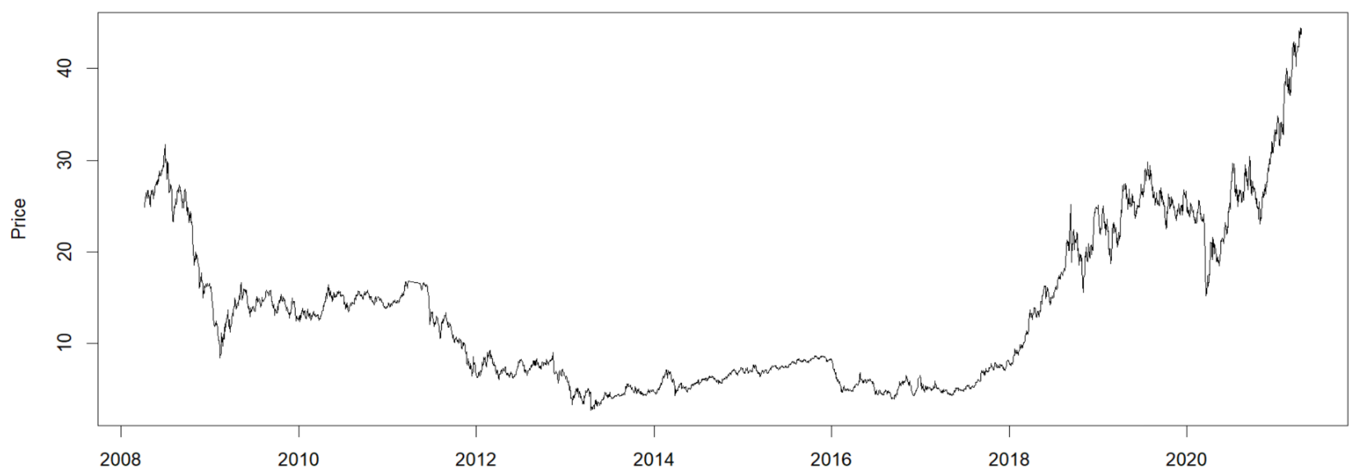


Figure 1: Price evolution of EU ETS carbon allowances from April 7, 2008, to April 16, 2021

In figure 1, the evolution of carbon prices from April 8, 2008, to April 16, 2021, is portrayed. As stated in Chapter 1, the EU ETS has operated in three phases and entered the fourth and final phase in 2021. Phase one was a pilot phase of "learning by doing" which lasted from 2005 to 2007. In this phase, the main goal was to prepare for the second phase in which the program would start assisting the EU in fulfilling its Kyoto Protocol commitments. The CO_2 emissions of power generators and energy-intensive industries were covered in this period. Most of the permits were given to the companies for free, but they were given a 40 Euro penalty per tonne when emitting more than allocated. Because of the free permits, this phase is not portrayed in figure 1. In the first phase they succeeded in pricing carbon, creating free trade in permits across the EU, and creating the infrastructure needed to monitor, report, and verify emissions covered by the scheme (Comission of the European Communities, 2023).

The second phase expanded the coverage and lasted from 2008 to 2012 (Newell et al., 2013). In this period, the EU ETS sought to solve the issues that came about in the previous phase. The proportion of free allocations fell slightly to about 90% and the auction quotas gradually grew (Comission of the European Communities, 2023). This led to a serious increase in the carbon price which is seen in the beginning of figure 1. Nevertheless, the demand for allowances decreased in 2008, caused by the financial crisis, which brought on a continuous decline in carbon prices (Zhao et al., 2023). In this phase the penalty for exceeding the number of allocations increased to a 100 Euros per tonne, and businesses were now allowed to buy international permits (Comission of the European Communities, 2023).

Phase three ranged from 2013 to 2020 and added a powerful range of industrial activity (Newell et al., 2013). In this period, the EU ETS gradually replaced the free quota with full auction, meaning that businesses must buy all the allowances they needed to cover their emissions (Batten et al., 2021). This measure led to an increase in carbon prices, but with a drop in 2020 caused by the COVID-19 pandemic, before continuing to increase into the fourth phase. The fourth phase started in 2021 and will continue until 2030. Here, there will be a significant increase in the yearly drop in carbon allowances from 1.74% in the third period, to 2.2%. Further, the member states of the EU must reduce carbon emissions by 55% in 2030 compared to 1990 levels. This has caused an increase in the carbon price from 33.56 Euros per tonne, to 73.28 Euros per tonne, which is highly visible in figure 1 (Zhao et al., 2023).

2.4 The Connection to Energy Commodity Markets

The connection between growth and carbon pricing can be explained using economic reasoning. Initially, as economic activity increases, there is a greater need for goods related to industrial production. Consequently, companies that fall under the regulations of the EU ETS are compelled to produce more and emit a larger amount of CO_2 to meet the demand of the consumers. This results in an increased demand for CO_2 allowances to cover the industrial emissions, ultimately leading to higher carbon prices. This reasoning is reinforced by the fact that supply side factors have minimal impact on the EU ETS, as the allocation is predetermined and known to all market participants in advance. The demand for CO_2 allowances is determined by anticipated CO_2 emissions, which in turn, are influenced by various factors. These factors depend on a wide range of elements, including unforeseen shifts in energy demand, fluctuations in energy commodity prices, e.g., oil, gas, and coal, as well as weather conditions i.e., temperature, rain, and wind (Chevallier, 2011).

Previous literature and studies have found that the main drivers of the carbon prices are energy commodities like oil, gas, and coal (Chevallier, 2011). According to these studies, the price of fossil fuels can directly affect the price of carbon through the production restraint effect, the substitution effect, and the aggregated demand effect, whereas the price of non-energy financial assets may do so indirectly through the energy price and directly through the industrial production path (Tan et al., 2020). More precisely, with regards to the indirect energy path, markets such as equities and bond markets can influence energy commodities through the paths of financial investment/speculation path (Tang & Xiong, 2012), the traders' funding liquidity path (Brunnermeier & Pedersen, 2009), and the paths of exchange rates (Cashin et al., 2004). Chevallier (2011) suggested a link between the macro-economy and the carbon price, and the correlation between carbon and energy and carbon and finance heavily depend on uncertain market conditions because of common macroeconomic shocks during the financial crisis (Koch, 2014).

3. Literature Review

In this chapter we introduce former literature that focuses on the relationship between carbon markets and different energy commodities. As stated in Chapter 1, this is a topic which previously has been researched, with different variables and methodologies. First, previous literature regarding the volatile spillover between a carbon market and different energy commodities will be discussed, followed by literature that studied different types of relations between the carbon market and energy market.

Chen et al. (2022) used quantile connectedness approach to investigate the dynamic linkages and tail risk connectedness between different energy markets, carbon markets, and metal markets. The authors found that the connectedness between the markets is about 51% at the median and mean, and about 87% under extreme conditions. Further, the authors also found that the connectedness between energy, carbon markets, and metal is time-varying, and that the volatility is relatively small under extreme negative and positive conditions. Chen et al. (2022) found it noteworthy that the dynamic connectedness of the energy, metal, and carbon markets vary in extreme upward and downward markets, reflecting the asymmetry and tail dependence of spillover effects between markets, and indicating that spillover effects vary between the periods of upward and downward markets.

Wu et al. (2020) investigated the volatility spillover between the three different energy future markets, i.e., Crude Oil, Natural Gas, and coal, and carbon emissions market by employing recurrence plot (RP) method and recurrence quantification analysis (RQA) method. The findings indicated that the coal market and the carbon emissions market have the strongest volatility spillover. Based on their findings, the authors suggest that businesses should transition from coal to Natural Gas or oil in order to minimize the risk associated with the carbon emission market. This action will reduce carbon emissions. For future research, the authors suggest looking into the regions or countries that have different policies, e.g., differences in prices, environmental policies, market acceptance, and other aspects.

Similarly, Zhang and Sun (2016) also studied the interaction of carbon prices and fossil energy prices. Exploring the issues for the daily data (Jan. 2, 2008, to Sep. 30, 2014) of European carbon futures process and the three fossil energy prices, i.e., coal, Natural Gas, and Brent Crude Oil, using the threshold dynamic conditional correlation generalized autoregressive conditional heteroskedasticity (DCC GARCH) model and the full Baba-Engle-Kraft-Kroner (BEKK) GARCH model. First, the authors found that there is significant unidirectional volatility spillover. This spillover goes from the coal market to the carbon market, and from the carbon market to the Natural Gas market. They also found that there is no significant volatility spillover between the carbon market and oil market. Second, they found that there is a significant positive correlation across time between the carbon market and the fossil energy market, whereas the coal market has the highest correlation with the carbon market. Thirdly, Zhang and Sun (2016) found that while the prices of fossil fuels decrease, they have a stronger impact on carbon price volatility than if their prices increase with the same degree. For future research, the authors suggest looking into the risk spillover effect between carbon and energy markets when they are influenced by the shocks of relevant economic and financial events.

The article by Reboredo (2014) investigated the extent to which volatility shocks in oil markets, using Brent Crude Oil prices, are transmitted to the EUA market and vice versa, using multivariate conditional autoregressive range model with bivariate lognormal distribution. Examining the data from the EU ETS Phase II daily prices of EUA futures, the authors found that there is an existence of volatility dynamics and leverage effects, and that there are no significant volatility spillovers between these markets.

Several studies have also looked at the relationship between carbon markets and different electricity markets, where Zhao et al. (2023) are one of these. Zhao et al. (2023) studied the spillover impact between the two markets and if the energy market has an intermediary role in carbon-electricity synergy. Using the vector autoregressive (VAR), BEKK and GARCH model, Zhao et al. (2023) analyzed the relationship between oil, Natural Gas, carbon, and the electricity markets. Using data from the Nordic electricity market and the EU ETS, the study found that the impact between the carbon market and the electricity market is more the transmission of price changes than the direct influence of returns. Furthermore, the energy markets help to "bridge" the gap between the carbon and electricity markets. For future research, Zhao et al. (2023) suggest studying the spillover effect in other countries, like China and the US, and at the same time expand the selection of energy markets as the intermediary variable.

Similarly, Qiao et al. (2023) investigated the time lag and periodicity of spillover intensity and direction among carbon, fossil energy, i.e., coal and gas, and electricity markets using TVP-VAR-

SV method and impulse response function. The results showed that time-varying asymmetry characterizes the intensity and direction of spillover among carbon, fossil energy, and electricity markets. In the short term, the rise in carbon and fossil energy prices will lower the value of the electricity market. Long-term, nevertheless, it may encourage the electricity market to speed up the adjustment of the energy structure, lower carbon emissions, and increase the electricity market's worth. For future research the authors suggest including other types of energy, i.e., nuclear energy and renewable energy, in the research.

Yu et al. (2015) also researched the carbon market and crude oil market, investigating the causality between the two markets. Using a multi-scale analysis approach on EUA futures and Brent futures as study samples, the authors arrive at several interesting findings. Without multi-scale decomposition, Yu et al. (2015) found that the evidence supports a neutrality hypothesis, i.e., no Granger causality between the carbon and crude oil markets. When investigating within one week, excluding non-workdays, the two markets might be uncorrelated and driven by their own respective supply-demand disequilibrium. For above one week but below one year, the authors found that between the two markets there is a strong bi-directional linear and nonlinear spillover. This is due to extra factors with medium-term effects, such as for example policy changes and significant events. For a long timescale, they found that the two markets have an obvious linear relationship. For future research the authors want to investigate the dynamic relationship varying with time to understand the linkage mechanism between two markets.

Soliman and Nasir (2019) used daily data from November 2007 to October 2017 on the quotes of Brent Crude Oil and Natural Gas spot returns, and quotes of EU ETS spots, to assess the risk dependency relationship between the EU ETS and energy prices. Using time-varying copulas connection function, the authors found that there is an asymmetrical dependence change rule between the EU ETS, oil, and gas spot index, having a significantly higher correlation in the lower tail than the upper tail.

Kim and Lee (2015) studied the interrelationship between the carbon emissions trading market in the US, called RGGI, and energy markets. Using Lag Augmented Vector Autoregressive method, a weak relationship between the markets was revealed. The authors found that this can be explained by the previously weak carbon credit demand caused by the reduced energy demand due to fuel switching. Another reason might be because the RGGI system is mostly powered by Natural Gas, which is perhaps related to the recent shale gas boom.

Through their study, Lutz et al. (2013) wanted to investigate the nonlinear relation between the EUA price and energy prices, macroeconomic risk factors and weather conditions, which they call fundamentals. By estimating a Markov regime-switching model, the authors found that the relations vary over time. Changes in the stock market and energy costs are the two main factors influencing EUA pricing. The EUA price is positively impacted by the price of gas and a large European equities index in both volatility regimes, but is only significantly and positively impacted by the price of coal and oil in the high and low volatility regimes, respectively.

Aatola et al. (2013) studied the price determination of the EUA of the EU ETS. Using several econometric models with multiple stationary time series, the authors found that there is a strong relationship between the fundamentals, i.e., German electricity prices, and gas and coal prices, with the price of EUA. They also found that the EUA forward price depends in fundamentals, especially on the price of electricity as well as on gas-coal difference, in a statistically significant way.

As seen above, several studies have previously researched the interrelationship between carbon markets and other markets such as energy, electricity, metal, fossil energy, crude oil, and Natural Gas. The studies found that there are linkages between the variables. In this thesis, we will further investigate the connectedness under extreme market conditions by applying quantile regression.

4. Data

In this chapter, the data used to research the relationship between carbon and energy commodities will be presented. Firstly, we explain where and how the data was collected, and what alterations were made to it. Further we give the descriptive statistics and various tests of hypothesis, finishing with copula to characterize the data.

4.1 Description of Data

To investigate the interrelationship between carbon markets and fossil energies under extreme market conditions, we obtained data from the EU ETS and the energy commodities Brent Crude Oil, Natural Gas, and Rotterdam Coal. The raw datasets are retrieved from three different sources. For the EU ETS[1], the daily settle prices of a two-month future contracts of EUA (hereafter carbon prices) were included. It represents the price of being allowed to emit one tonne of GHG, including CO_2. The observations were retrieved from ICE. Today, the EU ETS accounts for nearly 90% of the global carbon trading volume. It is therefore a typical representative of the global emission market (Wu et al., 2020). As stated in Chapters 1 and 2, the first phase of the EU ETS was a trial operating period, and due to this, the price of carbon subsidies in Europe was unpredictable until early in 2008. Therefore, the sample period in this thesis runs from April 8, 2008, to December 31, 2020, which includes the following two phases of the EU ETS.

The daily close prices of one-month future contracts of one barrel of Brent Crude Oil[2] and one unit of Natural Gas[3] are retrieved from Yahoo Finance. Yahoo Finance collects the prices of Brent Crude Oil futures (hereafter oil prices) and the prices on Natural Gas futures (hereafter gas prices) from the New York Mercantile Exchange. These are futures from the international market. The daily close prices of one-month future contracts of one ton of coal[4,5] are retrieved from Yahoo Finance and Investing.com. Yahoo Finance provides data from the dates December 17, 2010, to December 31, 2020. The remaining prices (Apr. 8, 2008 – Dec. 16, 2010) were retrieved from Investing.com. The prices of the Rotterdam Coal futures (hereafter coal prices) on Yahoo Finance are from the New York Mercantile Exchange. The contracts from both Yahoo Finance and

[1] https://data.nasdaq.com/data/CHRIS/ICE_C1-ecx-eua-futures-continuous-contract-1-c1-front-month
[2] https://finance.yahoo.com/quote/BZ=F?p=BZ=F&.tsrc=fin-srch
[3] https://finance.yahoo.com/quote/NG=F?p=NG=F&.tsrc=fin-srch
[4] https://finance.yahoo.com/quote/MTF=F?p=MTF=F&.tsrc=fin-srch
[5] https://www.investing.com/commodities/rotterdam-coal-futures-historical-data

Investing are financially settled based on the price of coal delivered from the Amsterdam, Rotterdam, and the Antwerp regions in the Netherlands and Belgium.

As stated in Chapter 1, fossil energy remains the primary source of electricity in Europe today, and the cost of fossil energy and the accompanying cost of carbon heavily influence the price of electricity production. Alternative fuels, such as nuclear energy or renewable energy, are thus not considered in this thesis. Since the data for fossil energy follow the trading days of the American market and the carbon prices follow the trading days of the European market, alterations on the data were necessary to conduct calculations, because of differences in trading days. Therefore, we removed dates and respective prices in order to get matching datasets with equal number of observations. The sample data after all alterations provided 2991 daily observations. Below, time series plots of the prices of each of the variables are presented.

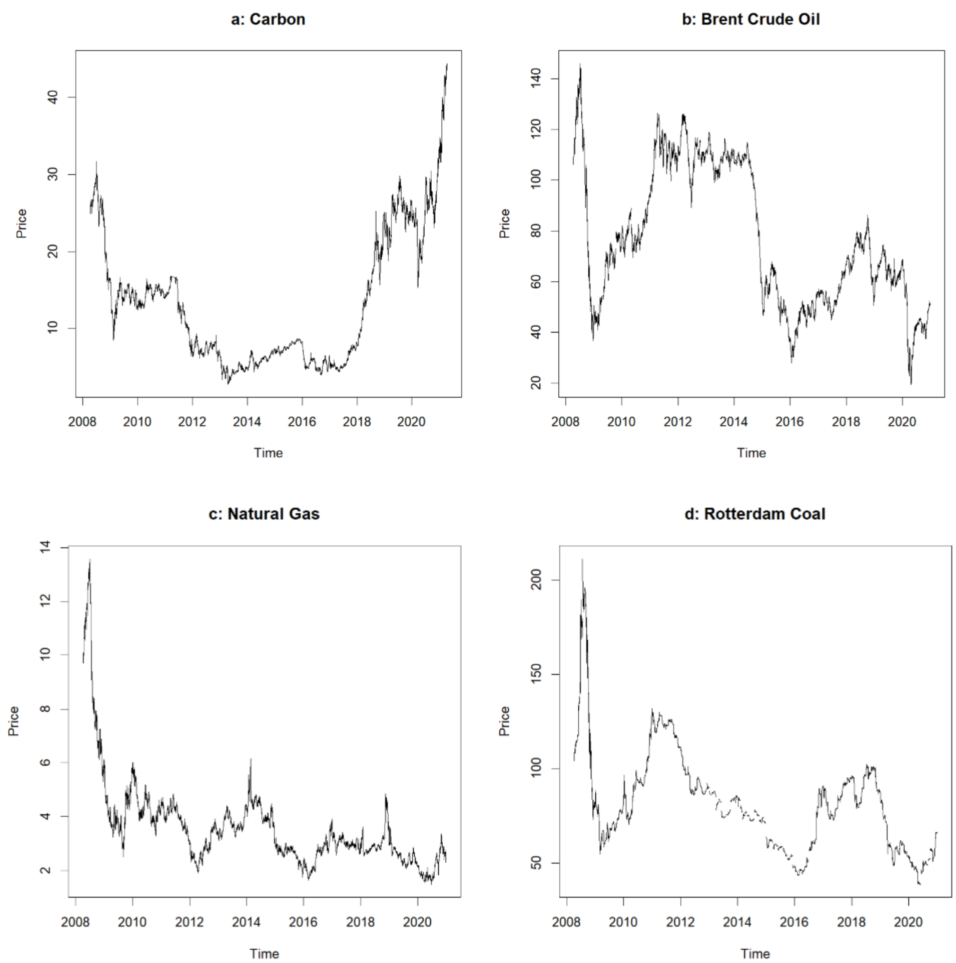


Figure 2: Daily carbon, oil, gas, and coal prices from Apr 8, 2008, to Dec 31, 2020

Figure 2a, b, c, and d illustrate the historical prices of each of the variables, i.e., carbon prices, oil prices, gas prices, and coal prices from April 8, 2008, to December 31, 2020. In figure 2a, the evolution of the price of carbon is portrayed. There is a significant decrease in the price in the period of 2008 to 2009, which can be explained by the financial crisis in 2008, where the demand for allowances significantly decreased, leading to a decrease in carbon prices (Soliman & Nasir, 2019). In figure 2b, c and d, the sharp drop in the prices of oil, gas, and coal in 2008 can also be explained by the financial crisis.

Further, in figure 2a another drop is observed from the middle of 2011 to 2012. This may be explained by the demand for allowances still being impacted by the financial crisis which led to a continuous decline in carbon prices. In 2013, the EU ETS entered phase three, where full auction was introduced, as mentioned in Section 2.3.1, which led to an increase in the carbon prices. In 2018, the EU ETS decreased the number of allowances, which further explains the increase in the price. From 2019 to 2020 the price is quite stable, except for a drop in 2020 which was caused by the COVID-19 pandemic. The prices continue to increase into the end of the third phase in 2020, caused by the yearly cap continuing to increase (Comission of the European Communities, 2023).

After the financial crisis in 2008, it can be observed from figure 2b and c that oil and gas prices increased from 2009 to 2011. This increase is an effect of economic stimulus by the governments to fight the financial crisis which resulted in expectations of increased inflation. This led to an increase in commodity buying. The oil prices were also driven up by the Arab spring and transport bottlenecks (Eia, 2012). In the period of 2014-2015, figure 2b illustrates another decrease in the oil prices, which can be explained by the oversupply compared to the demand. Part of the reason for the oversupply was the growth of production in the US (Stocker et al., 2018). Further, a steady increase with relatively minor fluctuations is portrayed with another drop in the beginning of 2020, due to the COVID-19 pandemic.

In the beginning of 2008, the demand and supply balance were rather tight, which led to an increase in gas prices (see figure 2c). Then the financial crisis came, and as mentioned, the prices dropped relatively significantly. The plot portrays relatively stationary prices with some bigger fluctuations in 2012, 2014, 2016 and 2019. The plot illustrates a drop in gas prices in 2011-2012, and then an increase. This decrease in gas prices can be explained by a mild winter, which lowered the demand for Natural Gas (Eia, 2013). The increase in the period of 2012-2014 can be explained by a shortage in gas supply across Europe caused by extreme temperature conditions and lack of inadequate storage. In 2016, gas prices reached the lowest value since 1999. The reason behind this is again weather conditions. Because of mild weather, the demand for Natural Gas and Brent Crude Oil decreased. Later in 2016, the demand for Natural Gas once again increased and the price followed, with a new peak in 2019 (Walton, 2017). The peak in 2019 can also be explained by cold weather which increased the demand for gas (Eia, 2020).

The plot of coal prices, figure 2d, portrays an increase in the beginning of 2008. This can be explained by weather conditions that led to a decrease in the supply, which led to an increase in the price. Towards the end of 2008 and continuing through 2009, the plot illustrates a significant drop in the prices, which as mentioned earlier can be explained by the financial crisis, because of the reduction in demand for energy. In 2010 and 2011 there was a period with increasing prices, with the main contributors being weather, political, mining, and geological factors. Further, between 2012 and 2015, the world entered an economic slowdown period, where the global GDP fell, leading to a decrease in energy demand, which resulted in a decrease in coal prices. Because of the decrease in coal mining output during 2012-2015, coal prices increased in 2016-2018. The last two years in the plot is characterized by a downward trend. The price of coal fell in 2019, which was brought on by the escalation of the US-China conflict, lower coal consumption (which hit record low levels), rising port stocks, an increase in the production of renewable energies, an oversupply of gas, and yet another mild winter (Stala-Szlugaj & Grudziński, 2021). Also, in the price evolution of coal prices there is a drop in the prices when COVID-19 hit.

4.2 Log Returns

From the plots in figure 2 it can be noticed that the prices of all variables are non-stationary. If a data series is non-stationary, it can produce a problem for the statistical analysis. Therefore, we compute the daily logarithmic returns from the raw data because the empirical analysis of this thesis requires that the variables are stationary. The log returns are given by:

$$r_{i,t} = \ln\left(P_{i,t} \,/\, P_{i,t-1}\right) \tag{4.1}$$

where $P_{i,t}$ is the price at time t, and $P_{i,t-1}$ is the price at time t - 1. Plots of the daily log returns and boxplots of all the variables were constructed and are depicted below. Further, descriptive statistics, Dickey-Fuller tests for stationarity, Bartlett autocorrelation tests, Ljung-Box tests, Q-Q plots, Jarque Bera tests, and unit square plots will be presented.

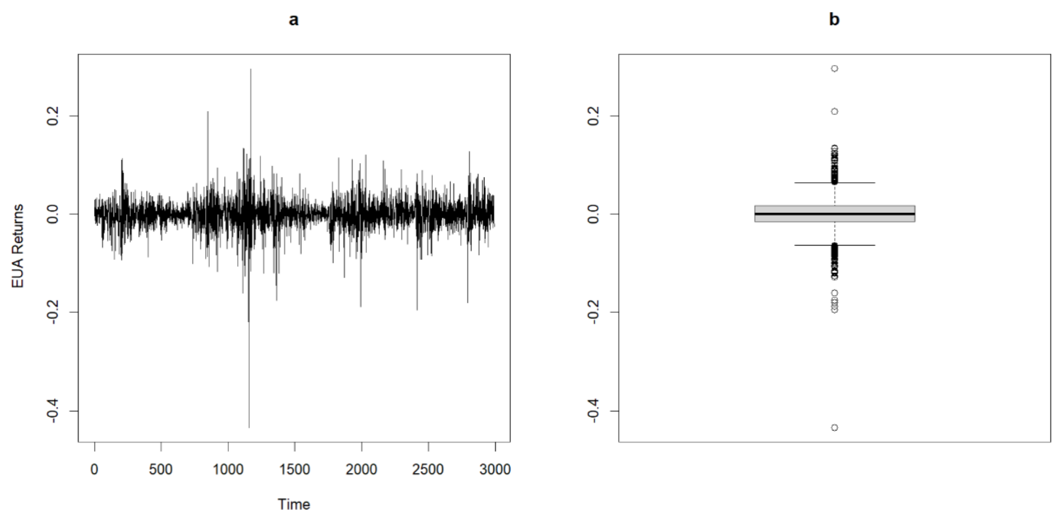


Figure 3: Time series plot (a) and boxplot (b) for the log-returns on carbon

From figure 3a, it can be observed that the log returns of carbon prices are relatively stationary in the beginning of the time-period, but in 2012 there are big volatile fluctuations. The downward spike in 2012 is the smallest return observed, and it is both visible in the log return plot and in the boxplot, and it is -0.4347.4 (see table 1). The observation can be explained by the allowance demand still being impacted negatively by the financial crisis in 2008. Furthermore, there are some smaller fluctuations in 2016, 2018, and 2020.

The line in the middle of the box in figure 3b represents the median, which in this case is 0. This corresponds with the median in table 1. The outer lines of the box represent the lower and upper quartile, also this is consistent with the results in table 1. The whole box represents the interquartile range and inside this box lies 50% of all the observations. From the boxplot in figure 3b, it can be observed that many of the observations lie outside the whiskers, which suggests that this data has many extreme observations, and that the data is not normally distributed. That the data is not normally distributed is also proved later in this chapter by Q-Q plots and Jarque Bera tests.

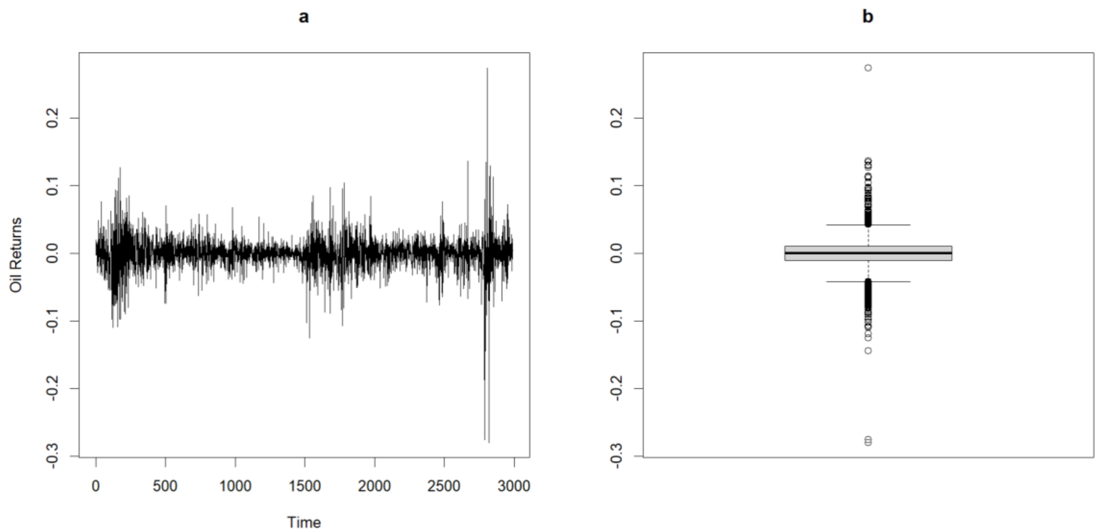


Figure 4: Time series plot (a) and boxplot (b) for the log-returns on oil

Figure 4a portrays the log returns of oil prices. Here it can be noticed that the returns are relatively stationary across the whole time-period, with smaller fluctuations in 2008, 2015 and 2016, and bigger fluctuations in 2020. The fluctuations in 2020 can be explained by the COVID-19 pandemic. In the boxplot in figure 4b, it can be observed that the data have heavy tails with some extreme observations. The minimum and maximum value seen in the boxplot is consistent with the values seen in table 1, as well as the median which is slightly positive. From the boxplot in figure 4b, one can also observe that the daily returns on oil do not seem to be normally distributed.

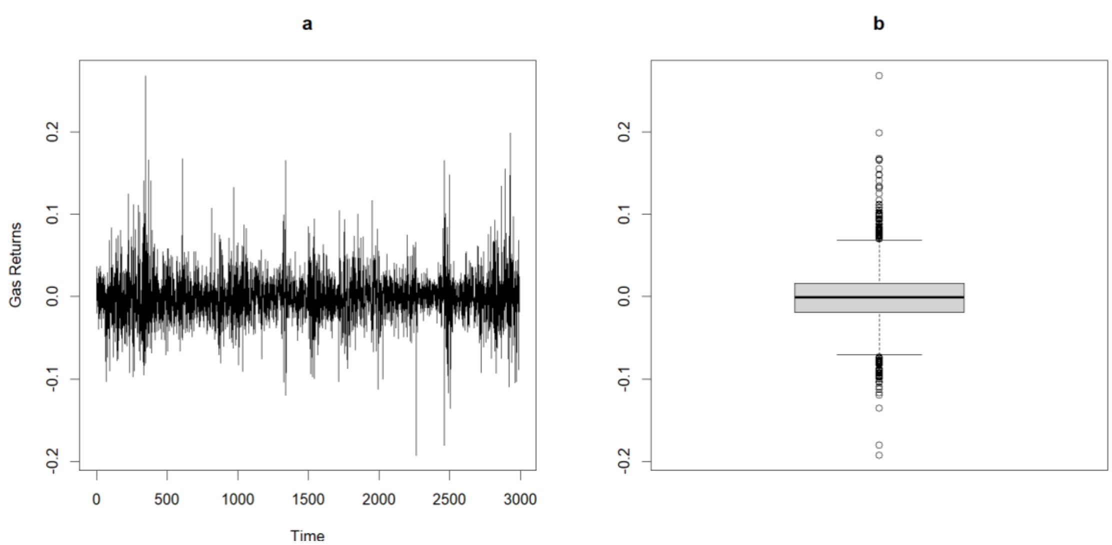


Figure 5: Time series plot (a) and boxplot (b) for the log-returns on gas

The log returns for gas prices are portrayed in figure 5a, and it can be observed that they are fairly volatile over the entire twelve-year period. The maximum value is observed in 2009 and is consistent with the maximum value in the boxplot (figure 5b). This value can be explained by the stimulus by the government to increase the price of commodities after the financial crisis of 2008 (Investopedia, 2022). The minimum value is observed in 2018 and is also consistent with the boxplot. From the boxplot in figure 5b, it can be noticed that the median for gas returns is slightly negative, which is consistent with the median in table 1. Moreover, the plot suggests that the observed returns do not follow a normal distribution. To substantiate this claim, we refer to the heavy tails represented by all the observations outside the whiskers in the boxplot.

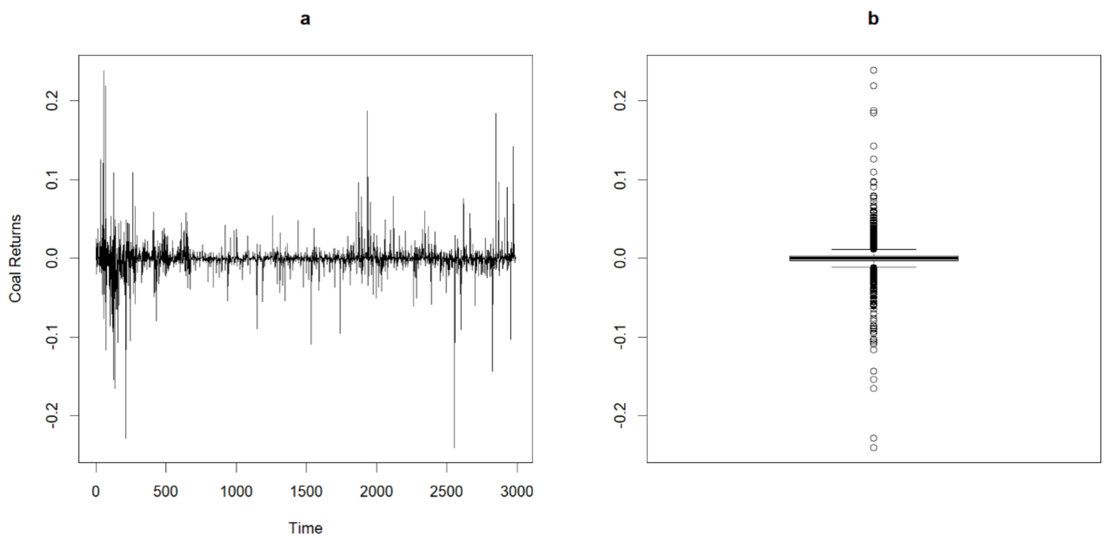


Figure 6: Time series plot (a) and boxplot (b) for the log-returns on coal

Figure 6a exhibits the evolution of the log returns computed from the coal prices, and one can see from the plot that there are several big spikes occurring in 2008-2009. This can be explained by the financial crisis in 2008. The returns are quite stationary from 2010, but in 2016, 2018, and 2020 we observe some bigger spikes. Compared to the boxplots in figures 3b, 4b, and 5b, the whiskers in figure 6b are much smaller and the interquartile range is also quite low. This indicates that 50% of all the returns are quite close to each other and that the remaining 50% of the returns are considered to be extreme observations. The maximum and minimum value in the log return plot is consistent with the boxplot and it can be observed that the returns of coal have more extreme observations compared to the other three variables. Based on figures 6a and b, we can draw the conclusion that the data is not normally distributed and that the data for coal has relatively heavy tails.

It is noticeable from figures 3a, 4a, 5a, and 6a that compared to their raw equivalents, all datasets are now closer to the ideal of stationarity. Below, we present the descriptive statistics, and further investigate the characteristics of the sample data.

4.3 Descriptive Statistics

Table 1: Descriptive Statistics

		Carbon	Oil	Gas	Coal
Parametric	**Min value**	-0.4347	-0.2798	-0.1926	-0.2405
	Max value	0.2964	0.2742	0.2677	0.2384
	Mean	0.000085	-0.00024	-0.00046	-0.00015
	Standard Deviation	0.0324	0.0254	0.0325	0.01802
	Skewness	-0.7896	-0.0412	0.509	0.02801
	Kurtosis	16.22	17.73	4.915	56.503
Non-Parametric	**Median**	0	0.00028	-0.00087	0
	Lower Quartile	-0.0151	-0.0103	-0.0189	-0.00296
	Upper Quartile	0.0169	0.0106	0.0161	0.002784
	Interquartile Range	0.0321	0.0205	0.0351	0.005743

Table 1 presents an overview of the descriptive statistics computed from the log returns of each of the variables. The mean for carbon returns is positive but relatively low, while for oil, gas and coal returns the mean is negative. From table 1 it can be noticed that all the return variables have fairly similar standard deviations, with a variation from the mean of respectively 0.0324, 0.0254, 0.0325, and 0.0180.

The returns for carbon and oil both have negative skewness, which indicates that the respective marginal distributions are not normal and are skewed to the left. Gas and coal returns have a positive skewness which suggests that the distribution is skewed to the right. Furthermore, the estimated kurtoses of all return variables exceed the value of three. This demonstrates that the tails are heavier than those of a normal distribution, and it points to the distributions being leptokurtic.

When data points are presented in a ranked order, the lower quartile or 0.25 quantile, is the value under which 25% of the data points are located. The number under which 75% of the data points are located is known as the upper quartile (Brooks, 2019, p. 53). In table 1, the lower quartile of all the variables is negative, and 25% of the sample returns are lower than -0.0151 (Carbon), -

0.0103 (Oil), -0.0189 (Gas), and -0.00296 (Coal). Looking at the median for carbon and coal returns, the value is 0, which means that half of the returns are negative, and the other half is positive. This indicates that half of the observations occurred under market recession and the other half in market expansion. Oil returns have a positive median of 0.00028, while gas returns have a negative median of -0.00087. For the upper quartile the values are 0.0169 (Carbon), 0.0106 (Oil), and 0.0161 (Gas), and 0.002784 (Coal), which means that 75% of the returns are lower than these numbers and 25% are higher.

Interquartile range is the difference between the upper and lower quartile, and it gives a more accurate illustration of the spread of a random variable as it is not as affected by extreme observations and is used as a robust measure of the scale (Brooks, 2019, p. 53). The values displayed in table 1 suggests that there is a 0.0321 spread from the median for carbon returns, 0.0205 for oil returns, 0.035 for gas returns, and 0.005743 for coal returns. Carbon and gas returns have a bit higher spread than the oil returns, and coal returns have the lowest spread.

To further investigate the stationarity of the data, augmented Dickey-Fuller tests were conducted. The p-values for all the variables are equal to 0.01. The smaller the p-value, the stronger the evidence against H_0 ($H_0 =$ the data are non-stationary). Hence, we reject the null hypothesis and conclude that there is no significant evidence against stationarity in any of the variables.

Table 2: P-values from Ljung-Box Tests

Variable	**p-value**
Carbon	<2.2e-16
Oil	1.852e-05
Gas	0.003917
Coal	<2.2e-16

Further we estimated the autocorrelation functions for all the return variables with 35 lags. From the correlograms in appendix 9.1 it can be observed that for oil and gas returns, about 6% and 3% of the autocorrelation estimates lags lie outside the Bartlett band, and for carbon and coal returns, about 14% and 28% of the autocorrelation estimates lags lie outside the Bartlett band. To further investigate if there is any autocorrelation present in the variables, Ljung-Box tests were conducted. The p-values from these tests are reported in table 2, and it can be observed that all p-values are smaller than 0.05. Therefore, we reject the null hypothesis (H_0: there is no autocorrelation present in the variables) and accept the alternative hypothesis (H_1: there is autocorrelation present in the variables). This suggests that there is strong evidence of the presence of autocorrelation, and that the variables are not independent. To address the presence of autocorrelation we have made the data stationary and will apply robust estimates in the analysis which will be discussed in Chapter 5.

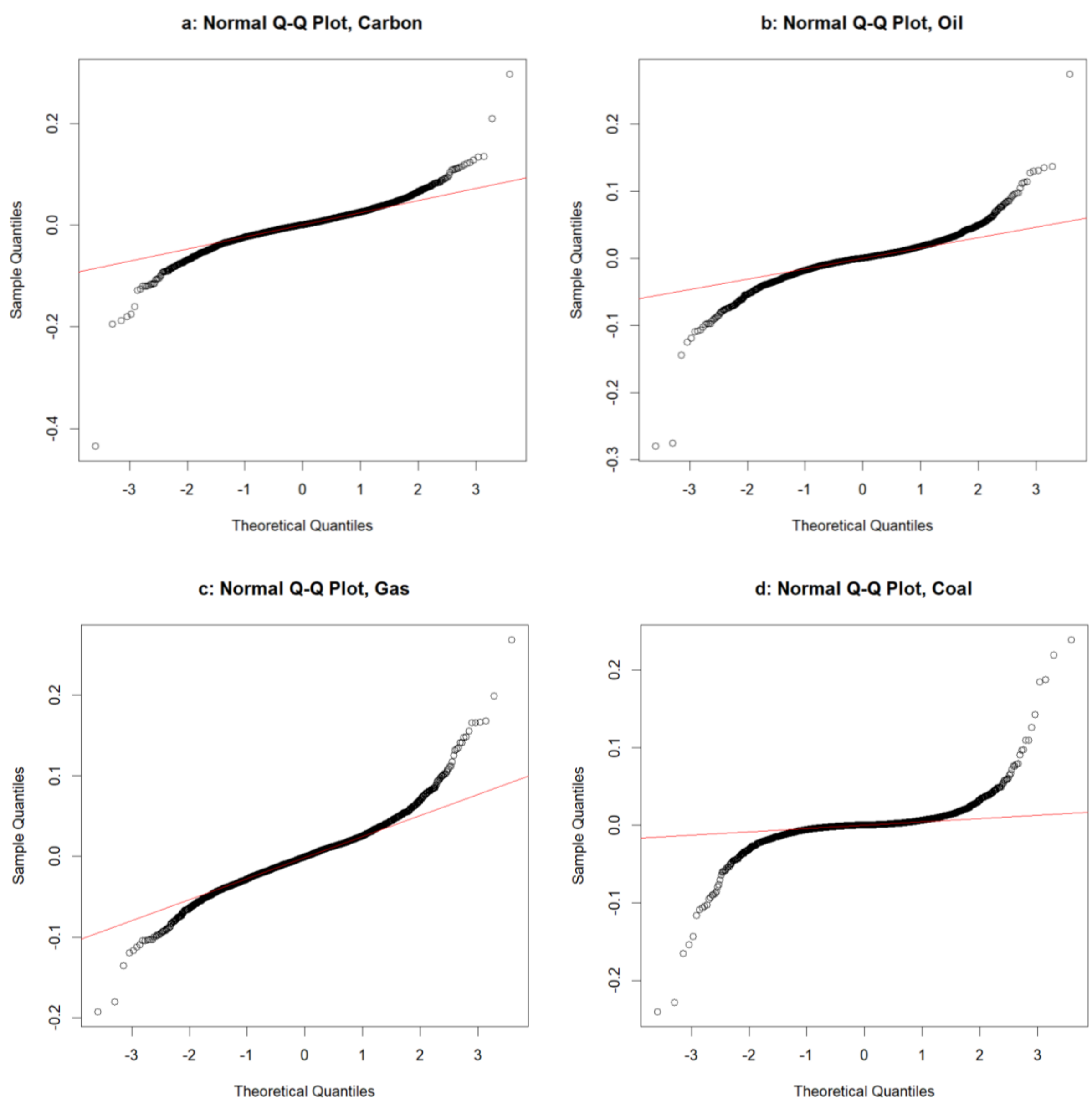


Figure 7: The normal Q-Q plots for carbon, oil, gas, and coal

Figure 7a, b, c, and d portray the normal quantile-quantile (Q-Q) plots of the return variables. It is clear from these plots that none of the variables are normally distributed as all the variables have heavy upper and lower tails, which corresponds to the high kurtosis values (see table 1) and indicates that there are more extreme observations compared to a normal distribution. Results from the Jarque-Bera tests for normality showed that for all variables, the p-value is lower than 2.2e-16. We can therefore conclude that the data are not normally distributed and reject the null hypothesis ($H_0: N \sim (\mu, \sigma^2)$) on a 0.05 significance level and accept the alternative hypothesis ($H_1: N \nsim (\mu, \sigma^2)$).

Table 3: Spearman's Correlation Matrix

	Carbon	**Oil**	**Gas**	**Coal**
Carbon	1	0.2088	0.0553	0.0055
Oil	0.2088	1	0.1362	0.0745
Gas	0.0553	0.1362	1	0.0366
Coal	0.0055	0.0745	0.0366	1

Since the variables in this thesis are not normally distributed, the Spearman's correlation coefficient is calculated to measure the strength and direction of the relationships between the variables. The results from the Spearman's correlation matrix are presented in table 3. For the returns of carbon and oil, the Spearman's rho equals 0.2088 which indicates that there is a positive but relatively weak correlation between the two variables. For carbon and gas returns, the correlation is estimated as 0.0553, and here there is a weak positive correlation. The correlation coefficient for carbon and coal returns is the lowest and is 0.0055, indicating a weak correlation and we found that it is statistically insignificant. Further we tested the correlation between the three different energy commodities. From table 3, we see that between all the independent variables there is a positive, but relatively weak correlation.

All variables have quite low correlation coefficients, which indicates that there is a tendency for the variables to move in the same direction, but the magnitude of the relationships is relatively weak. To further investigate the dependence between the variables and to get an understanding of the spread and density of the variables, we conducted copula.

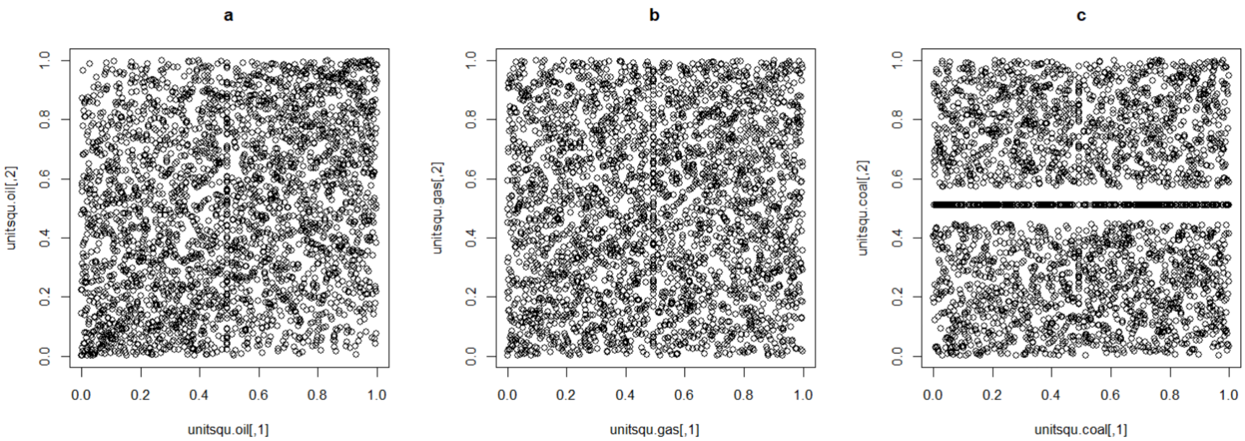


Figure 8: Pseudo returns for the dependent variable against the independent variables

Figure 8 displays the unit squares of the copula model of all three independent variables compared to the dependent variable. The plots portray the spread and density of the data for each of the variables and is a visual representation of the variables to better understand the skewness and fat tails. From figure 8a, it is visible that there is a large spread in the scatter, with some small clusters of points in the data. This is consistent with the theta value of 0.22 (see appendix 9.2), that indicates that the spread of the points is large. It is also visible that there is a gathering of points in the bottom left and upper right corner of the plot, which indicates that there is a weak tail dependence between the carbon and oil returns.

Figure 8b shows that there is a big spread in the scatter, with some small clusters of points in the data. In this plot there are some gathering of data points in the bottom left corner, which indicates that there is some tail dependence between carbon and gas returns. In both figures 8a and b, there is a weak vertical line visible in the middle of the plot. This line indicates that there is a weak vertical relationship between the two variables. In figure 8c, the strong line in the middle of the plot indicates that there is a strong horizontal relationship between carbon and coal.

In conclusion, the carbon returns are characterized by the presence of extreme observations, heavy tails, pronounced non-normality, and heterogeneity. This observation is central as it is associated with the construct that will serve as our dependent variable in the subsequent modelling effort. Now that the data is thoroughly examined and altered, we proceed to Chapter 5 where the statistical methodology is presented.

5. Methodology

This chapter presents the statistical methodology applied to investigate the relationship between the carbon market and fossil energy. Further, we present the estimation of the model, motivation, and lastly how to carry out the analysis in the programming software R.

5.1 Quantile

A quantile, denoted as τ, refer to a position in an ordered series where an observation lies for y in the interval of $[0,1]$. A quantile is synonymous with percentile, and it carries the information of a percentage, e.g., 0.5 is 50%, also known as the median (Yu et al., 2003). Brooks (2019) defines the τ-*th* quantile $Q(\tau)$ of a random variable Y having cumulative distribution $F(y)$ as:

$$Q(\tau) = inf\ y : F(y) \geq \tau \tag{5.1}$$

where Q is a specific level of Y of which we can state that all y will be lower than that specific level. In equation 5.1 the term inf refers to the infimum, also known as the greatest lower bound, which is the smallest value of y satisfying the inequality (Brooks, 2019, p. 170).

In the figure below, the cumulative distribution function illustrates a quantile.

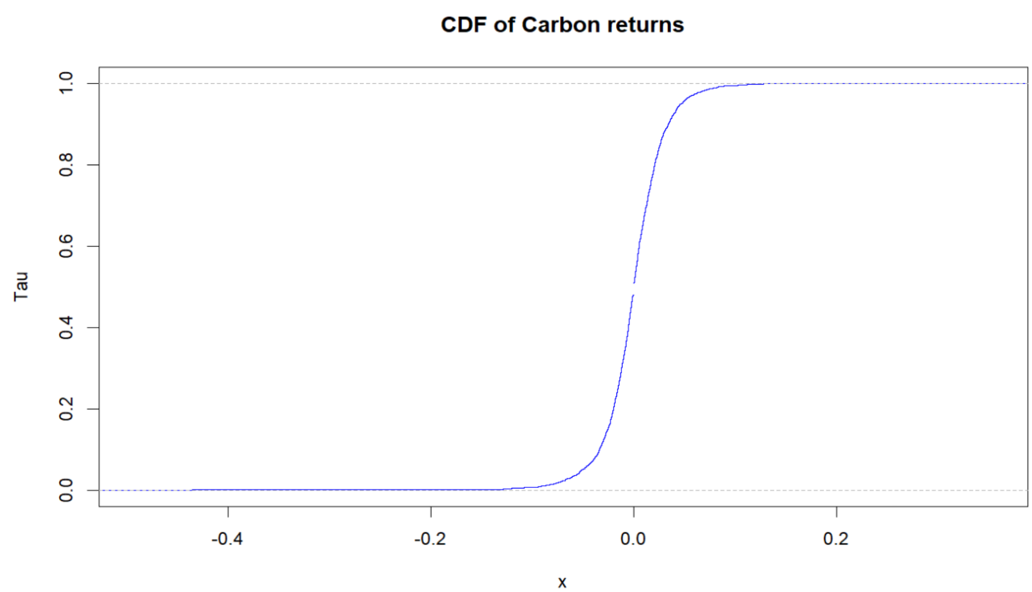


Figure 9: Cumulative distribution function of carbon returns

If we have a distribution function $F(Y)$ of carbon returns, we can calculate a quantile by inverting the function. A value between 0 and 1 is chosen because that is the range of the distribution function. We fix a percentile value (80%) at the vertical axis, from here we invert down to the domain and find the observation; this is the quantile. We find that $C = 0.02$, and in 80% of all cases, the return on the carbon futures will be less than or equal to $q_{0.8} = 0.02$.

A quantile can be defined through an optimization problem, and it is the median which is defined as the solution to the problem of minimizing the sum of absolute residuals. The sample median is used as an estimate of the population median *m*, a number that divides the ranked distribution into two halves in the sense that if a random variable Y can be measured on the population, then $P(Y \leq m) = P(Y \geq m) = \frac{1}{2}$. For a continuous random variable, m is a solution to the equation $F(m) = \frac{1}{2}$, where $F(y) = P(Y \leq y)$ is the cumulative distribution function (Yu et al., 2003).

Because of the symmetry of the piecewise linear absolute value function, minimizing the sum of absolute residuals must equate the number of positive and negative residuals, ensuring that there are the same number of observations above and below the median. Since the median is yielded by the symmetry of the absolute value, having asymmetrical weighted residuals will yield the quantiles (Koenker & Hallock, 2001). This is solved:

$$\min_{\xi \in \Re} \sum \rho_\tau(y_i - \xi), \tag{5.2}$$

where $\rho_\tau(\cdot)$ is the tilted absolute value function that yields the *τ-th* sample quantile. Further, it is now possible to define the conditional quantiles in an analogous fashion. To obtain an estimate of the conditional median function:

$$\min_{\xi \in \Re} \sum \rho_{\tau=\frac{1}{2}}\big(y_i - \xi(x_i, \beta)\big). \tag{5.3}$$

By replacing $\rho_\tau(\cdot)$ for the absolute values, we can solve this equation:

$$\min_{\xi \in \Re p} \sum \rho_\tau\big(y_i - \xi(x_i, \beta)\big) \tag{5.4}$$

for the other conditional quantile functions to obtain the estimates (Koenker & Hallock, 2001). Below, we will discuss multiple linear regression and its drawbacks. Further, in Section 5.3, we argue as to how the concept of quantiles can be used to overcome various drawbacks of the multiple linear regression model.

5.2 Multiple Linear Regression

Regression is a technique which is used for determining the cause-effect relations between a dependent variable and several independent variables. For decades, linear regression has been one of the most essential statistical tools for applied research (Yu et al., 2003). The multiple linear regression model is defined as:

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p + \varepsilon, \tag{5.5}$$

where y is the dependent variable, β_i are the parameters, x_i are the independent variables, and ε is the error term (Uyanık & Güler, 2013). The most common method to estimate the unknown parameters in the multiple linear regression model is the ordinary least squares method (OLS). The OLS estimation consists of squaring each vertical distance from the points, which are observations on the dependent variable, to the regression line, and then minimizing the sum of the areas of squares, thus, "least squares" (Brooks, 2019, p. 98). The solution of this minimization problem is given by:

$$\hat{\beta} = (X'X)^{-1}X'Y. \tag{5.6}$$

If the assumptions underlying the classical linear model – to be discussed in the subsequent section – are fulfilled, then the OLS estimator $\hat{\beta}$ given in (5.6) is the best linear unbiased estimator (BLUE). However, these assumptions often do not hold, and the BLUE property is lost. This calls for a discussion of the weaknesses and drawbacks of the multiple linear regression model and considering other possibilities.

5.2.1 Drawbacks of the Multiple Linear Regression Model

There are several weaknesses and drawbacks concerning multiple linear regression that may have an impact on the results. Multiple linear regression tends to oversimplify a variety of real-world issues. One of the assumptions of multiple linear regression is that the observations on the dependent variable must follow a normal distribution, and the assertion that real life financial data can hardly be adequately modelled by a Gaussian distribution is clearly substantiated in Chapter 4. In the presence of heavy tails and extreme observations, it is difficult to obtain accurate results relying on standard OLS estimation in the linear model (Yu et al., 2003) (Brooks, 2019, pp. 106-107).

Multiple linear regression model will often only give a partial picture of the relationship between the variables (Yu et al., 2003), as in this method it is the conditional mean that is used to calculate the average relationship between the response variable and the covariates (Nusair & Olson, 2019). When using the conditional mean, heavy tails and outliers will not be displayed and it is not possible to give an accurate picture of the results. Another assumption of the multiple linear regression model is that the observations of the dependent variable must be independent (Uyanık & Güler, 2013). If this is violated it can lead to biased estimation of the regression coefficients and inaccurate predictions. Lastly, one of the assumptions of multiple linear regression is that there is no homoscedasticity exhibited in the residuals. Homoscedasticity refers to the condition where the variability of the residual is consistent or constant across different values of the independent variable. In other words, the spread of the residual should not systematically change as the values of the independent variable change. To overcome these drawbacks, we present a new modelling approach, quantile regression, developed by Koenker and Bassett (1978).

5.3 Quantile Regression

Quantile regression (QR) models the relationship between the quantiles of the dependent variable y, and a set of independent variables x_i:

$$Q_\tau(y_i) = \beta_0(\tau) + \beta_1(\tau)x_{i1} + \cdots + \beta_p(\tau)x_{ip} \quad i = 1, \dots, n \tag{5.7}$$

where $0 \leq \tau \leq 1$ represents the percentage of the population with a score lower than the quantile at τ. The j-th regressor's coefficient $\beta_j(\tau)$ is dependent on the quantile τ.

In QR it is the conditional median that is estimated, compared to multiple linear regression where it is the conditional mean that is estimated. The median is provided by minimizing the sum of the absolute values of the residuals. The absolute value function is by definition symmetrical. We can calculate the quantiles of the distribution if the absolute residuals are weighted differently, depending on whether they are positive or negative. This is a minimization problem which Brooks (2019) defines as

$$\hat{\beta}_\tau = argmin_\beta \left(\sum_{i:y_i > \beta x_i} \tau |y_i - \beta x_i| + \sum_{i:y_i < \beta x_i} (1-\tau)|y_i - \beta x_i| \right) \tag{5.8}$$

for a set of QR parameters $\hat{\beta}_{\tau}$, each element of which is a $k \ x \ 1$ vector. In equation (5.8), the weight on positive observations is set to τ, the quantile of interest, and the negative observations to $1 - \tau$ to estimate the τ-*th* quantile. For all other quantiles, except the median, the weights are asymmetric which is shown in this equation (Brooks, 2019, p. 170).

QR represents a more thorough way to analyze the relationship between a set of variables than multiple linear regression (Brooks, 2019, p. 169), because QR is much more robust to extreme observations, non-normal errors, skewness, and heterogeneity in the dependent variable compared to multiple linear regression (Nusair & Olson, 2019). QR is much more robust because it is a non-parametric technique as it does not require any distributional assumptions, i.e., normality, homoscedasticity, linearity, and independence, to estimate the parameters (Brooks, 2019, p. 169). One advantage of applying the QR analysis is that it provides a much more complete picture of dependency, including asymmetric and nonlinear connections between independent variable(s), which explains the relationship at several locations in the conditional distribution of the dependent variable (Nusair & Olson, 2019).

One would apply QR in a situation where it is likely that there is a non-linear relationship between the variables. Implementing a multiple linear regression model in a situation like this could potentially lead to deceiving estimates of the relationship between the variables because of the discussed limitations of multiple linear regression (Brooks, 2019, p. 169).

QR extends the notion of quantiles by essentially modeling the full conditional distribution of y given the explanatory factors, allowing them to study not just the location and scale of the distribution of y, but also the shape of the distribution (Brooks, 2019, p. 169). One significant challenge in QR is quantile crossing. This occurs when the predicted value for a quantile at a higher level is less than the predicted value for a quantile at a lower level. Quantile crossing is inconsistent with the definition of quantiles, and to avoid the occurrence of this phenomenon one must estimate multiple quantiles simultaneously (Das et al., 2019).

There are many various statistical methods for analyzing data. Choosing QR was an obvious choice given the financial data at hand. As demonstrated in Chapter 4, the daily returns clearly violate some of the key assumptions underlying the classical linear model. Below we will discuss the estimation method bootstrapping, and the implementation of the analyses in the programming software R.

5.4 Bootstrapping

One approach to obtaining QR estimates is bootstrapping. Bootstrapping is a commonly used method in applied statistics because it may provide estimates that would otherwise be challenging to obtain. It consists of repeated estimating, called subsampling, to characterize the distribution function (Wehrens et al., 2000). The bootstrap can greatly simplify the construction of confidence intervals based on the QR estimator, and it is a method which provides robust estimates. The bootstrap distribution converges weakly to the appropriate limit distribution in probability for both deterministic and random regressor cases. This implies that the method provides confidence intervals with the correct asymptotic coverage probabilities (Hahn, 1995).

5.5 Implementation in R

In this thesis, the programming software R is applied to carry out the statistical analyses. To implement QR in R, we used the package *quantreg* (Koenker, 2019). For our dataset of $n = 2991$ observations and $p = 4$ coefficients, where we include one dependent variable and three independent variables, we applied the *rq* function to perform the QR analyses. By specifying the parameter τ, R will tell the *rq* function which conditional quantile we want. If τ is set to be a vector, then the function will give the fits for all the quantiles. For τ, the default value is 0.5 which corresponds to median regression. When printing a fitted object to the console it provides some basic information on the regression fit, including the estimated coefficient value for the intercept and the independent variables. In order to obtain more information, we use the *summary* function. The primary objective of the *summary* function is to generate inferential data to support parameter point estimations (Koenker, 2019).

The results table from the *summary* function gives the estimated coefficient value, standard error, t-value, and p-value for the intercept in the first row and the same for the independent variables in the following rows. Further, one can compute the estimated values with bootstrapping, using *summary* and specifying the option *se=boot*. By specifying this, R performs subsampling of the original data with replacement, estimating a new QR model for each bootstrap sample. Bootstrapping in QR calculates the variance of the uncertain coefficient estimates (Koenker, 2019).

Further, one can calculate confidence intervals. There are several ways these confidence intervals can be computed in R. By default, the confidence interval is computed by the rank inversion method by Koenker. Another way of calculating the confidence interval is through bootstrapping as discussed above. In our analysis we will use the last method to calculate the confidence intervals. Further, in Chapter 6, we will visualize and interpret results from the analyses by using construct plots including QR lines to see each of the chosen quantile levels, and tables with quantitative results.

6. Empirical Results

In this chapter we present the empirical results from our analyses. First, we present results of OLS analyses, then we continue with results from the QR analyses for the dependent variable, carbon returns, conducted separately against the independent variables, oil, gas, and coal returns. Further, we give the results from the QR analysis for all three independent variables together against the dependent variable. Lastly, we present results from QR with bootstrapping, and both standard and bootstrapped confidence intervals.

6.1 Results from Multiple Linear Regression

Table 4: Results from OLS

	Variable	**Estimate**	**Std. Error**	**t-value**	**p-value**
	Oil	0.27569	0.02276	12.116	<2e-16
	Gas	0.05375	0.01821	2.952	0.00319
Separate	**Coal**	0.07300	0.03283	2.220	0.02630
	Oil	0.26913	0.02310	11.65	<2e-16
All variables	**Gas**	0.02180	0.01801	1.211	0.22600
tested together	**Coal**	0.03749	0.03221	1.164	0.24500

In table 4, we present results from OLS analyses. These analyses are included to compare the results with the results from the 0.50 quantile level, which are given in Section 6.2. The OLS estimates indicate that when conducting individual linear regression for each independent variable, we found that there is a statistically significant relationship between carbon returns and oil, gas, and coal returns. The significance is demonstrated by all p-values being smaller than 0.05. When conducting multiple linear regression including all variables, we found that only oil returns have a statistically significant relationship, given the returns on gas and coal in the model are fixed, as the p-value for gas and coal are higher than 0.05. We also found that the estimated coefficient value for oil returns is relatively high, compared to the other variables, suggesting that there is strong evidence of a statistically significant relationship between carbon and oil returns.

Comparing the OLS results from the individual analysis with the 0.50 quantile for oil returns, it is visible in table 5 that the estimated coefficient value is relatively similar in both OLS and the QR analysis. The p-value from OLS and the 0.50 quantile level are both smaller than 0.05 which suggests that with both these analyses, there is a statistically significant relationship between carbon and oil returns at this level. Further, comparing the OLS results from the separate analysis for gas returns to the 0.50 quantile level (see table 6), we see that the OLS estimated coefficient value is relatively similar to the QR estimated coefficient value. For the OLS estimate, the relationship between carbon and gas returns is statistically significant, similarly to QR. Analyzing the results retrieved from the OLS analysis from the separate analysis of coal returns, there is a statistically significant positive relationship between carbon and coal returns at the mean. When comparing these results with the QR median, we find that they have quite similar results, with a slightly higher standard error and p-value (see table 7).

6.2 Results from Quantile Regression

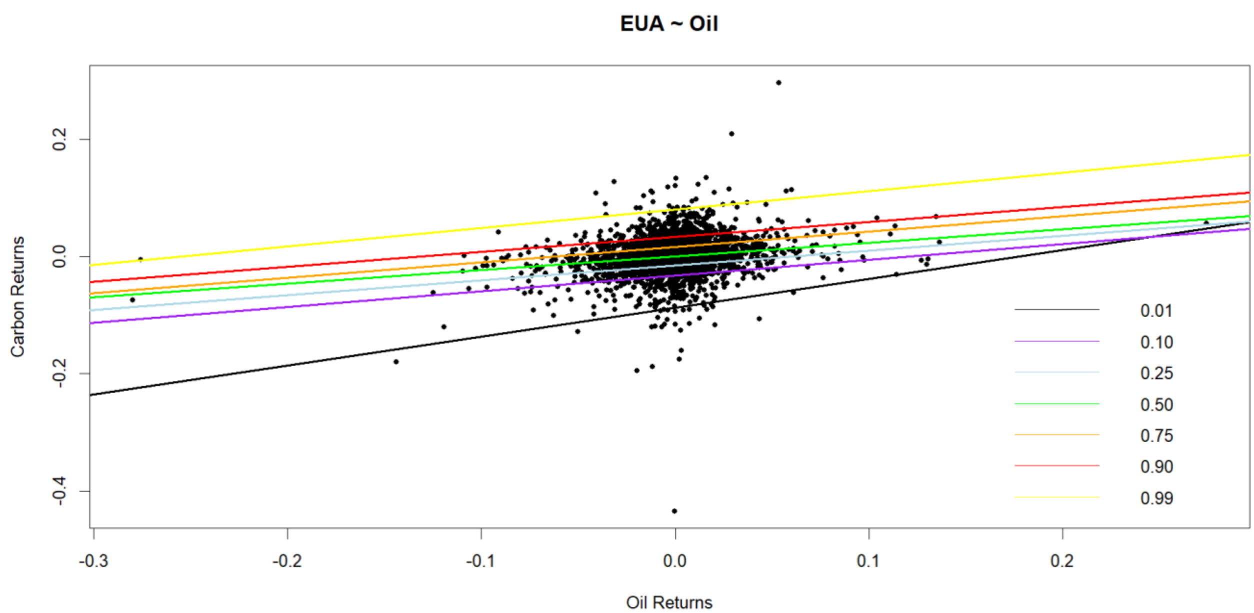


Figure 10: Quantile regression (Carbon; Oil)

Table 5: Results from Quantile Regression (Carbon; Oil)

Quantile, τ	Value	Std. Error	t-value	p-value
0.01	0.49248	0.21193	2.32382	0.02020
0.10	0.26942	0.03929	6.85800	0.00000
0.25	0.25296	0.02469	10.24513	0.00000
0.50	0.23122	0.01023	22.61056	0.00000
0.75	0.26226	0.02515	10.42728	0.00000
0.90	0.25577	0.04092	6.25066	0.00000
0.99	0.31380	0.18454	1.70048	0.08914

Figure 10 and table 5 present the results from the QR analysis with carbon returns against oil returns. In figure 10, we present the QR lines that predict the 0.01, 0.1, 0.25, 0.50, 0.75, 0.90 and 0.99 quantile levels of carbon returns in relation to oil returns. It is visible from the figure that the 0.1, 0.25, 0.5, 0.75, and 0.90 quantile lines have a relatively similar pattern, with the median QR line being slightly less positively tilted than the others. When looking at the 0.01 and 0.99 QR line there is a change in the relationship between the variables, as these lines are more tilted in a positive direction than the other quantile lines. This is consistent with the estimated coefficient values in the table, as these values are higher than the others. All estimated coefficient values in table 5 are positive, which is consistent with the QR lines in figure 10 and indicates that there is a positive direction of the relationship between carbon and oil returns. Examining the factor tilts, moving from the 0.01 to the 0.99 quantile level, we can see that the estimated coefficient value of oil returns monotonically fall from 0.49 to 0.31. This indicates that the impact of the oil returns has on carbon returns, diminishes from the lower to the higher quantile level.

It can also be observed from table 5 that all the p-values are lower than 0.05, except at the 0.99 quantile. This indicates that there is a statistically significant relationship at all the selected quantile levels throughout the distribution, except at the 0.99 quantile. From table 4, one can also see that the insignificant relationship at the 0.99 quantile level is not detected by the OLS analysis. At quantile level 0.01, there is strong evidence for a significant relationship between carbon and oil returns as the estimated coefficient value is relatively high at this level. The highest estimated coefficient value is 0.49248 and is found at the 0.01 quantile, and based on the p-value, we draw the conclusion that there is strong evidence for a statistically significant relationship between carbon and oil returns under extreme downward market condition, e.g., market crisis.

Table 6: Results from Quantile Regression (Carbon; Gas)

Quantile, τ	**Value**	**Std Error**	**t-value**	**p-value**
0.01	0.22406	0.09510	2.35616	0.01853
0.10	0.06801	0.03204	2.12288	0.03385
0.25	0.04553	0.01927	2.36250	0.01822
0.50	0.03574	0.01406	2.54111	0.01110
0.75	0.02200	0.01528	1.44032	0.14988
0.90	0.02954	0.03709	0.79645	0.42584
0.99	0.03297	0.03983	0.82771	0.40790

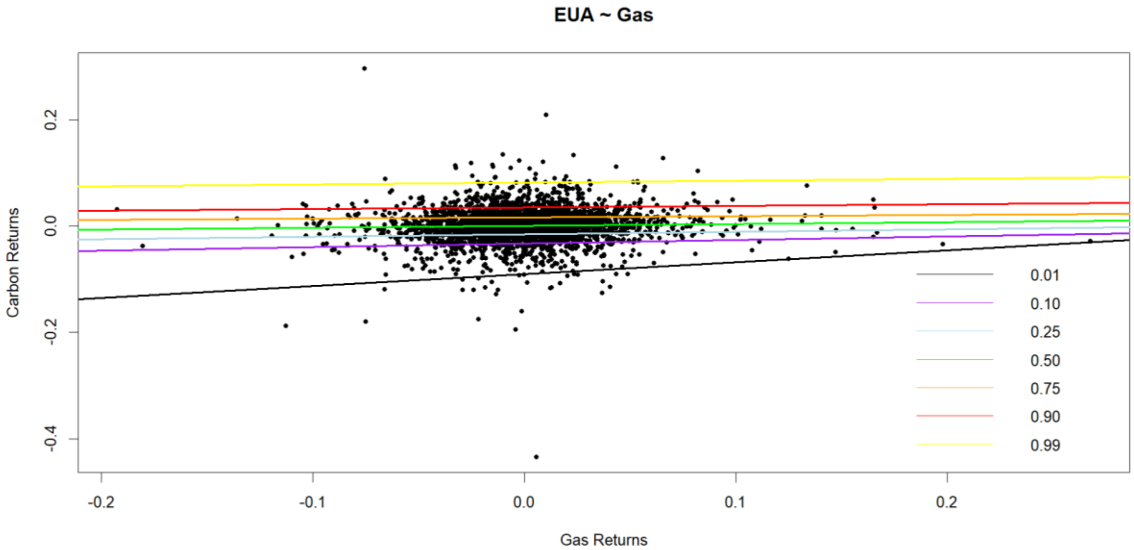


Figure 11: Quantile regression (Carbon; Gas)

In figure 11 and table 6, results from the QR analysis with carbon and gas returns is presented. Portrayed in the figure are the QR lines that predict the 0.01, 0.1, 0.25, 0.50, 0.75, 0.90 and 0.99 quantiles of carbon returns in relation to gas returns. In table 6, all estimated coefficient values are positive, which indicates that there is a positive direction in the relationship between these two variables. This is consistent with the results in figure 11, where all the QR lines are tilted in a positive direction. This indicates that a marginal change in the returns of gas will change the expected returns on the carbon returns in a positive direction. When examining how the QR lines tilts, moving from the 0.01 to the 0.99 quantile level, we can see that the estimated coefficient values of gas returns monotonically fall from 0.22 to 0.03. Which indicates that the impact of gas returns on carbon returns diminishes from the lower to the higher quantile level.

When looking at the 0.01 and 0.99 QR lines, a change in the pattern is visible compared to the remaining quantile lines. The remaining lines are following a relatively similar pattern, except the 0.90 QR line that has a bigger distance to the other lines. This distance indicates that the values inside the 0.90 QR line have a bigger spread compared to the values in the other quantile lines. The 0.99 QR line does not show a significant increase or decrease, but similarly to the 0.90 QR line, it has a bigger distance to the other quantile lines indicating a bigger spread. The 0.01 QR line reveals a different result as this line is relatively more tilted.

In table 6, the p-value at the 0.01 quantile level is significant. The estimated coefficient value is relatively high, compared to the other coefficient values, suggesting that there is strong evidence of a statistically significant relationship between carbon and gas returns. The standard errors indicate that the precision of the estimated coefficient value is reliable, as it is relatively small for all quantile levels. For the 0.01, 0.10, 0.25 and 0.50 quantiles, the p-values are smaller than 0.05 which means that there is a statistically significant relationship between carbon and gas returns at these quantile levels.

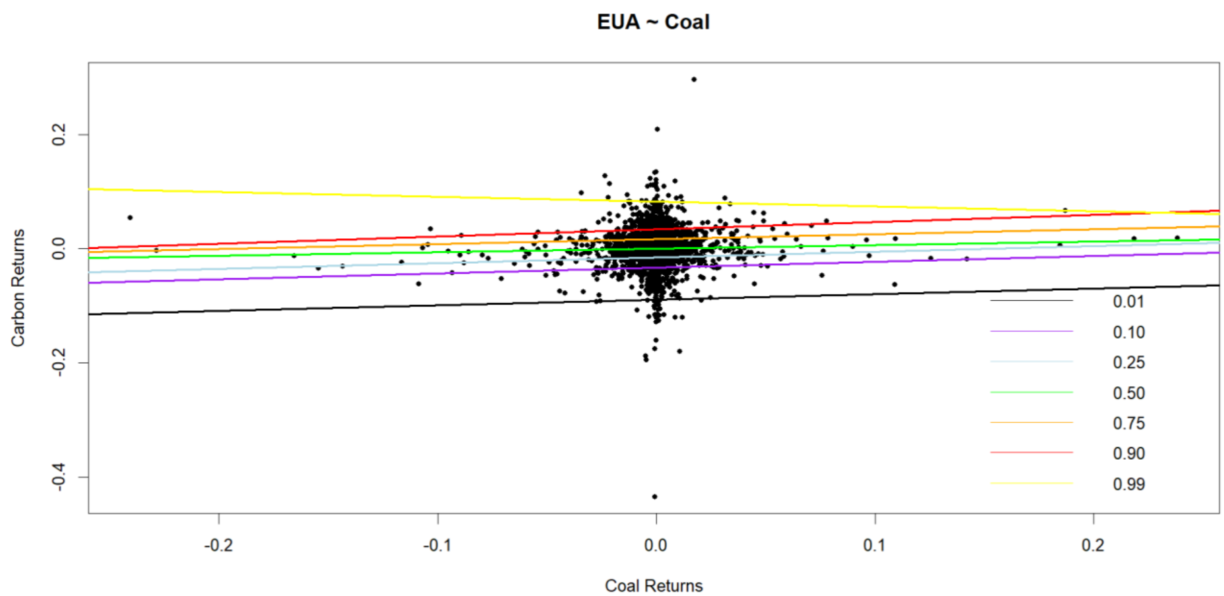


Figure 12: Quantile regression (Carbon; Coal)

Table 7: Results from Quantile Regression (Carbon; Coal)

Quantile, τ	Value	Std Error	t-value	p-value
0.01	0.09762	0.36792	0.26534	0.79076
0.10	0.10148	0.03325	3.05226	0.00229
0.25	0.09807	0.03449	2.84356	0.00449
0.50	0.06226	0.02642	2.35683	0.01850
0.75	0.08520	0.03587	2.37512	0.01761
0.90	0.12665	0.04739	2.67226	0.00758
0.99	-0.08355	0.09140	-0.91416	0.36071

Figure 12 visualizes the QR lines that predict the 0.01, 0.1, 0.25, 0.50, 0.75, 0.90 and 0.99 quantiles of coal returns in relation to carbon returns. In table 7, the results for the QR analysis are reported and one can observe for coal returns that all the estimated coefficient values are positive for each of the quantile levels, except for the 0.99 level. This is consistent with the plot in figure 12, where all the QR lines are pointed in a positive direction, except the 0.99 QR line which is tilting in a negative direction. When examining how the QR lines tilts, moving from the 0.01 to the 0.99

quantile level, we can see that the estimated coefficient values of coal returns monotonically fall from 0.097 to -0.08. Which indicates that the impact of coal returns on carbon returns decreases from the lower to the higher quantile levels. Given that the standard error is relatively low for all quantile levels (see table 7), it can be concluded that with the estimated coefficient values there is less variability in the estimates.

The p-values for the 0.99 and the 0.01 quantiles are higher than 0.05 which suggests that there is no statistically significant relationship between the variables at these quantile levels. For the remaining quantile levels tested, there is a statistically significant relationship between carbon and coal returns. Indicating that a marginal change in the returns of coal will change the expected returns on carbon returns in the same direction.

Table 8: Results from Quantile Regression (Carbon; Oil, Gas, Coal)

	Oil		**Gas**		**Coal**	
Quantile, τ	**Value**	**p-value**	**Value**	**p-value**	**Value**	**p-value**
0.01	0.36137	0.01151	0.09722	0.14760	-0.07272	0.79347
0.10	0.24706	0.00000	0.03540	0.22759	0.05119	0.04777
0.25	0.24769	0.00000	0.03229	0.07300	0.06805	0.04721
0.50	0.21690	0.00000	0.01375	0.36084	0.03189	0.11562
0.75	0.26891	0.00000	0.00673	0.74839	0.05541	0.08052
0.90	0.24905	0.00000	0.03012	0.35508	0.04893	0.22069
0.99	0.33678	0.06382	0.13222	0.31916	-0.09644	0.75125

Table 8 presents the result from the QR analysis investigating the relationship between carbon returns against oil, gas, and coal returns. In this table we observe that for oil returns, all p-values from the QR analysis are lower than 0.05, except at the 0.99 quantile level, which is consistent with table 5. This indicates that the relationship between carbon and oil returns is statistically significant at all quantiles except at the 0.99 quantile level. This relationship is not detected by the OLS analysis, as it portrays a significant relationship throughout the distribution. At the 0.01 quantile level, we found that the estimated coefficient value for oil returns is 0.36. This indicates that when there is a one percent change in oil returns, it will change the expected return on carbon returns with 0.36% in the same direction, given the returns on gas and coal in the model are fixed. This aligns to all quantile levels that have a statistically significant relationship.

For gas returns, the p-values from table 8 suggest that there is no statistically significant relationship between the variables at any of the quantile levels as all p-values are higher than 0.05. This is similar with the results from the OLS analysis where all variables were included, as the p-value from that analysis also was higher than 0.05 (see table 4). This indicates that the relationship between carbon and gas returns is not statistically significant controlling for the respective remaining variables.

Further, table 8 show that for coal returns, all p-values are higher than 0.05 at all quantile levels, except the 0.10 and 0.25 levels, where the p-values are just below 0.05, at 0.04777 and 0.04721. This indicates that at these quantile levels, the relationship between carbon and coal returns is statistically significant. The relatively similar p-values at these levels indicate that the statistical significance with carbon returns is quite consistent throughout these specific quantile levels, and when there is a one percent change in coal returns at these quantile levels, it will change the expected return on carbon returns with 0.0477% and 0.0472% in the same direction, given the returns on gas and oil in the model are fixed. These significant relationships were not detected by the OLS analysis.

6.3 Results from Quantile Regression with Bootstrapping

Table 9: Results from Quantile Regression with Bootstrapping ($\tau = 0.50$)

	Variable	Value	Std. Error	t-value	p-value
	Oil	0.23122	0.02262	10.21970	0.00000
	Gas	0.03574	0.02281	1.56650	0.11734
Separate	**Coal**	0.06226	0.02390	2.60522	0.00923
	Oil	0.21690	0.02305	9.40936	0.00000
All variables	**Gas**	0.01375	0.01680	0.81847	0.41315
tested together	**Coal**	0.03189	0.03800	0.83904	0.40151

Table 10: Results from Quantile Regression with Bootstrapping ($\tau = 0.01$)

	Variable	Value	Std. Error	t-value	p-value
	Oil	0.49248	0.13799	3.56896	0.00036
	Gas	0.22406	0.10861	2.06292	0.03921
Separate	**Coal**	0.09762	0.19052	0.51239	0.60841
	Oil	0.36137	0.12960	2.78825	0.00533
All variables	**Gas**	0.09722	0.14981	0.64895	0.51642
tested together	**Coal**	-0.07272	0.18784	-0.38713	0.69869

Table 11: Results from Quantile Regression with Bootstrapping (τ = 0.99)

	Variable	Value	Std. Error	t-value	p-value
	Oil	0.31380	0.13319	2.35607	0.01853
	Gas	0.03297	0.15229	0.21648	0.82863
Separate	**Coal**	-0.08355	0.15974	-0.52306	0.60097
	Oil	0.33678	0.12828	2.62540	0.00870
All variables	**Gas**	0.13222	0.12674	1.04319	0.29694
tested together	**Coal**	-0.09644	0.11373	-0.84794	0.39654

Table 9, 10, and 11 presents the results from QR analyses conducted with bootstrapping at three different quantile levels: τ = 0.01, τ = 0.50, and τ = 0.99. First, we conducted individual QR with bootstrapping for each independent variable. The analyses of the 0.50 quantile level in table 9 show that the estimated coefficient values are all positive. The p-values reveal that for both oil and coal returns, there is a statistically significant relationship with carbon returns at the 0.50 quantile level, similarly to the QR analyses without bootstrapping (see table 5 and 7). Further, as the estimated coefficient value for oil returns is quite high, we can conclude that there is strong evidence for a statistically significant relationship.

For gas returns, we found that the p-value is higher in QR with bootstrapping at the 0.50 quantile level than QR without bootstrapping and conclude that the relationship between carbon and gas returns is statistically insignificant. From table 9, one can see that the standard errors are higher for the independent variables' returns when performing QR with bootstrapping, than without (see table 5, 6, and 7). This indicates that there is higher variability around the mean, and more uncertainty in the estimates with bootstrapping than without.

When conducting the QR analysis including all independent variables with bootstrapping at the 0.50 quantile level, we see from table 9 that the relationship between carbon returns and gas and coal returns is statistically insignificant. The p-value for oil returns is 0 which is similar to the previous analysis when conducting the QR analysis with all variables separately and without bootstrapping. As the estimated coefficient value is relatively high, we can say that there is strong evidence for a statistically significant relationship between carbon and oil returns.

When conducting the QR analyses with bootstrapping regarding the 0.01 and 0.99 quantile levels, we find relatively similar results for all variables, except that the p-value for oil returns is now lower than 0.05 at the 0.99 quantile level (see table 10 and 11). This indicates that there is a statistically significant relationship between carbon and oil returns at this quantile level, and as the estimated coefficient value is relatively high, it gives strong evidence for a significant relationship.

6.4 Confidence Intervals

Table 12: Confidence Intervals from OLS and Bootstrap Estimation

	Variable	OLS		Bootstrapped	
		0.05	**0.95**	**0.05**	**0.95**
	Oil	0.2383	0.3132	0.1966	0.2632
	Gas	0.0238	0.0837	0.0000	0.0764
Separate	**Coal**	0.0190	0.1270	0.0251	0.1040
	Oil	0.2311	0.3071	0.1894	0.2598
All variables	**Gas**	- 0.0255	0.0514	- 0.0222	0.0386
tested together	**Coal**	- 0.0155	0.0905	- 0.0334	0.0899

The confidence intervals for all variables are given in table 12. In this table we present standard confidence intervals and bootstrap constructed confidence intervals. We first computed confidence intervals with the independent variables separately. Then we constructed intervals including all three independent variables. We conducted 95% confidence intervals, meaning that with probability 0.95, this interval contains the true but unknown parameter value. The 95% confidence interval indicates that 95 times out of a 100 we will get the same slope of the population value.

First looking at the individually calculated confidence intervals we found that for oil returns, the 95% standard confidence interval equals [0.2383, 0.3132], and the bootstrapped confidence interval equals [0.1966, 0.2632]. It can be noticed that for oil returns, the estimated coefficient values lie within the standard confidence interval (see table 4). For the bootstrapped confidence interval for oil returns, one can see that the coefficient values from table 9, 10, and 11 does not lie within the interval. We found that the 95% standard confidence interval for the parameter gas returns equals [0.0238, 0.0837], and for the bootstrap estimation, the 95% confidence interval for gas returns equals [0, 0.0764]. The estimated coefficient values are in this case found within the standard intervals, as for the bootstrap, the coefficient value at the 0.01 quantile level does not lie within the confidence interval (see table 10). Further, for the confidence intervals for coal returns we found that for OLS, the 95% confidence interval equals [0.019, 0.127]. The bootstrapped confidence interval equals [0.025, 0.104]. Also here, the estimated coefficient values lie within the standard confidence intervals. The bootstrapped confidence interval reveals that the estimated coefficient value at the 0.99 quantile level does not lie within the interval (see table 11).

For the standard confidence interval including all variables one can see from table 4, that the estimated coefficient values for oil, gas, and coal returns lie inside the interval. From the confidence intervals computed from the bootstrap including all variables, the estimated coefficient values at the 0.01 and 0.99 quantile levels does not lie within the interval (see table 9, 10, and 11).

7. Discussion

This chapter focuses on the interpretation and discussion of the empirical results presented in Chapter 6. To start, we will discuss our findings and results from the QR analyses, then we will compare these results to findings from existing studies on the topic. Further, we will discuss any limitations and implications to our thesis.

By examining the analyses with each of the independent variables against the dependent variable separately, the results from the QR analyses indicates that there is a relationship between carbon and oil returns at all quantile levels except for the 0.99 percentile. This indicates that oil returns are the most strongly related to carbon returns, as throughout the distribution, oil returns is the independent variable which has a statistically significant relationship with carbon returns at most of the quantile levels. For gas returns, we found a relationship with carbon returns at the lower quantiles including the 0.50 quantile level. Further, our findings suggest that for coal returns there is a significant relationship at all quantile levels except 0.01 and 0.99. When conducting the same analyses with bootstrapping we get fairly similar results, except at some quantile levels. From this analysis, we found a significant relationship between carbon and oil returns also at the 0.99 quantile level. For gas returns we found that the relationship is insignificant at the 0.50 quantile level. As for coal returns, results were the same as without bootstrapping.

First looking at the relationship between carbon and oil returns, we find that there are several potential reasons for why carbon returns are affected by oil returns at all quantile levels excluding the 0.99 level. One possible reason could be due to the relative importance of oil in the energy mix, or the availability of alternative fuels, and that the price of EUAs may be more influenced by industries and companies that are very energy intensive and are big polluters, which is mainly those that heavily rely on oil. As Brent Crude Oil is often refined as diesel or gasoline (Eia, 2023), the transportation and aviation sectors are more dependent on oil than for example Natural Gas or coal, which could make the price of emissions allowances more sensitive to the price of oil.

Industries like these can be heavily impacted by extreme market conditions, e.g., supply disruptions, shifts in demand due to macroeconomic factors, and geopolitical conflicts. This could possibly explain the significant relationship between the returns of carbon and the returns of oil. As mentioned in Chapter 6, the relationship between carbon and oil returns is strongest at the 0.01 quantile level. This might be because when the market is in recession, e.g., in a pandemic, there will for instance be less air traffic, which can decrease the demand for oil. This can potentially have an effect on the EUA prices, as industries will pollute less, and need less permits for emissions. As for the 0.99 quantile, the market is in an upswing, which means that industries may be less affected by increased oil prices or EUA prices, which might be the reason for the insignificant relationship at this level.

Further in our results we found that carbon returns are affected by gas returns in the lower part of the distribution. The relationship between carbon and gas returns at these quantile levels could potentially be impacted by several factors. Firstly, Natural Gas is a cheaper alternative in the energy mix (see figure 2), and it may substitute more expensive alternative fuels in times of a market recession. Increased demand for Natural Gas can increase the demand for EUAs and affect their prices. Another potential reason might be that in economic recession, energy consumption will be reduced in various sectors. Natural Gas is mostly used for heating and generation of electricity (European Commission, 2022), and it can potentially affect the price of EUAs, as use of electricity will decrease in times of economic recession.

A potential reason for why the relationship between carbon and gas returns is not significant at the upper quantiles might be because the energy mix often includes a variety of sources, i.e., Natural Gas, coal, renewable energy, and others. Despite the fact that Natural Gas may be an important component in the energy mix, changes in its prices may not have a substantial impact on the demand for EUAs. The direct influence of Natural Gas prices on EUA prices can be mitigated by the interaction of various energy sources and their associated costs. Further, as mentioned in Chapter 4, the production of Natural Gas is highly connected to extreme weather conditions. If there is extremely cold weather, the demand for Natural Gas will increase, but as the production is negatively affected by cold weather, the supply will decrease. This might be a reason for why carbon returns are not affected by gas returns in the upper quantiles. Therefore, depending on the specific market and context, the degree to which Natural Gas might have an influence on how gas returns and carbon returns relate at the lower and upper quantiles might differ.

The fact that carbon returns are affected by coal returns at all quantile levels except at the lowest and highest levels tested, might be because of similar reasons as discussed with gas returns. Coal is also mostly used for electricity production, and accounts for about 20% of total production in the EU (European Commission, 2020). Similarly, as gas returns potentially affects the price of

EUAs as the use of electricity will decrease in times of economic downturn, coal will most likely have the same effect. However, as stated, there is no significant relationship present between carbon and coal returns at the 0.01 quantile level. This might be caused by cut back production or temporary shut down operations in times of market recession, which will reduce coal consumption, and potentially lead to lower carbon emissions in this period.

A potential reason for why coal returns may affect carbon returns in a market expansion can be due to the increased use of coal. In a market expansion period, there will be increased economic activity and industrial production. Coal is a significant energy source in many industries, particularly those engaged in manufacturing, energy production, and heavy industrial processes. Increased economic activity may lead to more emissions, and the demand for EUAs could potentially increase accordingly. Through our results we also found that coal returns do not affect carbon returns at the 0.99 quantile level. A reason for this might be that when multiple energy sources contribute to overall emissions, changes in coal returns may not have a significant impact on changes in carbon returns.

Performing the same analysis with bootstrapping we found fairly similar results with some differences. The reason for these differences might be caused by the way bootstrapping is computed. When performing bootstrapping, the data is resampled or subsampled, which means that it generates multiple datasets with replacement from the original dataset. By generating several datasets, bootstrapping offers a way to assess the robustness of statistical inference. By including this method, it provided a more reliable and robust estimate of the model parameters, and it is a measure to deal with the issue of autocorrelation. In addition, bootstrapping gave us the opportunity to construct confidence intervals with the correct asymptotic coverage probabilities as stated in Chapter 5. With this said, we think that the statements previously discussed still holds, because the differences in the results are relatively small.

When performing the analysis including all the variables, the results are a bit different. For carbon and oil returns there is no difference in the result for each of the quantile levels. However, the results from this analysis show that there is no significant relationship between carbon and gas returns at any of the quantile levels, and for carbon and coal returns, the relationship is only significant at the 0.10 and 0.25 quantiles. A possible reason for the differences in results could potentially be due to multicollinearity among the independent variables. When all the independent variables are included, there occurs a possibility that there are interaction effects between them. Such interactions may change the significance of the relationship with the dependent variable. For example, when all independent variables are included, the relationship between carbon and coal returns is only significant in the 0.10 and 0.25 quantiles. This may be because the coal returns are now affected by oil and gas returns.

Comparing our results with previous literature, we find that there are some similarities. As stated in Chapter 3, the study by Chen et al. (2022) applied a quantile connectedness approach in their study to investigate the relationship between energy, metal, and carbon markets under extreme market conditions. Their results indicated that under extreme market conditions there is a connectedness between the markets. This is similar to our results as we also found that there is a relationship between fossil fuels and the carbon market under extreme market conditions by applying QR. The study by Chen et al. (2022) also included different metals in their analysis which we did not. Further, they used heating oil, while we chose to include Rotterdam Coal. In addition, they chose a slightly different time period than we did in our thesis, as they included data from April 1, 2008, to October 29, 2021. Overall, there are some differences between this study and our thesis, and it is important to note that they are not directly comparable seeing that we study different markets using different methodologies.

Other studies have also found partly different results than us. Wu et al. (2020) researched the volatility spillover between a carbon emission market and energy commodities by applying recurrence plot method and recurrence quantification analysis. Through their research they found that the volatility spillover between the carbon market and the coal market is the strongest. This differs from our findings, as we found that oil returns have a stronger connection to the carbon market. There are several potential reasons as to why we obtained different results. One is that the time period analyzed differs from their analysis compared to ours. Our thesis includes both phase one and two of the EU ETS (2008-2020), and Wu et al. (2020) only included data from January 2, 2013, to December 7, 2018. Underlying economic and political factors that affected the market can therefore potentially affect the results retrieved from the studies.

It is also important to note that there is a difference in studying volatility spillovers between markets and studying the relationship between markets under extreme market conditions. It is therefore possible that the difference in research focus is the reason for our varying results. Factors that determine relationships between markets under extreme market conditions are not necessarily the same factors that drive volatility spillovers. The different aspects of the relationship between the EU ETS and energy commodities are complex, and it is possible that both Wu et al. (2020) and our thesis's findings are valid.

There are some limitations to our thesis. Firstly, the prices on Rotterdam Coal futures were hard to obtain, and we had to do several alterations to be able to get a fully working dataset. Further, there were several not available (NA) data in all the datasets that we decided to exclude. When excluding these NAs from one dataset, we also exclude existing data from the other datasets. These alterations caused the number of observations to go from 3208 to 2991 observations. This could potentially have an impact on the accuracy of the results as there are 217 less observations when excluding prices and dates to get matching datasets.

Our study's findings may also be influenced by the choice of statistical methodology. There are alternative methods that may lead to different results. Another limitation is that we used prices from the European carbon market, while other results could potentially occur if several, or other carbon markets were included. Further, our study's findings are impacted by the choice of energy commodities, as they may not generalize to other energy commodities that were not included in this thesis. Lastly, when analyzing our data, we discovered that there was significant autocorrelation in our independent variables. This was dealt with by converting the prices to log returns to get stationary data. In addition, we also applied bootstrapping as a part of the analyses, as it constructs robust confidence intervals and provides more accurate estimates of standard errors which can account for the autocorrelation structure in the data.

Furthermore, the implications will be discussed. Policymakers and market regulators who are in charge of managing the EU ETS and energy commodity markets should take note of our findings. This is because our results suggest that the Brent Crude Oil market is the most connected to the EU ETS under extreme market conditions, which could have implications for the design and application of policies aimed at reducing carbon emissions. Our study's findings may also have implications for market participants and investors who are exposed to risks related to the EU ETS and energy commodity markets. Our results indicate as stated that there is a relationship between the EU ETS and energy commodities under extreme market conditions, and this could influence the risk exposure and volatility of portfolios that include such assets.

Overall, the QR analysis gave us the opportunity to investigate the relationship between the variables under extreme market conditions and contribute to existing studies by adopting a different approach i.e., QR. Results from the analysis provided us with an understanding of the relationship between carbon returns and the three different energy commodities at different points in the distribution of carbon returns, and that depending on the quantile level, the relationship may vary.

8. Conclusion

The main goal of our thesis was to contribute to the existing literature regarding the interrelationship between carbon markets and different energy commodities under extreme market conditions. This was done by analyzing carbon returns against oil, gas, and coal returns using quantile regression.

Through our research we investigated the relationship between a carbon market and different energy commodity markets using QR. More specifically, we conducted three separate QR analyses with carbon returns against oil returns, then gas returns, and lastly against coal returns. Then we conducted one QR analysis including all variables (carbon returns against oil, gas, and coal returns). Further we included similar OLS analyses to investigate whether the QR analyses could detect relations not identified by OLS. In addition, we performed QR analysis with bootstrapping, and made standard and bootstrapped confidence intervals.

When performing QR analyses with one independent variable at a time, it appears that generally, the relationship between the EU ETS and energy commodities is significant. However, the strength of these relationships varies across different quantiles and the specific energy commodity. The results from the OLS analysis with one independent variable at a time also show that there is a relationship between the variables, but it fails to detect these relationships when market conditions are extreme, i.e., at the lowest and highest quantile levels.

Further, the results when including all variables provided a slightly different picture. For oil returns, we obtained the same results as in the individual QR analysis, while the results for gas and coal returns varied. From this analysis we found that there was no significant relationship between carbon and gas returns at any of the quantile levels, and for carbon and coal returns there is a significant relationship only at the 0.10 and 0.25 quantile levels.

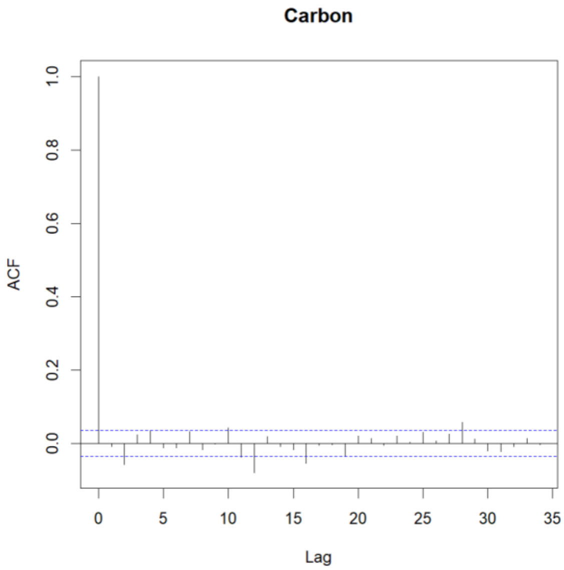
When conducting individual QR analyses with bootstrapping ($\tau = 0.01, 0.50$, and 0.99), the results were somewhat different. For carbon and oil returns we found that there is a significant relationship at all the tested quantile levels, whereas the significance at the 0.99 quantile level was not shown without bootstrapping. From the analysis with carbon and gas returns, there is a significant relationship only at the 0.01 quantile level, which also is found without bootstrapping. However, with bootstrapping the relationship is insignificant at the 0.50 quantile level, which differs from results in the individual QR analysis. Results from the analysis with carbon and coal returns are the same both with and without the bootstrap. Furthermore, the bootstrapped analysis including all variables gives the same results as the individual analysis for oil returns. For gas and coal returns we found no evidence of a significant relationship at any of the bootstrapped quantile levels when all variables were included.

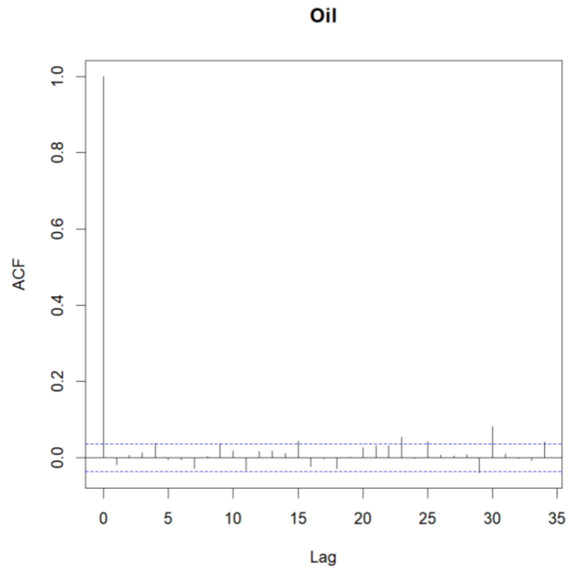
Our results can provide a better understanding of the interrelationship between energy commodities and carbon markets under several market conditions. There is a significant impact on the environment from energy consumption and production, particularly regarding global warming and climate change. It is therefore important to continue to study this relationship, as our findings highlight the need for investors and policymakers to particularly consider the interrelationship between these markets to manage opportunities and risks in the energy sector, at the same time as addressing the pressing need to reduce carbon emissions and mitigate the effects of climate change.

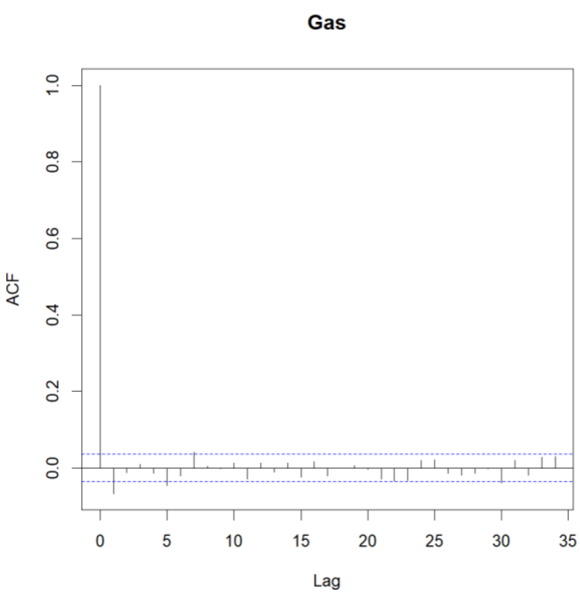
Lastly, while our study reveals that there is a relationship between energy commodities and the EU ETS under extreme market conditions, there is still much to be explored in this area. Regarding future research, it could be interesting to investigate the relationship between the same energy commodities and other carbon markets such as for example the US carbon market, RGGI, or the New Zealand emissions trading system, to see if there emerge different results. Further, the EU ETS is now in its final phase which will last until 2030, it could be interesting to re-examine this relationship after this date and assess the impact of any changes in the market. Overall, in order to combat climate change, the development of effective strategies and ensuring sustainable energy production and consumption practices, continued research on this topic is necessary.

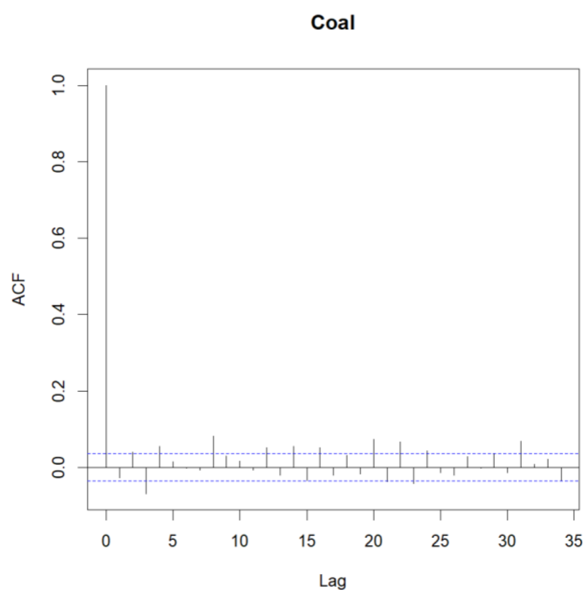
9. Appendix

9.1 Correlograms









9.2 Copula

Statistic	Symbol	Carbon and Oil	Carbon and Gas	Carbon and Coal
Family		Gaussian	Survival Gumbel	Rotated Tawn type 1, 180 degrees
Parameters	θ	0.22	1.04	1: 1.18 2: 0.03
Dependence measures	Kendall's Tau Upper TD, λ_u Lower TD, λ_l	0.14 0 0	0.04 0 0.05	0.01 0 0.02
Fit statistics	Log likelihood AIC BIC	75.54 -149.08 143.08	8.93 -15.86 -9.86	2.9 -1.8 10.21

9.3 R-Script

```
rm(list=ls(all=TRUE))

library(readxl)
library(writexl)
library(Quandl)
library(zoo)
library(tseries)
library(moments)
library(pastecs)
library(stats)
library(copula)
library(VineCopula)
library(car)
library(quantreg)
library(boot)


#=============Institutional Background=================#
carbon_allphases <- Quandl("CHRIS/ICE_C1", type="zoo", start=2008-07-04, end=2021-16-04)
carbon_allphases <- carbon_allphases[,4]
plot(carbon_allphases, ylab = "Price", xlab = "Time")

#===================== Data =====================#
carbon <- Quandl("CHRIS/ICE_C1", type="zoo", start=2008-08-04, end=2020-31-12)
EUA <- carbon[,4]
length(EUA)
```

```
oil <- get.hist.quote(instrument= "BZ=F",
                      start = "2008-04-08",
                      end = "2020-12-31",
                      quote="Close",
                      provider = "yahoo",
                      compression = "d",
                      retclass="zoo")

gas <- get.hist.quote(instrument= "NG=F",
                     start = "2008-04-08",
                     end = "2020-12-31",
                     quote="Close",
                     provider = "yahoo",
                     compression = "d",
                     retclass="zoo")

coalyah <- get.hist.quote(instrument= "MTF=F",
                         start = "2010-12-18",
                         end = "2020-12-31",
                         quote="Close",
                         provider = "yahoo",
                         compression = "d",
                         retclass="zoo")

coalyah <- as.data.frame(coalyah)
coalexcel <- write_xlsx(coalyah, "~/UIA Master/Masteroppgave/Coalyahoo.xlsx")  #Download
to excel

coalxl <- read_excel(file.choose())

#Merge Data
coal <- zoo(coalxl$Close, order.by = as.Date(coalxl$Date, format = "%d-%m-%Y"))

data <- data.frame(cbind(EUA, oil, gas, coal))
colnames(data)<- c("EUA", "Oil", "Gas", "Coal")

data.na <- na.omit(data)

EUA.na <- data.na[,"EUA"]
oil.na <- data.na[,"Oil"]
gas.na <- data.na[,"Gas"]
coal.na <- data.na[,"Coal"]
```

```
#Plot Data
par(mfrow=c(1,2))
plot(EUA, type = "l", col = "black", ylab = "Price", xlab = "Time", main="a: Carbon")
plot(oil, type = "l", col = "black", ylab = "Price", xlab = "Time", main="b: Brent Crude Oil")
plot(gas, type = "l", col = "black", ylab = "Price", xlab = "Time", main="c: Natural Gas")
plot(coal, type = "l", col = "black", ylab = "Price", xlab = "Time", main="d: Rotterdam Coal")

#Log Returns
EUA.r <- diff(log(EUA.na))
oil.r <- diff(log(oil.na))
gas.r <- diff(log(gas.na))
coal.r <- diff(log(coal.na))

plot(EUA.r, type="l", xlab = "Time", ylab = " EUA Returns", main = "a")
boxplot(EUA.r, main = "b")

plot(oil.r, type="l", xlab = "Time", ylab = "Oil Returns", main = "a")
boxplot(oil.r, main = "b")

plot(gas.r, type="l", xlab = "Time", ylab = "Gas Returns", main ="a")
boxplot(gas.r, main = "b")

plot(coal.r, type="l", xlab = "Time", ylab = "Coal Returns", main = "a")
boxplot(coal.r, main = "b")

par(mfrow=c(1,1))

data.r <- data.frame(cbind(EUA.r, oil.r, gas.r, coal.r))

#Descriptive Statistics

stat.desc <- stat.desc(data.r, basic=TRUE, norm=TRUE)
IQR(EUA.r)
IQR(oil.r)
IQR(gas.r)
IQR(coal.r)

quantile(EUA.r)
quantile(oil.r)
quantile(gas.r)
quantile(coal.r)

adf.test(EUA.r)
adf.test(oil.r)
adf.test(gas.r)
adf.test(coal.r)
```

```
jarque.bera.test(EUA.r)
jarque.bera.test(oil.r)
jarque.bera.test(gas.r)
jarque.bera.test(coal.r)

cor.test(EUA.r, oil.r, method="spearman")
cor.test(EUA.r, gas.r, method="spearman")
cor.test(EUA.r, coal.r, method="spearman")
cor.test(oil.r, gas.r, method="spearman")
cor.test(oil.r, coal.r, method="spearman")
cor.test(gas.r, coal.r, method="spearman")

par(mfrow=c(1,2))
acf(EUA.r, main="Carbon")
acf(oil.r, main = "Oil")
acf(gas.r, main = "Gas")
acf(coal.r, main = "Coal")

lag <- 35  # Number of lags to consider
ljungbox.EUA <- stats::Box.test(EUA.r, lag = lag, type = "Ljung-Box")
ljungbox.oil <- stats::Box.test(oil.r, lag = lag, type = "Ljung-Box")
ljungbox.gas <- stats::Box.test(gas.r, lag = lag, type = "Ljung-Box")
ljungbox.coal <- stats::Box.test(coal.r, lag = lag, type = "Ljung-Box")

qqnorm(EUA.r, main = "a: Normal Q-Q Plot, Carbon")
qqline(EUA.r,col="red")

qqnorm(oil.r, main = "b: Normal Q-Q Plot, Oil")
qqline(oil.r,col="red")

qqnorm(gas.r, main = "c: Normal Q-Q Plot, Gas")
qqline(gas.r,col="red")

qqnorm(coal.r, main = "d: Normal Q-Q Plot, Coal")
qqline(coal.r,col="red")

#Copula oil
par(mfrow=c(1,3))
cop.oil <- cbind(as.vector(EUA.r), as.vector(oil.r))

unitsqu.oil<-pobs(cop.oil)
u<-unitsqu.oil[,1]
v<-unitsqu.oil[,2]

plot(unitsqu.oil, main = "a")
selectedCopula.oil <- BiCopSelect(u,v,familyset=NA)
```

```
summary(selectedCopula.oil)

#copula gas
cop.gas <- cbind(as.vector(EUA.r), as.vector(gas.r))

unitsqu.gas <-pobs(cop.gas)
u<-unitsqu.gas[,1]
v<-unitsqu.gas[,2]

plot(unitsqu.gas, main = "b")
selectedCopula.gas <- BiCopSelect(u,v,familyset=NA)
summary(selectedCopula.gas)

#copula coal
cop.coal <- cbind(as.vector(EUA.r), as.vector(coal.r))

unitsqu.coal <-pobs(cop.coal)
u<-unitsqu.coal[,1]
v<-unitsqu.coal[,2]

plot(unitsqu.coal, main = "c")
selectedCopula.coal <- BiCopSelect(u,v,familyset=NA)
summary(selectedCopula.coal)
par(mfrow=c(1,1))

#================== Methodology ================== #
#CDF
cdf <- ecdf(EUA.r)
plot(cdf, col="blue", xlab="x", ylab="Tau", main= "CDF of Carbon Returns")
legend("bottomright", legend="CDF", col="blue", lty=1, bty="n")
points(y=0.8, x=0.02, pch=20)
abline(h=0.8, lty=3)
abline(v=0.02, lty=3)

#==================  Results ================== #
#Oil + gas + coal
sr <- lm(EUA.r ~ oil.r + gas.r + coal.r, data = data.r)
summary(sr)
confint(sr, level=0.90)

rqfit <- rq(EUA.r ~ oil.r + gas.r + coal.r, data = data.r)

summary(rqfit)
summary(rqfit, se = "boot")

rq_boot <- function(data, indices) {
```

```
  fit <- rq(EUA.r ~ oil.r+ gas.r + coal.r, data = data[indices, ])
  return(coef(fit))
}
boot_results.all <- boot(data = data.r, statistic = rq_boot, R = 1000)
confint_all <- t(apply(boot_results.all$t, 2, quantile, c(0.05, 0.95)))

qr1 <- rq(EUA.r ~ oil.r + gas.r + coal.r, data = data.r, tau = 0.01)
qr10 <- rq(EUA.r ~ oil.r + gas.r + coal.r, data = data.r, tau = 0.1)
qr25 <- rq(EUA.r ~ oil.r + gas.r + coal.r, data = data.r, tau = 0.25)
qr50 <- rq(EUA.r ~ oil.r + gas.r + coal.r, data = data.r, tau = 0.5)
qr75 <- rq(EUA.r ~ oil.r + gas.r + coal.r, data = data.r, tau = 0.75)
qr90 <- rq(EUA.r ~ oil.r + gas.r + coal.r, data = data.r, tau = 0.9)
qr99 <- rq(EUA.r ~ oil.r + gas.r + coal.r, data = data.r, tau = 0.99)

summary(qr1)
summary(qr10)
summary(qr25)
summary(qr50)
summary(qr75)
summary(qr90)
summary(qr99)

#Oil
rqfit.oil <- rq(EUA.r ~ oil.r, data = data.r)
rqfit.oil1 <- rq(EUA.r ~ oil.r, data=data.r, tau = 0.01)
rqfit.oil99 <- rq(EUA.r ~ oil.r, data=data.r, tau = 0.99)

summary(rqfit.oil)
summary.rq(rqfit.oil, se="boot")
summary.rq(rqfit.oil1, se="boot")
summary.rq(rqfit.oil99, se="boot")

rq_boot <- function(data, indices) {
  fit <- rq(EUA.r ~ oil.r, data = data[indices, ])
  return(coef(fit))
}
boot_results.oil <- boot(data = data.r, statistic = rq_boot, R = 1000)
confint_oil <- t(apply(boot_results.oil$t, 2, quantile, c(0.05, 0.95)))

sr.oil <- lm(EUA.r ~ oil.r, data = data.r)
summary(sr.oil)
confint(sr.oil, level=0.90)

#Gas
rqfit.gas <- rq(EUA.r ~ gas.r, data=data.r)
rqfit.gas1 <- rq(EUA.r ~ gas.r, data=data.r, tau = 0.01)
```

```
rqfit.gas99 <- rq(EUA.r ~ gas.r, data=data.r, tau = 0.99)

summary(rqfit.gas)
summary.rq(rqfit.gas, se="boot")
summary.rq(rqfit.gas1, se="boot")
summary.rq(rqfit.gas99, se="boot")

rq_boot <- function(data, indices) {
  fit <- rq(EUA.r ~ gas.r, data = data[indices, ])
  return(coef(fit))
}
boot_results.gas <- boot(data = data.r, statistic = rq_boot, R = 1000)
confint_gas <- t(apply(boot_results.gas$t, 2, quantile, c(0.05, 0.95)))

sr.gas <- lm(EUA.r ~ gas.r, data = data.r)
summary(sr.gas)
confint(sr.gas, level = 0.90)

#coal
rqfit.coal <- rq(EUA.r ~ coal.r, data=data.r)
rqfit.coal1 <- rq(EUA.r ~ coal.r, data=data.r, tau = 0.01)
rqfit.coal99 <- rq(EUA.r ~ coal.r, data=data.r, tau = 0.99)

summary(rqfit.coal)
summary.rq(rqfit.coal, se="boot")
summary.rq(rqfit.coal1, se="boot")
summary.rq(rqfit.coal99, se="boot")

rq_boot <- function(data, indices) {
  fit <- rq(EUA.r ~ coal.r, data = data[indices, ])
  return(coef(fit))
}
boot_results.coal <- boot(data = data.r, statistic = rq_boot, R = 1000)
confint_coal <- t(apply(boot_results.coal$t, 2, quantile, c(0.05, 0.95)))

sr.coal <- lm(EUA.r ~ coal.r, data = data.r)
summary(sr.coal)
confint(sr.coal, level = 0.90)

#----------Quantile regression plots-------------#

#plot for oil
qr1.oil <- rq(EUA.r ~ oil.r, data = data.r, tau = 0.01)
qr10.oil <- rq(EUA.r ~ oil.r, data = data.r, tau = 0.1)
qr25.oil <- rq(EUA.r ~ oil.r, data = data.r, tau = 0.25)
qr50.oil <- rq(EUA.r ~ oil.r, data = data.r, tau = 0.5)
```

```
qr75.oil <- rq(EUA.r ~ oil.r, data = data.r, tau = 0.75)
qr90.oil <- rq(EUA.r ~ oil.r, data = data.r, tau = 0.9)
qr99.oil <- rq(EUA.r ~ oil.r, data = data.r, tau = 0.99)

plot(rq(EUA.r ~ oil.r), data = data.r, pch = 20, main = "EUA ~ Oil",
     xlab = "Oil Returns", ylab = "Carbon Returns")

# The quantile regression line
abline(qr1.oil, col = "black", lwd = 2)
abline(qr10.oil, col = "purple", lwd = 2)
abline(qr25.oil, col = "lightblue", lwd = 2)
abline(qr50.oil, col = "green", lwd = 2 )
abline(qr75.oil, col = "orange", lwd = 2)
abline(qr90.oil, col = "red", lwd = 2)
abline(qr99.oil, col = "yellow", lwd = 2)

legend("bottomright", legend = c("0.01","0.10","0.25","0.50","0.75","0.90","0.99"),
       col = c("black","purple","lightblue","green","orange","red","yellow"), bty="n", lty=1)

abline(sr.oil, col="pink", lwd = 2) #standard regression

#plot for gas
qr1.gas <- rq(EUA.r ~ gas.r, data = data.r, tau = 0.01)
qr10.gas <- rq(EUA.r ~ gas.r, data = data.r, tau = 0.1)
qr25.gas <- rq(EUA.r ~ gas.r, data = data.r, tau = 0.25)
qr50.gas <- rq(EUA.r ~ gas.r, data = data.r, tau = 0.5)
qr75.gas <- rq(EUA.r ~ gas.r, data = data.r, tau = 0.75)
qr90.gas <- rq(EUA.r ~ gas.r, data = data.r, tau = 0.9)
qr99.gas <- rq(EUA.r ~ gas.r, data = data.r, tau = 0.99)

summary(qr90.gas)
plot(EUA.r ~ gas.r, data = data.r, pch = 20, main = "EUA ~ Gas",
     xlab = "Gas Returns", ylab = "Carbon Returns")

# The quantile regression line
abline(qr1.gas, col = "black", lwd = 2)
abline(qr10.gas, col = "purple", lwd = 2)
abline(qr25.gas, col = "lightblue", lwd = 2)
abline(qr50.gas, col = "green", lwd = 2)
abline(qr75.gas, col = "orange", lwd = 2)
abline(qr90.gas, col = "red", lwd = 2)
abline(qr99.gas, col = "yellow", lwd = 2)

legend("bottomright", legend = c("0.01","0.10","0.25","0.50","0.75","0.90","0.99"),
       col = c("black","purple","lightblue","green","orange","red","yellow"), bty="n", lty=1)
```

```
#plot for coal
qr1.coal <- rq(EUA.r ~ coal.r, data = data.r, tau = 0.01)
qr10.coal <- rq(EUA.r ~ coal.r, data = data.r, tau = 0.1)
qr25.coal <- rq(EUA.r ~ coal.r, data = data.r, tau = 0.25)
qr50.coal <- rq(EUA.r ~ coal.r, data = data.r, tau = 0.5)
qr75.coal <- rq(EUA.r ~ coal.r, data = data.r, tau = 0.75)
qr90.coal <- rq(EUA.r ~ coal.r, data = data.r, tau = 0.9)
qr99.coal <- rq(EUA.r ~ coal.r, data = data.r, tau = 0.99)

plot(EUA.r ~ coal.r, data = data.r, pch = 20, main = "EUA ~ Coal",
     xlab = "Coal Returns", ylab = "Carbon Returns")

# The quantile regression line
abline(qr1.coal, col = "black", lwd = 2)
abline(qr10.coal, col = "purple", lwd = 2)
abline(qr25.coal, col = "lightblue", lwd = 2)
abline(qr50.coal, col = "green", lwd = 2)
abline(qr75.coal, col = "orange", lwd = 2)
abline(qr90.coal, col = "red", lwd = 2)
abline(qr99.coal, col = "yellow", lwd = 2)

legend("bottomright", legend = c("0.01","0.10","0.25","0.50","0.75","0.90","0.99"),
       col = c("black","purple","lightblue","green","orange","red","yellow"), bty="n", lty=1)
```

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11. Discussion Paper

11.1 Sofie Skau Fodstad – Responsible

As a requirement from the School of Business and Law at the University of Agder, I have written a discussion paper which will discuss the concept responsible and how this concept relates to our thesis. Before discussing how our thesis relates to different aspects of responsibility, I will give a brief introduction to the concept of responsibility, before giving an overview of our thesis topic, carbon trading, and the results from our thesis.

Responsibility is a concept that can be defined as the ability and willingness of being accountable for their actions, decisions, and behavior. Companies have the obligations and responsibility to operate in a manner that benefits society and the environment as much at it benefits themselves. In today's society companies should prioritize ethical practice, sustainability, and social impact in their decision-making processes (Youmatter, 2019). As a step towards having companies act more responsible and sustainable, carbon trading has become a more and more spread-out concept, that has become very important in the battle against global warming.

Carbon markets are marked-based trading systems where carbon permits are sold and bought. In these markets one tradeable unit equals one tonne of carbon dioxide (CO_2) or other greenhouse gases reduced, stored, or avoided (United Nations, 2022). The United Nation Framework Convention on Climate Change created the Paris Agreement, an offspring of the Kyoto Protocol, which was created as a way for the world to combat climate change. Through these agreements and protocols, they presented the idea of carbon markets and carbon trading as a way to limit greenhouse gas emissions and reduce climate change. The general idea behind this concept was that if companies had to pay for each tonne of CO_2 emitted, they would be more aware of their emissions, which would lead to the companies being more responsible and willing to reduce their emissions (Wu et al., 2020).

In our thesis we have decided to focus on one specific carbon market, the European Union Emissions Trading Scheme. This is an international market that the EU member states, Norway, Iceland, and Liechtenstein are a part of. It is the largest carbon trading system in the world as of today and is covering about 40% of the EUs total amount of greenhouse gas emissions (Øvrebø, 2023). In this thesis we have investigated if carbon prices are affected by different energy commodities, i.e., Brent Crude Oil, Natural Gas, and Rotterdam Coal futures, in different market conditions. By performing a quantile regression analysis, we could study different quantile levels and find if there were different results at different market conditions. Through our research we found that the price of Brent Crude Oil is the energy commodity that has the biggest statistically significant relationship with the prices of carbon. Further, we also found that the price of Natural gas is affected by carbon prices at the lower quantile levels ($\tau \geq 0.5$) and that Rotterdam Coal future prices is affected by carbon prices at all levels except the extreme quantile levels.

Trading in carbon credits and the production of energy commodities, i.e., oil, gas, and coal are closely related to the idea of responsibility. The main contributor to greenhouse gas emissions, which account for much of the global carbon footprint, is fossil fuels (United Nations, n.d.). As a result, it is essential to utilize and manage these resources responsibly in order to reduce the effects of climate change. Carbon trading offers incentives for reducing emissions while encouraging the switch to more environmentally friendly energy sources.

At the same time, a larger perspective that considers social and economic aspects in addition to environmental considerations is necessary for the responsible management of energy commodities like oil, gas, and coal. Energy security, job development, and universal access to affordable energy are just a few examples of the concerns that must be solved. This calls for a comprehensive approach that takes into account the whole lifespan of energy commodities, from extraction and throughout consumption and disposal. Companies and governments must make sure that energy resources are used in a way that balances environmental, social, and economic issues and supports sustainable development for all by implementing responsible energy management methods. Further I will discuss some of the many ways I think carbon trading is related to the concept of responsibility and what must be done to behave responsibly.

The idea of accountability is one of the main ways in which the concept of responsibility and carbon trading are intertwined. Through the carbon trading system, the businesses and organizations that produce greenhouse gas emissions are held accountable for them. The scheme provides a financial incentive for businesses to decrease their emissions by providing a market where they purchase and sell carbon permits. Companies may earn money if they lower their emissions below the limit, by selling the extra permits to businesses who need them. Similarly to this, businesses who exceed their allocated number must buy extra permits on the market or pay fines, which is a financial penalty for emitting more than permitted (Commission of the European Communities, 2000).

Through this system of accountability, businesses are more likely to be responsible for their environmental impact and make efforts to lessen their carbon footprint. The carbon trading system promotes responsible behavior and establishes a market-based mechanism for minimizing the effects of climate change by making it financially advantageous for businesses to cut their emissions. The accountability that is built into the system also ensures that emissions reductions are transparent and verifiable, helping to build trust and confidence in the market. In the end, the accountability principle is an essential part of the carbon trading system and aids in ensuring that businesses accept responsibility for their emissions and strive towards a more sustainable future (L, 2023).

The essential premise behind carbon trading is the "polluter pays" principle, which is strongly tied to the notion of responsibility. According to this concept, those who engage in activities that harm the environment by polluting should be held responsible for their damage and pay for the expenses incurred in their negative effects on the environment, rather than passing those costs onto the society as a whole. The "polluter pays" theory states that businesses and organizations that produce greenhouse gas emissions are accountable for the costs associated with the effects of their operations on the environment. The carbon trading system places the financial penalties and responsibility of emissions reduction on the firms that create the emissions, rather than on taxpayers or the general public, by establishing a market-based system where companies must purchase credits to offset their emissions. This pushes businesses to cut their emissions and move toward more sustainable business models and ensures that they are accountable for their environmental effect (*What is the polluters pay principle?*, 2022).

The “polluter pays” concept, which has been embraced by several nations and organizations worldwide, is now an established principle of environmental policy. It is intended to make sure that those who profit from the utilization of natural resources and take part in economic activities that have a negative impact on the environment are held accountable for their actions. The “polluter pays” concept fosters the development of more sustainable practices and technology and helps to drive a change towards a more sustainable and environmentally responsible economy by internalizing the costs of pollution and laying responsibility on polluters (*What is the polluters pay principle?*, 2022).

An essential part of responsibility is the introduction of fines through carbon trading for businesses that emit more than they are allowed to. Businesses who do not take action to minimize their emissions and produce more than they are allowed to must buy extra credits on the market or risk penalties for noncompliance. These sanctions, which may include fines or other legal consequences, serve as a financial disincentive for not complying with the initiative. The carbon trading system serves to guarantee that businesses take responsibility for their environmental effect and strive towards lowering their carbon footprint by holding corporations accountable for their emissions and enforcing fines for non-compliance. This helps reduce the effects of climate change and stimulates the adoption of more environmentally friendly corporate practices (Comission of the European Communities, 2023).

Governments and regulatory organizations are responsible for establishing the emissions cap and market regulations under the carbon trading system. These organizations are accountable for making sure the carbon trading market is equitable, open, and efficient. This includes setting emissions reduction targets, determining the number of carbon credits available for sale, and establishing mechanisms to ensure that companies comply with regulations and do not engage in fraudulent activities. Governments must also make sure the carbon trading system is connected with other programs and initiatives designed to reduce the effects of climate change. Governments play a key role in ensuring that businesses accept responsibility for their emissions and try to reduce their carbon footprint by developing and implementing legislation that controls the carbon trading market (Commission of the European Communities, 2000).

The effectiveness of carbon pricing and responsible climate action depends on the idea of worldwide collaboration. Since climate change is a global problem, nations, and organizations from all over the world must work together in a coordinated manner to address it. Countries can cooperate internationally to set goals for emissions reduction, exchange best practices, and work together on the development of innovative technologies. This may contribute to the equitable and fair mitigation of the effects of climate change as well as the effectiveness, efficiency, and equity of initiatives to reduce emissions.

By establishing a market-based system that enables organizations and nations to transact in carbon credits across national boundaries, carbon trading offers a means for global collaboration. This makes it possible for nations to collaborate in order to meet their emissions reduction goals, even if they have different levels of domestic emission reduction capacity. Additionally, projects that support sustainable development in developing nations can be funded by carbon trading, which can support both economic growth and the reduction of greenhouse gas emissions. Carbon trading helps to ensure that responsibility for reducing greenhouse gas emissions is shared by all countries, and that the impact of climate change is reduced in a just and equitable manner by fostering international cooperation and promoting a coordinated global response to climate change (Zhang & Pan, 2023).

In conclusion, carbon trading is a market-based method of lowering greenhouse gas emissions that encourages responsible behavior among businesses and organizations. This is accomplished by providing financial incentives for emissions reductions, enforcing penalties for non-compliance, and putting the responsibility of establishing and enforcing rules regulating the carbon trading market on governments and regulatory agencies. By giving nations an opportunity to collaborate to meet emission reduction goals and advance sustainable development, carbon trading also fosters international collaboration.

All parties, including governments, corporations, and people must actively engage in and cooperate with one another for carbon trading and responsible climate action to be successful. Carbon trading can assist in reducing the effects of climate change and achieve a more sustainable future for everybody by encouraging a shared responsibility for lowering greenhouse gas emissions. To accomplish a complete and successful response to climate change, it is crucial to understand that carbon trading is only one instrument of many. It must be accompanied by a variety of other policies and initiatives. We can create a more sustainable future for ourselves and for future generations by cooperating and taking responsibility for our influence on the environment.

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11.2 Athena Cassandrea Haver Levang – International

This discussion paper aims to examine the relationship between the European Union Emissions Trading System (EU ETS) and three energy commodities (oil, gas, and coal) under extreme market conditions in relation to international trends and forces. I will discuss how this relationship and our findings relate to several different trends and forces. Understanding these trends and forces may potentially be of great importance in order for researchers, stakeholders, and policymakers to navigate global challenges, address issues that go beyond national boundaries, and make informed and good decisions.

By researching the interrelationship between energy markets and carbon pricing mechanisms, this paper highlights the implications for sustainable energy transitions, policy developments at the international level, and climate change mitigation efforts. Firstly, I will present an introduction of our thesis background and topic. In the next Section, I will discuss how it relates to international trends and forces. The last Section consists of a summary and conclusion of the discussion.

Introduction

Today, global warming is a significant issue which has a big impact on the environment (Chen et al., 2022). Already, global warming is causing several serious environmental damages around the world such as floods, heatwaves, sea level rise, droughts, forest fires, and hurricanes. Because of these damages, there is a need to limit global warming to between 1,5°C and 2°C to decrease global warming and the consequences that come with it. For this to be possible, a decrease in greenhouse gas emissions (GHG) and carbon dioxide (CO_2) is necessary. By 2030, emissions need to be reduced by 25 or 50 percent compared to 2019 levels (Black et al., 2022).

In order to tackle and reduce carbon emissions, carbon markets have been developed and carbon pricing strategies are now utilized in 45 countries. To reach the 2030 goals, the global average carbon price needs to be 75$ per tonne, and today, this price is only 5$ per tonne. (Black et al., 2022). Due to the global recession, carbon prices have been decreasing since 2008 (Newell et al., 2013). Between 2020 and 2022 global coal, gas, and oil prices increased significantly due to a recovery in demand for global energy. Concerning the political acceptability of carbon pricing, these prices are a challenge. The price of carbon needs to gradually increase, and a decrease in fuel and gas prices will bring an opportunity for this increase in carbon price (Black et al., 2022).

Most of carbon markets back in 2012 took place on five platforms. These five platforms are the European Union's emissions trading system (EU ETS), the clean development mechanism (CDF), the regional greenhouse gas initiative (RGGI), New Zealand's emissions trading system, and voluntary markets. Including these five, there are two new carbon markets that have emerged in California and Australia. To this point, it is the EU ETS which dominates the marketplace (Comission of the European Communities, 2023).

The linkages between carbon markets and other energy commodities under extreme market conditions is a topic which we found interesting, and a topic that has been researched previously. Based on this, we wanted to research this relationship and see what linkages could be drawn between the markets under extreme market conditions. Our thesis is inspired by the study by Chen et al. (2022) which researched the connectedness between energy, metal, and carbon markets. In our thesis we use a similar approach, but with different variables and a different methodology as Chen et al. (2022) used a quantile connectedness approach. Our thesis aims to investigate the connectedness between a carbon market (EU ETS), and energy commodities (i.e., Natural Gas, Brent Crude Oil, and coal) under extreme market conditions, where carbon is the dependent variable and oil, gas, and coal are the independent variables. This is done by analyzing 2991 daily observations from each variable in the time period of April 8, 2008, to December 31, 2020. We do this by applying the quantile regression (QR) method introduced by Koenker and Bassett (1978).

Our thesis is a quantitative approach to analyzing the interrelationship between carbon prices and energy commodities under extreme market conditions. Our findings based on the quantile regression analysis indicate that there is a relationship between the variables under extreme market conditions and that the relationship varies across different quantiles. The findings are also different when doing the analyses separately with the independent variables, and when we conduct the analysis including all variables. The relationship between each independent variable and the dependent variable is stronger when doing separate analyses. When all variables are included, the relationship between carbon and gas returns are not significant in any of the quantile levels. Also, for carbon and coal the relationship is only significant in two of the quantile levels.

Discussion

The topic of our thesis relates to several international trends and forces. Firstly, it relates to climate change and environmental policy. Being the largest carbon pricing mechanism in the world, the EU ETS is an important policy tool for reducing greenhouse gas emissions. By putting a price on carbon, an economic incentive is created for companies to reduce their GHG emissions (Comission of the European Communities, 2023). This can for example be achieved through adopting different measures such as investing in renewable energy, adopting low-carbon technologies, and improving energy efficiency. Oil, gas, and coal are energy commodities which also are affected by environmental policies and regulations i.e., emissions standards (Erickson et al., 2018). These standards can potentially have an effect on the supply and demand of these energy commodities.

Further, economic and geopolitical trends are factors which also relate to our thesis in terms of their possible influence on the supply and demand of the energy commodities and potential effects on the EU ETS market. For example, changes in the prices of the energy commodities can potentially influence the competitiveness of renewable energy sources. Also, conflict in regions where oil is produced, or political instability may impact the energy markets and affect the prices. There is also a shift towards renewable energy sources and energy efficiency, which possibly can change or have some sort of effect on the landscape of the energy market (Vakulchuk et al., 2020).

Moreover, advances in technology are an additional relatable international trend to the topic of our thesis. Advances in technology can drive changes in the energy market and affect the EU ETS and the energy commodities. An example is the change in the energy market driven by this trend. The increasing efficiency and affordability of renewable energy technologies like solar power and wind are becoming more competitive with traditional energy sources like oil, gas, and coal. This is creating opportunities for the EU ETS in terms of renewable energy credit markets. In the industrial sector, advances in carbon capture and storage technologies are also creating new opportunities for the EU ETS (Covert et al., 2016).

Other factors that also potentially may impact the energy and EU ETS markets are international trade and investment. For example, international trade agreements can create new opportunities for the exchange of energy commodities and carbon credits between countries (Weber & Peters, 2009). In addition, foreign investment in renewable energy projects may also create demand for renewable energy credits and drive the development of new carbon trading markets (Mathews, 2008). Further, the EU ETS is also linked to other carbon markets around the world, such as the New Zealand emissions trading system market and the carbon market in the US (Regional greenhouse gas initiative), which creates opportunities for international cooperation and emissions reduction.

The findings of our analyses suggest that there is a relationship between the EU ETS and energy commodities under extreme market conditions, and that the relationship varies depending on quantile levels, the specific energy commodity, and if we include all independent variables separately or together with the dependent variable in the analyses. Our findings contribute to the understanding of carbon market dynamics and their connection to energy commodities. This aligns with international trends in terms of the development and expansion of carbon markets where countries and regions are implementing or considering similar mechanisms to price carbon and incentivize emission reductions.

Also, our findings can help policymakers in assessing the effectiveness of carbon pricing mechanisms and finding potential areas where there is potential and room for improvements. Policymakers can evaluate the impact of existing policies and explore opportunities to enhance the integration of carbon markets within broader energy market frameworks by examining the relationship between the EU ETS and energy commodities. The research on extreme market conditions and its impact on the relationship between the energy commodities and the EU ETS relates to international trends in understanding market volatility and risk management. Energy markets can be receptive to price fluctuations and disruptions, and because of this it is important to assess the implications and/or disruptions of extreme market conditions for energy commodities and the EU ETS.

Further, our findings contribute to the discussion on sustainable energy transitions by providing insights into the interrelationship between carbon markets and energy commodities. Having an understanding of this relationship under extreme market conditions can help with policy decisions and strategies for achieving sustainable energy systems, and also in reducing GHG emissions. Moreover, our findings draw attention to the importance of aligning national and regional policies with global climate objectives and collaboration across countries to ensure that carbon pricing mechanisms are effective and consistent.

Conclusions

By examining the relationship between the EU ETS and energy commodities under extreme market conditions, these points enhance how our findings relate to international trends and forces. This is by emphasizing the significance of clean energy transitions, market volatility, carbon pricing mechanisms, international policy coordination, and sustainable development goals.

Today, 80% of the global energy in the world is reliant on fossil fuels. The world is a growing economy which is dependent on fossil fuels. This indicates that the global emissions are going to increase. However, there are now emerging signs of a clean-energy transition. For example, the power sector in many countries is now turning cleaner and greener, partly due to an increase in more affordable solar and wind resources, in addition to a transition to Natural Gas from coal. There are also several climate policies being implemented, and to some degree these are effective but there is still a need for these to accelerate quicker in order to reach the global climate goals (Tollefson, 2022).

In conclusion, the relationship between the EU ETS and energy commodities under extreme market conditions is closely related to international trends and forces, including climate change and environmental policy, economic and geopolitical trends, technological advances, and international trade and investment. These factors are shaping the development of the EU ETS and influencing the supply and demand of energy commodities around the world.

Based on this, it will be interesting over the next years to further research this relationship as the world is constantly changing and adopting new ways of dealing with global climate issues. As the world continues to work with the challenges of climate change, the EU ETS and energy commodities will continue to play an important role in shaping the global energy landscape. This calls for ongoing research to monitor the evolving dynamics and identify potential policy adjustments that are necessary to ensure effective and sustainable outcomes in the context of international efforts towards decarbonization.

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