Abu Jubair MD Nayeem

Vector Autoregression and Cointegration Analysis of Brent Crude Futures and Carbon Futures

Master's thesis in International Business and Marketing
Supervisor: Per Bjarte Solibakke & Erik Nesset
December 2020

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Abstract

The dynamic relationship between Brent Crude Futures and Carbon Futures has long been a crucial research topic, hampered in part by lack of empirical evidence due to the focus on spot market only. Here we try to identify the dynamic relationship between the Futures of EU ETS and the Futures of Brent Crude listed on the Intercontinental Exchange. By deploying a Vector Autoregressive model on the Futures returns and Cointegration on the price relationship. Our study revealed that there is no significant dynamic relationship between Brent Crude Futures and EU ETS Futures in terms of returns and price.

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1 Introduction

Climate change is a shared issue, and it likely remains one in the foreseeable future. From the perspective of each country, if each country had an individual climate, then the self-interested countries would attain the climate goal - much like other goals in the country such as education, transportation infrastructure, and other public goods and services. However, our climate is shared by everyone, which makes it challenging to gain benefit all by oneself. A CO2-receding country reaps only a smaller portion of the benefits, yet obtain the total costs of its abatement. A self-interested response in this type of scenario is to free-ride. In today's globalized economy where the energy prices extensively alter the economic viability and competitiveness, self-interested behaviour of free-riding is notably correct. However, some countries do not display this kind of self-interested behaviour and still pursue their national climate policies.

Several strategies have been taken to reduce fossil fuel usage in our environment, e.g., utilizing hydropower, solar, and/or nuclear energy. However, a price on carbon is often viewed as the most cost-efficient way to deal with this problem (MacKay JC, et al., 2017). A price on carbon is flexible. It can incorporate fossil fuel taxes and restrict usage by introducing a cap-and-trade system, and it fits well with other national policy actions. The European Union Emission Trading Scheme (EU ETS) is the most active and largest cap-and-trade scheme globally (European Commission, 2015). This scheme provides a price on carbon emission to be traded like other commodities, such as crude oil, natural gas, and coal. As EU ETS puts an overall cap on the amount of emitted greenhouse gasses in the atmosphere, we can assume that EU ETS and fossil fuel has some liaison. Thus, the dynamic relationship between the fossil fuel market and the carbon emission market is essential for government planning since it will affect the overall market of both fossil fuel consumption and fossil fuel production. Climate change has been primarily attributed to burning of fossil fuel, which releases significant amount of chemical gases into the atmosphere. Amongst the fossil fuel, coal is the most harmful for environment and researchers have developed several policies to avoid coal as an energy source (Union of Concerned Scientists, 2008). In recent times, natural gas and oil is the primary driver of energy source (Ritchie & Roser, 2014).

The carbon price will influence the marginal cost of production for industries using fossil input (such as coal, oil, and gas), and the power market and the market for carbon emissions will mutually affect each other. An increase in the price of power will increase the production and lead to more CO2-emissions, and thus an increase in the carbon price. On the other hand, a higher carbon price will – due to higher demand for CO2 emissions – increase the costs of producing power. If the price elasticity of power is low, this cost increase will primarily increase the price of power. A carbon price will, however, influence the relative cost of the different production forms with high CO2 emissions. Coal-based production will cause higher CO2 emissions per kWh than oil-and gas-based production. Depending on the form of production, there is an influence of carbon price on the price of power. Even though coal has a lower marginal cost of production than gas, an increase in the carbon price can make gas cheaper than coal. The relationship between different power prices and the carbon price is thus very complex, and there is a large uncertainty connected to the development of future carbon prices. This uncertainty is important for economic analyses and industry decisions regard CO2 emissions. High uncertainty will probably reduce the private sectors willingness to accept measures to reduce CO2 emissions.

There are several Carbon policies designed to understand the impact of Carbon pricing on various factors of an economy such as Gross Domestic Product (GDP), federal deficit, energy independence, household costs, and other energy sources (gasoline, coal). Researchers and economists have explored the economic analysis of both carbon pricing and EU ETS. According to a research paper by OECD (Dechezleprêtre & Venmans, 2018) conducted using installation-level data from the National Pollutant Release and Transfer Register's (PRTR) of France, the Netherlands, Norway, and the United Kingdom, the researchers found a statistically significant reduction of carbon emissions in the range of 10 – 14% (Dechezleprêtre & Venmans, 2018). The authors have found most of the reduction around the time of 2008 to 2012 largely driven by large installations. From the research, the authors concluded that the chemical sector displays the largest reductions. Few researchers have attempted to identify the relationship between Brent Crude Futures and Carbon Futures prices and returns. Contemporary research has mostly focused on the spot market of fossil fuel prices and carbon prices, or they have been based on the early period of carbon trading. Our study will help bridging the gap in this literature by exploring the dynamic relationship between the Carbon Futures market and the Brent Crude Futures market. To be more precise, we will explore the dynamic relationship between the oil future price and the European Union Allowances (EUAs) futures by employing a Vector Autoregression Regression (VAR) method. We will also extend our research to find a long-run relationship between oil futures and EUA futures by employing the Cointegration technique along with the Vector Error Correction Model (VECM). For EUA allowances, we will use the data from European Climate Exchange (ECX), and for oil futures, we will use the Brent Crude Futures from Intercontinental Exchange (ICE). Our paper explores the implied dynamic relationship between the Carbon Futures and Brent Crude Futures prices and returns. The identification of this dynamic relationship can help us understand the effectiveness of Carbon Futures on the usage of Brent Crude Futures. Futures offer a fast, cost-efficient way to trade in the financial and commodity markets. The reason behind the importance of Futures market are several among which we will mention some. Futures markets are substantially liquid which makes it easier to trade. The Futures can help investors with diversification and hedging. For the above-stated reason we have focused our paper on the Futures market for both Carbon and Brent Crude. We constrained our analysis on the one-month Futures contract for both the commodities. Based on the background information and brief theoretical discussion stated above, we, therefore, formulate our research questions as follows:

1. **What is the dynamic relationship between the oil futures price and carbon futures?**
2. **Are the prices Cointegrated? Is there any long-run relationship between the prices?**

There are some limitations that we faced while conducting the research. Firstly, we need to narrow down our scope of research to oil futures based on Brent Crude of Europe. The primary reason is as EU ETS only covers Europe and Brent Crude is the benchmark for oil in Europe, the results will be applicable to only Europe and cannot be generalized to other locations. Secondly, a VAR analysis does not incorporate the moving average (MA) terms in the analysis, which might be useful in capturing the overall dynamics of the process. For example, a Vector Autoregressive Moving Average (VARMA) could capture the overall underlying process of the oil futures and carbon futures. However, a VARMA process suffers from the problem of invertibility and might produce unreliable results. Lastly, COVID-19 has altered the current scenario of the fossil fuel market, which we exclude in our paper and left out for future analysis.

The rest of the paper follows the following sequence. We start with a comprehensive overview of both EU ETS and Oil Market in the literature review section. We also describe the mechanism of how both the futures market works. In the methodology section, we provide a comprehensive overview of the methodology that we apply to analyze the dynamic relationship between oil futures and carbon futures, i.e., estimation and forecasting techniques of a VAR model and estimation and Error Correction Form of the Cointegrated model.

2 Context and Literature Review

The warmer planet and economic efficiency using fossil fuels have become a paradox for researchers and practitioners. Two-thirds of total carbon dioxide emissions come from electricity/heat generation and transportation systems (International Energy Agency, 2020). The consumption pattern varies across countries: carbon dioxide emissions through the transportation system are predominant in many North American countries, one-half of the emissions in Asia comes from power generation, and less than one-sixth from transportation (Ritchie & Roser, 2019). After reallocation of emissions from power generation to final sectors, the picture changes. Industry accounts for 43 percent of total CO_2 emissions, while buildings and transport account for 25 percent each (International Energy Agency, 2020). On one side, there is wealth, which is necessary for everyone who wants to achieve a higher standard of living, and on the other side, the usage of fossil fuel for efficient productivity leads us to a warmer planet with unprecedented weather volatility. However, to replace fossil fuel energy, several renewables technologies have been introduced, but most of them come with their disadvantages. For example, solar energy is an excellent source of electricity, but it is not deployed widely due to weather variability.

The theoretical framework of our paper has been divided into three distinct sections. The first section provides a comprehensive literature overview of the European Union Emissions Trading System. In this section, we have explored the rationale behind the EU ETS, political and theoretical foundations of the EU ETS, the three Phases of the EU ETS, and the Mechanism of the market. The second section describes the history and structure of the futures market for crude oil. We have described the volatile history of oil from its inception until recent times. In the final section of our theoretical framework, we review the contemporary literature that has been done on carbon price and crude oil price.

2.1 Literature Review of EU ETS

We start our theoretical framework by extensively studying the foundational rationale behind the development of the EU ETS, the compliance periods, and the mechanism of the Carbon Market. We finish our review by discussing the current condition of the market along with the discussion on the subsequent changes the EU ETS has adopted in recent times.

2.1.1 Theoretical and Political Background of EU ETS

While pollution reductions may be beneficial for global society in the long run, states will only choose to abate pollution if the short-term net benefit of abatement is positive from a national perspective (Napoli, 2012). This attraction towards the selfish equilibrium is the primary reason why the Kyoto protocol failed (Cooper, 2001). The carbon emission reduction vows undertaken by 184 countries in the Paris Agreement for 2030 were not enough to keep the global warming well below 2° celsius (Leahy, 2019). The best candidate for a common commitment in international climate policy is carbon pricing. Tackling climate change is difficult because of the free-rider problem. The atmosphere provides countries that emit with the option to free-ride. Some nations relax and rely on when others give the effort, the incentive to tackle climate change weakens. A collective pledge can give assurance to participants that others will match their efforts and will not free-ride. "I will if you will" - strategy will stabilize higher levels of cooperation. A carbon price – would be the ideal basis for a collective commitment in our view. A price is easy to administer, relatively impartial. Climate change is a problem of the commons, and it likely remains one in the foreseeable future. If each country had its climate, then self-interested countries would reach climate goal-much like self-interested countries provide education, transportation infrastructure, parks, and other public goods. Nevertheless, with a shared climate, a CO_2-abating country receives only a small fraction of the benefits, yet incurs the full costs of its abatement. Naturally, the self-interested response is to free-ride which is particularly true (Cooper & Cramton, 2017).

The role of the European Union Emissions Trading System (EU ETS) is significant in the EU. The EU ETS is a 'cap-and-trade' system which puts a cap on the total amount of Greenhouse-Gases (GHG) emissions from several installations and aircraft operators primarily responsible for approximately 50 per cent of the European Union's GHG emissions (European Commission, 2015). Within the system, parties can trade emission allowances so that the allocated emissions of the installations and aircraft operators remain within the cap. This motivation ensures that the parties would take the least-cost measures to reduce emissions. From the classic book of J. H. Dales published in 1968, Pollution, Property and Prices, the EU ETS draws its inspiration (Dales, 1968). Explicitly, Dales stated that 'if it is feasible to enact a marketplace to enforce a policy, no policymaker can afford to do without one'. One of the primary underlying reason for the problem of climate change is the failure of the market to perceive the scarcity value of our atmosphere as a sink for Greenhouse-Gas emissions. However, no price appropriately signals this increasing scarcity, which leads to the fact that there is no incentive to reduce these emissions. Economists recognize two broad policy instruments to repair this failure (Cooper & Cramton, 2017). The first instrument was to introduce environmental taxes, i.e., a tax imposed on every unit of emissions produced (Cooper & Cramton, 2017). The second market-based policy instrument is emissions trading, which draws on humanity's singular impulse to trade (Cooper & Cramton, 2017). Broadly expressed, the trade would involve setting an overall cap per unit of time on the emissions to be permitted. Determination of the overall cap will lead to the allocation of allowances/permits to emitters. The sum of the allowances allocated will not exceed the cap. These emitters can then pollute as they wish, but only on the condition that they hold sufficient allowances at the end of the period to cover their emissions. If they wish to emit more than the allowances they have received, they must buy allowances from those who had a lower emission or have a surplus on the allowances. These transactions produce a price per unit of pollution that provides the incentive to polluters to reduce emissions and sell the surplus to those who need to buy to cover their emissions. With the concept in mind and some inspirations taken from the trading scheme for sulphur dioxide (SO2) in the power sector from the United States, the European Union Emissions Trading Scheme came into being as a Europe Wide Market for Carbon dioxide (CO2) (Ellerman, et al., 2010).

Coase (Coase, 1960) provided a trenchant argument that the assignment of suitably defined property rights would allow for the use of environmental endowments to negotiate and trade their way to the economically efficient outcome. The above theoretical framework was given more explicit expression as a way of creating an emissions market by Crocker (Crocker, 1966), Dales (Dales, 1968) and Montgomery (Montgomery, 1972), by using hypothetical cases to illustrate the potential. They all make the case that fixing the number of emissions, allocating quotas to the emitters such that the sum of these did not exceed the overall ceiling then allowing a price to emerge as the product of trades would allocate abatement automatically to those market participants who could abate at least cost. Besides, the price signal would create a continuing incentive to innovate, thereby yielding dynamic efficiency, and the approach adhered to the 'polluter pays principle' by automatically rewarding those who reduced emissions and penalizing those who did the contrary. The US Acid Rain Program provided the meat in the analytical sandwich and nourished the development of the instrument in Europe (United States Environmental Protection Agency, 2020). The program was aimed for substantial reductions in sulphur dioxide emissions by power stations at costs that were substantially below the likely alternative policies.

The EU ETS was the product of two failures. The first one is the failed attempt to levy a carbon energy tax. In 1992, the EU proposed a Union-wide carbon energy tax (Ellerman, et al., 2010). Primarily for two reasons, the proposal failed. Firstly, some nations regard member state autonomy in taxation as a core value, not to be relinquished even if the environment would benefit. Secondly, the leading industry lobbies represented most clearly by the Union of Industrial and Employers' Confederations of Europe (UNICE), also opposed the tax. The second one is the Kyoto negotiations. The third Conference of Parties to the UN's Framework Convention on Climate Change convened in Kyoto, Japan, in December 1997.

2.1.2 The compliance periods

We start the section by explaining the different compliance periods that the EU ETS has been experienced. The system started out in 2005 and has undergone drastic and minor changes since then. According to the EU ETS handbook, the implementation of the system has been subdivided into distinct trading periods over time which can be addressed as phases. The current phase of the EU ETS began in 2013 and will last till 2020.

The first trading period (2005-2007) constituted a process of 'learning by doing'. The objective of the period was to establish the infrastructure and institutions and to gain the experience to make the subsequent 'real' period a success. The cap that was to be decided for the trial period was a voluntary one assumed by the European Union to prepare for the subsequent trading period when a legally binding obligation would exist. The criteria for cap-setting in the trial period were closely tied to expected business-as-usual (BAU) emissions. A BAU scenario

assumes that there will be no significant change in people's attitudes and priorities, or no significant changes in technology, economics, or policies so that normal circumstances can be expected to continue unchanged (Oxford Reference, 2020). The self-contained nature of the trial period, created by the short-time period and the inability to bank first-period allowances for use in the second period, made a zero price at the end of the period inevitable. The task of setting a cap that was at or close to BAU emissions was made enormously more difficult by weak data (European Commission, 2015). The problem was that no member state government had a good idea of the exact emissions within the ETS sectors. Through UNFCCC processes, good inventory data had been developed for the national and sector levels. However, these data were calculated on an upstream basis – based on fuel consumption at the sectoral and economy-wide levels. Furthermore, the definition of sectors differed, as did the criteria by which installations and emissions were included in the ETS. As a result, there were no accurate models that could predict ETS sector emissions. The problem of data was also extended into the allocation of allowances to installations, which required installation-level emissions data. As there was no legal and regulatory framework for collecting these data, the practical expedient was dependence on the voluntary submission of data by the owners of included installations.
The agreement among the EU15 member states concluded in July 2003 and formally issued in October 2003, required first-period national allocation plans to be submitted by the end of March 2004 (European Commission, 2015). Then the Commission was to complete its review within three months of having been notified of each member state's NAP. In theory, the entire process would be concluded and the cap determined by August 2004, five months before the scheduled start of the system on 1 January 2005 (European Commission, 2015). This proved to be an impossible timeframe given the significance and preparation needed to implement the emissions trading scheme.

We can attribute this situation with the planning fallacy, which was first pointed out by the Nobel Laureate Daniel Kahneman and Amos Tversky. A belief that one's project will proceed as per plan, even knowing that most of the similar nature projects have run late, is known as the planning fallacy (Buehler, et al., 1994). The delays incurred resulted not only from late submissions but from the Commission's review. The total proposed annual amount by the EU25 members was 2278.8 Million EUAs, whereas the allowed annual amount was 2181.3 Million EUAs (Ellerman, et al., 2010). A 4.3 per cent reduction was required to put it under the cap. However, for a myriad of reasons, this 4.3 per cent of reduction turned to be a surplus of 4.3 per cent. One of the reasons was due to the unavailability of data from Eastern Europe

(Ellerman, et al., 2010). Some of the other significant reasons include the accession of Romania and Bulgaria in 2007; the European Court of First Instance's ruling on Germany's challenge to the Commission's disallowance of ex-post adjustments; the treatment of opt-outs and opt-ins; and the incomplete distribution of allowances in the new entrant reserves (NERs).

The final first-period cap and emissions can be summarized in the following table:

(data in millions)	**EUAs**	**Verified Emissions**	**Surplus**
Final first-period results	6467	6200	267

Table 1 The Final First-period cap and emissions

Most of the problems that had plagued the first-period NAP process had disappeared by the time the second-period (2008-2012). NAPs were developed and reviewed. The problem of weak data was solved at one fell swoop by the release of verified emissions data for 2005. Also, the deadline for the submission of NAPs (June 2006) was no longer an impossible one, which solved the planning fallacy problem. Nonetheless, the first-period problems were replaced by new ones created by the EU ETS status in the second period as a cap within a cap and the need to make sure that the second-period allocation did not jeopardize the European Union’s achievement of its obligations under the Kyoto Protocol. These problems concerned the trade-off required by the fact that the ETS was now a cap within a broader cap and that limits on the use of credits from Joint Implementation and the Clean Development Mechanism. The Commission announced its expectation that the second-period EU-wide cap would be 6 per cent lower than the comparable first-period cap on an annual basis (European Commission, 2015). Moreover, the Commission also announced that it would apply uniform assumptions concerning the growth of CO2 emissions – an annual rate of growth of 0.3 per cent for the EU15 and 0.2 per cent for the new member states – instead of relying on member state projections (European Commission, 2015). In the second phase of EU ETS, Iceland, Norway and Liechtenstein joined as new state members on 1 January 2008. The total allowances were dwindled by 6.5 per cent for the period (European Commission, 2015). Furthermore, the economic dip due to the financial crisis caused a low demand for emissions in the second period. Due to the surplus credits, available from the Joint Implementation and the Clean Development Mechanism, there was an excess amount of unused allowances and credit, which put pressure on the carbon prices. Nevertheless, previously not included Aviation Industry was also brought into the system.

After the two-compliance period, the ETS Directive proposed some significant changes on 23 January 2008 primarily concerned with the issues of auctioning, harmonization and cap-setting (Ellerman, et al., 2010). We will briefly review these in this section. The most radical and contested issue was related to auctioning. The Commission's proposal consisted of a principle and a proposal for implementation. The principle was that free allocation would be ended and allowances distributed entirely through auctioning. The proposed implementation consisted of three elements:

- The power sector would receive no free allowances from 2013 on, except for heat delivered to district heating or for industrial uses;
- Installations in non-power sectors would receive a free allocation of 80 per cent of their share of the cap in 2013, which would be reduced by ten percentage points each year so that free allocation would be phased out in 2020;
- Energy-intensive sectors or subsectors that face a significant risk of carbon leakage from competitors in countries without equivalent CO2 measures could receive free allowances of up to 100 per cent of their need.

2.1.3 Mechanism of the Market

The EU ETS is a cap-and-trade system. It works by putting a cap on the overall greenhouse gas (GHG) emissions of all the participants in the system. To emit GHG emissions, EU ETS legislation created allowances which are attributed as rights to emit one tonne of CO2 equivalent (tCO2e). The overall level of the cap determines the total number of allowances available in the EU ETS system. From 2013, the cap is redesigned to decrease annually, which in turn will reduce the number of allowances available to the businesses that fall under the EU ETS system. The amount of reduction will circulate 1.74 per cent per year, which would allow the firms to gradually adjust in meeting the increasingly ambitious target for emissions reductions (Brohé, et al., 2009).

The allowance is allocated either by free allocation or via auction. In phase one and two, allowances were primarily handed out for free, which has changed starting from phase three.

From the third phase, the default method of allowance allocation is through auction. Although free allocations are still valid for the industry sector with a cap on the maximum amount of free allocation limiting to approximately 43 per cent of the total phase three cap (European Commission, 2015). One hundred per cent auctioning is subject to the power generation section that started from 2013 onwards except for the Member States engaged in the modernization of the power sector (Brohé, et al., 2009). The industrial and heating sectors are given free allocation based on the ambitious GHG performance benchmarks. By 2020 the free allocation rules for the industrial sector is set to decrease by 30 per cent. The ambition extends to 0 per cent by 2027. Factors that deemed to face a severe issue of carbon leakage will receive 100 per cent of the quantity freely. Allowances follow the basic economic principle of supply and demand. There is a capped supply, and there is a demand from the participants. There is also the case where the participants have a higher cost of reductions compared with other participants. To ensure compliance, penalty and enforcement structure is available. If a firm fails to comply by surrendering sufficient allowances in time, the amount of fine is set at €100 per tCO2e adjusted with the EU inflation from 2013 (Brohé, et al., 2009). Besides, firms are obligated to surrender the allowances owed.

The coverage of EU ETS has expanded significantly since the start of phase one in 2005 in terms of geography, sectors, and types of GHGs (European Commission, 2015). From phase three, the EU ETS approximately incorporate half of the overall GHG emissions that take place in the EU. Furthermore, the European Commission, EU Member States are always looking for new prospects to include.

Geographically speaking, the EU ETS started with 25 EU Member State and grew to 27 Member States when Romania and Bulgaria joined under the EU in 2007. At the start of phase two, the EU ETS expanded and started covering the European Economic Area (EEA) with Norway, Iceland, and Liechtenstein. The area expanded, even more, when the largest stationary emitters in Croatia joined the EU ETS from January 2013 and the aviation sector of Croatia from 2014. The most GHG intensive sectors in the power and manufacturing industry are covered by the EU ETS starting from phase one. The scope was broadened in 2012 to cover CO2 emissions from the aviation sector. The horizon was further extended from phase three with the inclusion of aluminium, carbon capture and storage, petrochemicals, power stations and combustion plants with ≥ 20 Mega Watts (MW) thermal rated input (except for hazardous or municipal waste), oil refineries, steel and iron, glass, lime, paper and board, ammonia and many more (European Commission, 2015). The EU ETS covers CO2 emissions, N2O emissions, and from phase three, PFC emissions.

According to the ETS directive (European Commission, 2015), a single EU full cap is set for the percentage of emission reduction. The cap is expressed in tCO2e for each of the trading phases. The European Commission calculate and establish the cap before each trading period. For the phase three, the cap ensures the meeting of the EU's 2020 GHG reduction target which in total can be attributed to 20 per cent reduction of the EU GHG emissions compared to the 1990 levels (European Commission, 2015). According to the EU ETS directive, the cap can be separated into two distinct categories:

- A fixed installation cap decreases each year by a linear factor of 1.74 per cent. Factually the total number of EUAs reduced annually will be 38,264,246 (European Commission, 2015).
- A fixed cap for the aviation sector decreasing at a fixed level of 210,349,264 allowances per year (European Commission, 2015).

Setting a cap is essential for the economic survivability of the market. The price of the carbon is determined by the harmonic combination of demand and supply. Scarcity is a critical factor for any economic assets. The cap stringency plays a critical role to ensure scarcity, thus circulating the demand and supply EUAs.

The allowances are allocated in a transparent way of auctioning. The auctioning methodology enables the market participant to buy the allowances at the market price. The auctioning methodology for the EU ETS has changed a lot since its inception in 2005. At that trading phase, only five per cent of the emissions allowances were allowed to auction (Ellerman, et al., 2010). From phase three all the EUAs are auctioned except for the allocated free allowances. Primarily the Member States are liable to ensure their share of allowances auctioned. From phase 3, the auctioning can take place on a common auction platform such as the European Energy Exchange AG (EEX) through a joint procurement procedure or on an 'opt-out' auction platform under the supervision of the procurement procedure stated by the Member States. Except for Germany, Poland and the UK, other 25 Member States follows the joint procurement approach. The common platform for these Member States is the EEX. Norway, Liechtenstein, and Iceland also use the EEX. Alternatively, the ICE Futures Europe (ICE) is an opt-out auction platform for the UK. A bidder can apply for admission to bid at the auction

platforms residing anywhere in the EU and the EEA. Then the auction platform verifies the eligibility of the application under the regulatory framework of the Auctioning Body.
The EUAs can be traded in five ways like any other financial instrument. In case of the spot trade, the settlement takes place on the spot. The trade date is generally within two business days after the completion of the trade. Futures are a standardized contract among two parties with delivery and payment occurring at a specified future date, which is the delivery date also. Our paper analyzes the dynamic relationship between the price of the futures contract of EUAs with the price of the futures contract on oil. The EUAs can also be used as a forward contract, swap or options. However, in case of swaps, the buyer can also swap any amount of EUAs for a proportionate amount of Kyoto carbon credits which usually sells at a discount to EUAs.
A National Allocation Tables were established replacing the National Allocation Plan Tables to issue allowances. A Central Administrator is responsible for issuing all allowances by creating them on the EU total quantity account in the Union Registry. The Central Administrator is also held responsible for the transfer of allowances for auctioning and free allocation to the applicable accounts. After the activity of the Central Administrator, the Member States are then responsible for the allocation of allowances free of charges.
The EUAs can also be surrendered throughout the trading period. ETS operators have an obligation to surrender the quantity of EUAs equivalent to the volume of their GHG emissions of the previous year. The process usually takes place by the end of April each year. International credits are also allowed in the process of submission. However, from phase 3, international credits cannot be directly surrendered. Instead, the credits need to be exchanged for EUAs first. A failure for surrendering allowances is met with a penalty for €100 per tCO2e, adjusting for EU inflation (Brohé, et al., 2009). Voluntary cancellation and transfer of allowances are also permissible by the ETS directive. The instructions for a transfer is carried out electronically by the authorized delegate of the seller account. The delegate indicates and ensures the transfer of the number of units.

Transparency, accuracy, monitoring, reporting and verification is essential to create trust in any trading. These are also applicable to emissions trading. Since the third phase of ETS, the monitoring and reporting of GHG emissions are in line with the European Union Monitoring and Reporting Regulation, according to No 601/2012 (European Commission, 2012). Annually, installations and aircraft operators hand in the Annual Emission Report (AER). The document provides the details regarding the total amount of emitted GHGs of the operator in that given year. An independent accredited verifier verifies the AER.

2.2 Literature Review of Oil

The history of oil is theatrical. Oil is extensively used in our economy and a vital source of energy. In this section of our paper, we will be briefly addressing the volatile history of oil from 1859 to the present day. Furthermore, we will address the futures market for oil, which will be used for our analysis along with the EUA futures.

2.2.1 A History of Oil

The modern oil industry started because of a scarcity of whales (York, 2017). Until 1859, most of the people obtained light by burning animal fats in the form of beeswax candles or whale oil (Britannica, 2011). The purest light of all available fuels was the whale oil, and it soon became a luxury product. Due to overfishing of whale, a decline in the whale population resulted, which in turn led to the increase in whale oil prices (Davis, et al., 1988). In 1854, George Bissell and his business associates sent a sample of crude oil skimmed from a surface pool in North Western Pennsylvania to Professor Benjamin Silliman of Yale University for analysis (Aoghs.org Editors, 2019). Professor Silliman confirmed that the sample could be distilled to produce kerosene. The fundamental process of distillation involves separating different products by heating them. The products have different boiling points, so they evaporate and are condensed separately, which remains the basic refining technique used today. Silliman's analysis was used to raise capital for the formation of the Pennsylvania Rock Oil Company in 1855 (American Chemical Society National Historic Chemical Landmarks, 2009).

The Pennsylvania Rock Oil Company hired a railroad conductor named Colonel Edwin Drake to carry out the drilling. Edwin Drake struck oil on August 27, 1859 (American Chemical Society National Historic Chemical Landmarks, 2009). The first well was on a salt dome rock formation. The well was 69 feet deep and yielded 15 barrels a day. The petroleum that flowed from the world's first wells is known as Oil Creek, near Titusville, Pennsylvania and started the modern oil industry (McNally, 2017). Crude oil was stored and transported to refineries in any readily available container. Wooden whiskey and wine barrels were the most common means of transporting liquids at the time and were requisitioned to haul crude oil (International Association of Oil Transporters, n.d.). By 1870s, railroad tanker cars and pipelines began to replace barrels as the preferred and less expensive methods of moving crude oil. Drake's first well created a scramble reminiscent of California Gold Rush of 1849 (Roske, 1963). Oil became known as black gold. In January 1869, one barrel of crude oil was sold for $18 which is equivalent to $553 in today's market value (CPI Inflation Calculator, n.d.). About 90 per cent of the new oil industry was gradually consolidated by John D.Rockefeller and the Standard Oil Company.. Rockefeller purchased his first refinery in Cleveland in 1865 and founded the Standard Oil Company in 1870 (McNally, 2017). Journalist Ida Tarbell brought the anti-competitive practices of Standard Oil to public attention in a series of investigative reports published from 1902 through 1904 (Tarbell, 1904). Hastened by the Tarbell information, the Sherman Antitrust Act of 1890 was used in 1911 to split Standard Oil into several competing firms (Tarbell, 1904). Thus, sprang forth 34 companies including Exxon now known as ExxonMobil, Chevron and Texaco, now known together as Chevron; and Conoco, now part of ConocoPhillips (Downey, 2009). Barrel remained the default volume measure in oil markets. Standard Oil standardized the volume of a barrel to be a Standard Oil Blue Barrel, or bbl (an acronym used to this day), which is 42 US gallons (approximately 159 litres).

Following the initial discovery of crude in Pennsylvania, additional small discoveries were made in Texas, Oklahoma, and California. In 1901, a gusher named Spindletop (Johnson, 1966) was discovered in 1901 just south of Beaumont, Texas, which produced over 50,000 barrels per day. Patillo Higgins made the discovery (Johnson, 1966). This individual well produced 20 per cent of daily US production at the time. In addition to the significant US discoveries such as Spindletop, major discoveries began to occur in other parts of the world. Production began in Baku, Russia, which is a part of modern-day Azerbaijan, along the shores of the Caspian Sea around the 1870s (Mir-Babayev, 2002). This development was led and funded by the Rothschild Banking Family (Mir-Babayev, 2002). Production in the Middle East commenced in Persia when the UK government-controlled Anglo-Persian Oil Company, as BP was then known, struck oil in 1908 (BP, n.d.). Royal Dutch discovered oil in the 1890s on the island of Sumatra, nowadays part of Indonesia (Royal Dutch Shell, n.d.).

These discoveries created the needed cheap and ubiquitous supply of fuel to launch the automotive age. Up until the First World War, oil was not of much strategic significance. The strategy changed when Winston Churchill decided to replace slow coal-powered vessels with rapid response oil-powered military ships in WWI, which became a decisive factor in the outcome of the war (Philpott, 2006). Ocean-going commercial and military ships continue to use residual fuel oil as their primary fuel to this day.

A significant challenge for the oil industry was the exploration. The prices of oil remained in equilibrium until the demand caught up. In 1928, following significant oil production increases from Russia, English and American oil companies became worried that the world was again moving into a dangerously oversupplied situation (Bamberg, 1994). To address the glut, the heads of the most powerful oil companies in the world resulted in an agreement Achnacarry Agreement (Bamberg, 1994). Under the Agreement the oilmen agreed that they would not compete against each other outside of the US and instead would act to ensure price and profit stability for each of them. The Soviet Union in 1929 agreed to participate in the Agreement. However, the Agreement failed as the participants did not hold sufficient market share to control supply and prices. The need to stabilize prices at profitable levels in the face of oversupply was satisfied three years later by the US government. While dealing with the Great Depression and trying to kick start US industry including the oil business, the US federal government required the Texas Railroad Commission (TRC) and similar but smaller organizations in other oil-producing states to impose production restrictions to ration the amount of crude produced in each state (McNally, 2017). TRC control of East Texas production spare capacity made it the arbiter of global prices from 1931 to 1971. The Seven Sisters dominated the exploration and production outside the US until the 1970s (Sampson, 1985). The Seven Sisters, through mergers and acquisitions, are now four: ExxonMobil, Chevron, BP, and Royal Dutch Shell. The four remaining Sisters have been joined by two other large international oil corporations, ConocoPhillips and TOTAL, to form a group known today as the six Majors. Today, the Majors have lost their market dominance. Together, they control only 14 per cent of global crude oil production, although they still own 24 per cent of global refinery capacity (U.S. Energy Information Administration , 2020). Much of the oil produced outside of the US until the 1970s was carried out based on concessions which is a legal Agreement between and International Oil Corporation, most often a Major, and the government of the country in which the oil was being produced. Concessions negotiated by the Majors were as a rule on a 50/50 profit sharing basis (Yamani, 1975).

Cracks in the 50/50 concession arrangements began to emerge in 1951 as Mohammed Mossadegh, the democratically elected prime minister of Iran, nationalized his country's oil industry (McNally, 2017). OPEC (Organization of Petroleum Exporting Countries) was formed in 1960 in Baghdad (McNally, 2017). The organization was based in Vienna and modelled after the TRC. Five founding member countries: Saudi Arabia, Kuwait, Iran, Iraq, and Venezuela, were joined in later years by a further nine nations, the UAE, Qatar, Libya, Algeria, Nigeria, Angola, and Ecuador. Organization for Economic Cooperation and Development (OECD) in response to the energy crisis of 1973, formed the International Energy Agency (IEA) in November 1974 to coordinate the response of developed nations to restrictions in supply (International Energy Agency, 2019). The IEA recommended minimum stockpile levels of oil to be created in consumer countries to enable petroleum consumers to shelter themselves better from such crises. In 1975, President Gerald Ford established a Strategic Petroleum Reserve (SPR) of crude oil to be used for US emergency purpose (Lantero, 2015). In 1978, during the Iranian dethroning, Saudi production had rapidly and very briefly ramped up to 10.5 million barrels per day (McNally, 2017). Total global oil production in 1978 was 67 million barrels per day (Federal Reserve History, 2013). Subsequently, in order to keep prices from collapsing during the early 1980s as Iranian oil production resumed, and to bring production back to more optimal rates, Saudi Arabia cut its production back to two million barrels per day, which is a massive swing for any producer. Saudi Arabia became known as the swing producer for its singular attempts to manage prices (Yousef, 2011). However, the more the Saudis cut back, the more other OPEC countries produced by cheating on their quotas. In August 1985, Saudi Arabia decided a new form of netback pricing where they linked the Saudi crude oil price to the retail gasoline and other product prices in the US and elsewhere (Biddle, 1985). The international market did not need additional Saudi oil. Within a year, oil prices collapsed more than 70 per cent and remained between $10 and $20 until 1990 (McNally, 2017).

During the late 1970s, oil started trading on the future exchanges. A futures exchange is a marketplace where one can buy or sell a commodity for delivery at a point in the future. Heating oil futures first started trading on New York Mercantile Exchange (NYMEX) in 1978 (Ederington & Lee, 2002). Subsequently, in 1981 gasoline futures started trading (Bird, 1987). After the US domestic crude oil prices were deregulated in 1981, crude oil futures started trading on the NYMEX in 1983 (Reuters Staff, 2009). In 1988 oil began to trade on the International Petroleum Exchange (IPE) in London (Intercontinental Exchange, n.d.). The IPE now trades electronically as the Atlanta-based Intercontinental Exchange (ICE). The oil traded on these two exchanges (NYMEX and ICE) created price transparency between producers and consumers. Heating oil, gasoline and other finished product prices being openly quoted on futures exchanges enabled Saudi Arabia, followed by other large producers, to begin using refining margin netback pricing in 1984, linking the price at which they sold their crude oil to the price of finished products (McNally, 2017). For example, if a western oil refiner managed to sell gasoline, heating oil, and the other products in its basket of finished products linked to futures prices for $50 per barrel, and the pre-agreed netback margin between the OPEC crude oil producer and the refiner is $10 per barrel, then the refiner pays $40 per barrel for the crude oil. In this way, the revenue of the crude oil producer is more closely linked to the final market price for the refined petroleum products, and a refiner is guaranteed a profit margin. However, the refining margin netback pricing began to be replaced by crude oil formula netback pricing.

Crude oil formula netback pricing, which is the mechanism still in use today, links the price at which OPEC crude producers, and others, are willing to sell crude oil to an openly traded free-market crude oil benchmark or a combination of benchmark prices (Stevens, 2005). Benchmark oil prices, also known as price markers, are oil prices set at the close of business each day on futures exchanges, such as the NYMEX or ICE futures exchanges. They also include prices assessed daily by oil trade journals S&P Global Platts and Petroleum Argus, two most widely used oil trade journals (Mathur, 2013). They assess prices during a window of time at the end of each business day for hundreds of grades of oil at various locations around the world based on spot market trading in physical oil at those locations. Oil traders and their brokers report to these journals in real-time during the daily time window, the price and quantity of any trades they have transacted, or are willing to, transact.

For OPEC and the oil industry, the 1990s and early 2000s were relatively stable and orderly compared with the preceding periods. Nevertheless, once again, starting soon after the turn of the twenty-first Century, tectonic shifts in global oil demand and supply began to reshape the oil market, subjecting oil producers, consumers, and governments to massive oil price volatility not seen since the 1920s and 1930s and shattering perceptions that OPEC could maintain oil price stability. On the demand side, global GDP growth picked up sharply between 2003 and 2007, averaging a healthy five per cent per year (McNally, 2017). The vigorous economic activity caused oil consumption to grow by 6.5 million barrels per day (eight per cent) over the period. The average consumption of oil had been rising by one million barrels per day from 2000 through 2003 (McNally, 2017). However, the consumption rose 60 per cent faster from 2004 to 2007, i.e., 1.6 million barrels per day. In China, demand exploded stemming from faster economic growth and rapid industrialization and urbanization. Electricity shortages played a significant role, too. To keep the lights on, China was forced to fall back on older power plants burning distillate and heavy fuel oil (McNally, 2017). Many businesses, facing periodic compulsory shutdowns to save energy, also invested in diesel power generators. The confluence of these factors more than doubled China's oil demand growth, from 0.4 million barrels per day in 2003 to 0.9 million barrels per day in 2004 (McNally, 2017). European countries tightened regulations on distillate fuel by lowering the amount of sulphur it could contain, sending refiners scrambling to make the cleaner fuel. Besides, the introduction of the EU ETS in the European market caused the industry to move towards clean and renewable sources of energy. On the supply side, production growth outside OPEC was unexpectedly weak while the costs of production soared due to increases in the cost of steel pipe, drilling rigs, oil field services, and cement. Amid dire warnings about peak oil and demands to crack down on speculators and release strategic stocks, oil prices kept rising into 2008. In February 2008, the price escalated to $100 for the first time (McNally, 2017). As the summer approached in 2008, the price of crude was over $140. Unbeknownst to oil market participants gawking at oil's towering spike in the middle of 2008, a collapsing real estate bubble was about to drop the floor out from under crude oil prices, triggering a price bust as sudden and spectacular as the boom. We know that consumers do not quickly adjust their consumption of gasoline when oil prices change—but they do when their income changes. An employed worker has little choice but to pay whatever the pump price is to drive to work, but after losing his job, an unemployed person's need to drive drops quickly. In 2008 incomes were collapsing and oil demand along with them, falling by 0.7 million barrels per day in 2008 and by 1.1 million barrels per day in 2009. As it became clear that the world was entering a massive recession, oil prices plummeted. In October of 2008, prices fell to almost $60 per barrel—half their level just two months earlier (McNally, 2017). By December prices had tumbled to $33, an astounding crash of 78 per cent in just six months.

2.2.2 Oil and Coronavirus

The impact of Coronavirus (COVID-19) is still immeasurable on the economy. As the COVID-19 is spreading around the world, travel and tourism, economic activities are in astringing. China is one of the highest energy consumer among other nations. They were accounted for more than 80 per cent of demand growth in global oil (International Energy Agency, 2019). IEA predicted than the demand for oil would grow by 825,000 barrels a day in 2020 (International Energy Agency, 2020). However, the IEA is now re-evaluating their prediction. The IEA has developed two scenarios. In the pessimistic scenario, failure to contain the COVID-19 globally will lead to a decrease of global demand for oil by 480,000 barrels per day in the remaining months of 2020 (International Energy Agency, 2020). On a more optimistic scenario, containment of the COVID-19 globally will lead to a demand of 730,000 barrels per day. As a measure of recuperate, Members of OPEC and their allies, except Mexico, agreed to a production cutback of 9.7 million barrels per day deal to balance the global oil market (Duffy & Disis, 2020). For the first time in history, the price of West Texas Intermediate (WTI) dropped by almost 300 per cent, to a negative $37 per barrel (Bayly, 2020). However, the price has steadily recouped by 90 per cent in May (Stevens, 2020). Also, the petroleum industry is still in a high degree of uncertainty. Whiting Petroleum became the first major firm to file for bankruptcy protection (Reuters Staff , 2020).

2.2.3 Futures Market for Oil

The spot price is the price of oil for immediate delivery. The price of oil for delivery at a specified date in the future is called a forward price. Oil for delivery in the future is most commonly traded using exchange-traded futures contracts and Over-the-Counter (OTC) swap contracts. A useful feature of futures and swaps is that, if one chooses, one never actually should take or make delivery of physical oil. As one does not have to get involved in the physical oil market, such contracts are referred to as paper barrels as opposed to real physical wet barrels. Less than one per cent of paper barrel contracts such as futures or swaps are converted into physical oil, but it is still vital that the link between paper and physical exists as it ensures that paper contracts have real underpinnings. Charting the various dates and forward prices of either futures or swaps create a forward curve of prices going out into the future. Each benchmark grade of oil has its forward curve. The parts of the forward curve closer to expiry date are referred to as the front-end of the curve. The parts that are further along the curve into the distant future is referred to as the back-end. Price differentials between the front of the curve and further out parts of the curve are referred to as front-to-backs, or time spreads. Forward curves can be in contango, which is upward sloping as one goes further into the future, or in backwardation, which is downward sloping. Contango is a case that occurs when there is excessive oil around today relative to today's demand and implies that there may be money to be made in storing oil as one can sell oil on the forward curve at a higher price than today's low price (Constable, 2020). Backwardation usually occurs when there is a relative shortage of oil today, and the forward curve discourages storing oil as one can sell oil today at a better price than in the future. As there has always tended to be spare capacity globally in oil storage, refining, and transportation, changes in spreads due to fundamental economic and seasonal differences have typically not been as significant as changes in absolute prices of crude oil up or down. The relationship implies that oil spot prices and forward curves are relatively highly positively correlated.

2.2.4 Exchange Traded Futures Contracts:

A futures contract gives one the right to buy a standardized quantity of oil for delivery at a date in the future. If one buys future, then one is said to be going long futures, and the trade will make money if market prices rise. If one sells futures, then one is said to be going short, and the trade will make money if market prices fall. There are five actively traded, or liquid, futures contracts for petroleum globally, three listed on the NYMEX and two on ICE. The fossil fuel contracts are summarized in the table below:

ICE Futures (London)	**Ticker Root**
Brent Crude (contract size: 1000bbls)	LCO (Reuters) CO (Bloomberg)
Gasoil (contract size: 100 metric tonnes)	LGO (Reuters) QS (Bloomberg)

Table 2 Fossil Fuel Contracts traded on the Exchange

The ICE Futures exchange in London is a public company and is regulated by the UK Financial Services Authority (FSA). At the end of trading each day, settlement prices for each futures contract are posted by the exchange. These settlement prices are determined by trading over the last few minutes of the trading day. Daily settlement prices are used for mark-to-markets, which show the financial state of positions at the end of each trading day and are used for calculating variation margin payments required. The Exchange Traded Futures Contracts are standardized with fixed volumes contrary to the OTC contracts. An upfront initial margin deposit is required, which is managed by the clearinghouse.

2.3 Literature of Oil Futures and EUAs

Previous literature on the association between oil prices and carbon prices focused on the spot market rather than the futures market. However, the background of the market, attributes of the market, and structure of the market of Phase two and three differ from Phase one, the outcomes of the research papers may not be generalized to Phase two and three. Our research paper tends to bridge the gap by focusing on the futures market for both oil and carbon. Existing studies also analyzed both the markets using traditional multiple regression techniques. This paper focuses on the maximum likelihood estimation techniques for VAR analysis, which is more robust and less prone to multicollinearity problems and outliers. Furthermore, the timing of our paper is very relevant. The Earth is getting warmer, and the primary reason is the usage of fossil fuel burning. The dynamic relationship pointed out in our paper might help with policymaking and may shed light on the importance of a carbon market for tackling the climate change problem. Contemporary works of literature on the relationship between oil futures and EUA futures is sparse. In this section, we will give a brief overview of the contemporary works of literature on the oil price and emission allowance price in this section.

The Kyoto Protocol enacted in 2005. Since then GHG emission permit has been a scant resource which is endowed with a commodity attribute. Under such events, carbon market came into being in the terrain to deal with the global climate change. Global carbon market represented by the EU ETS has marked a rapid development: the turnover increases to $176 billion in 2011 from $10 billion in 2005, with an annual growth rate of 60 per cent (Brohé, et al., 2009). The market is expected to be one of the biggest and most active trading markets in the world. The existing methods used for pricing and forecasting carbon market can be roughly categorized into two distinct groups: econometric models and artificial intelligence approaches (Zhu & Chevallier, 2017). However, these approaches cannot function well on the real data of carbon price because of some constraint and nature of the market. A carbon market is typically complexed in nature compared with other markets in the economy. Carbon price exhibits uncertainty, nonlinearity, anomalous behaviour, and volatility due to its interactions among multiple factors and their external heterogeneous environments, as well as their influences. The reasons, as mentioned above, make the methods unlikely to achieve satisfactory performance on the pricing and forecasting carbon market. The integral drivers of a carbon price can be generalized to the price of energy (oil, natural gas, coal), external heterogeneous environments (policies), temperature conditions (summer, winter), and economic activity (boom, recession).

CO2 emission primarily results from fossil energy consumption. Power plants can also selectively use various fuels such as coal, gas, and oil. Due to this reason, there is an internal price transmission mechanism between fossil energy market and the carbon market. Consequently, rising energy price is likely to cause an increase in the carbon price and vice versa. The above finding is consistent with that of Kanen (Kanen, 2006), Convery & Redmond (Convery & Redmond, 2007), Mansanet Bataller, et al. (Mansanet Bataller, et al., 2006), Oberndorfer (Oberndorfer, 2009), and Hintermann (Hintermann, 2010).

In recent years, an increasing amount of researchers around the world has begun to pay attention to the EU ETS carbon market. Several researchers have studied the Phase on to date, considering the environmental benefit and cost-efficiency of the EU ETS carbon market. For instance, Mansanet Bataller, et al. (Mansanet Bataller, et al., 2006) and Alberola, et al. (Alberola, et al., 2008) investigated the driving factors of EU ETS Phase one from 2005-2007 successively. The key findings of their papers are that carbon price drivers, such as energy prices and weather factors could influence EUA prices. They also demonstrated that the essential variables in the determination of CO2 returns are the most emission-intensive energy variable, i.e., prices of coal, represented by electricity returns in EEX, and the prices of Brent. Besides, the weather variables influencing CO2 returns are not significantly imperative, although days with high and low temperatures have a positive influence on CO2 prices. External heterogeneous environments also have a considerable effect on the carbon price. As the carbon market is a policy-based artificial market, it is influenced by both the mechanism of the market and heterogeneous environments such as global climate negotiations, quotas allocation, financial crisis, and information pronouncements.
Furthermore, the sensitivity of temperature conditions with a carbon price is also evident in papers. Fifty-five per cent leaseholders of EUA are from thermal and electric departments. The shortage of EUA and rising carbon price appears to have an interrelationship to dry and cold winter calls for large amounts of heats which decrease the demands in hydropower. High temperature also leads to the frequent maintenance of nuclear power. Thus, power consumption based on coal makes CO2 emission rise, and carbon therefore increase. The above view is supported by Mansanet Bataller, et al. (Mansanet Bataller, et al., 2006), Alberola, et al. (Alberola, et al., 2008), Daskalakis, et al. (Daskalakis, et al., 2009), Benz & Trück (Benz & Trück, 2009), and Hintermann (Hintermann, 2010).

A considerable amount of contemporary studies are focused on the EU ETS Phase one. Since the background of the market, attributes of the market (flexibility and intensity), and decree of the market of Phase two and three differ from Phase one, the outcomes of the research papers may not be generalized to Phase two and three. Furthermore, most of the contemporary results are basically obtained from carbon spot prices. Presently, carbon spot trading is still very low, while carbon futures trading is the preeminent product in carbon markets. Nevertheless, studies relating to carbon futures are scarce. Since carbon futures enjoy substantial trading volume than carbon spot prices theoretically speaking, carbon futures prices are much less receptive to the structural changes that have occurred on the spot market (e.g., 2006). Hence, carbon futures prices show less volatile fluctuation than spot price equivalents. For this reasoning, the research inference from carbon spot prices is probably not applicable to carbon futures prices. Besides, existing studies primarily employ traditional multiple linear regression methodology, which is susceptible to the problem of multicollinearity. Therefore, the reliability of the research results might be inadequate in some cases, and the dynamic relationship between the energy futures (e.g., oil) and carbon futures cannot be adequately grasped.

To aid our previous discussion, we provide some insights from different research papers comprising of EU ETS Phase one and two and other exogenous factors, including energy prices. The drivers of carbon prices of EU ETS at Phase one and Phase two are somewhat different. Wei, et al. (Wei, et al., 2010) used the Cointegration technology to examine the interactions of the carbon price and energy prices at both long and short terms. They found that energy prices are marginally associated with carbon futures price at Phase one, and has a long-run equilibrium relationship with carbon futures price at Phase two. The deviation of energy prices has been the leading driver of carbon price at Phase two. Keppler & Mansanet-Bataller (Keppler & Mansanet-Bataller, 2010) adopted the Granger causality test to explore the "granger-causes" relationship between the carbon price and energy prices. They concluded that coal and gas prices at Phase one influenced carbon price, which further impacted electricity price. However, at Phase two, gas price is still influential to the carbon price, but the carbon price no longer influences coal price. Moreover, electricity price is a driver of carbon price at Phase two contrary to Phase one. Creti, et al. (Creti, et al., 2013) also conducted a Cointegration analysis to compare the drivers at Phase one and two. They remarked that there existed two different long-term Cointegration relationship between carbon prices and energy prices at Phase one and two when the structural breaks are considered. Zhu & Chevallier (Zhu & Chevallier, 2017) extended the study of Creti, et al. (Creti, et al., 2013) to identify the determinants of the carbon price from 2006 to 2012 using cointegration analysis. Their results indicated a long-term cointegrating relationship between carbon prices and its driving factors, including energy prices, weather conditions, economic activities, and institutional decisions. Bredin and Muckey (Zhu & Chevallier, 2017) employed a cointegration VAR model with likelihood ratio test statistics and proposed that the carbon futures market in Phase two is inefficient. Fezzi & Bunn (Fezzi & Bunn, 2010) by employing a VAR procedure, implied that shocks on electricity prices influence the carbon prices. Their findings suggest that one per cent increase in the price of emission permits resulted in an increase of 0.32 per cent in UK electricity prices during Phase one. Milunovich & Nazifi (Milunovich & Nazifi, 2010) also reported links between electricity and emission permit prices, as well as between emission permits and oil prices. Contrary to other studies, their results indicate that there is no evidence of a long-run relationship between carbon prices and oil prices. The result implies that the prices are not cointegrated and may wander apart without bounds in the long-run.

There are several other research works conducted from an economic point of view to identify the connection between various drivers of carbon prices. From the supply point of view, the number of total allowances is decided by each Member-State of EU ETS through the implementation of National Allocation Plans (NAPs). The NAPs are then coordinated at the EU-level under the supervision of EC. From the demand side, the usage of CO_2 allowances by Member-State is a function of the expected CO_2 emissions in the Member-State. The degree of CO_2 emissions depends on a myriad of factors, such as unanticipated volatility in energy demand, price of energy products, condition of weather. Based on the demand and supply fundamentals stated above, Christiansen et al. (Zhu & Chevallier, 2017) have identified policy and regulatory issues, market fundaments (emissions-to-cap ratio), the role of fuel-switching, weather and production levels as the price determinants in the EU ETS. Using an extended dataset, Mansanet Bataller, et al. (Mansanet Bataller, et al., 2006) and Alberola, et al. (Alberola, et al., 2008) uncovered the dynamic relationship between energy markets and CO_2 price. The essence of the relationship between energy and carbon prices varies depending on the period under consideration and the dominant influence of institutional events. Hintermann (Hintermann, 2010), under the efficient market hypothesis, derived a structural model of the allowance prices. He examined the degree to which marginal abatement costs can explain the volatility in price. Boutaba (Zhu & Chevallier, 2017) investigated interactions among the European carbon markets that trade EUAs and Certified Emission Reductions (CERs) using the data from European Climate Exchange, Nordic Power Exchange, Powernext, European Energy

Exchange, Energy Exchange Austria, and SendeCO2. He employed a cointegration test, and the results revealed several cointegrating relationships that exist between the different markets, and hence, a high degree of price transmission. Powernext, Nordic Power Exchange and Energy Exchange Austria displayed leading roles as short-term channels of causality from changes in the carbon markets. Milunovich & Nazifi (Milunovich & Nazifi, 2010) explored the dynamic interaction between EUA and CER prices through cointegration analysis and concluded that EUA and CER prices are not cointegrated. Mark et al. (Zhu & Chevallier, 2017) studied the interactions of EUA and CER emission prices with key energy markets across the EU. Their results indicated that in Phase two, significant interactions existed between the prices of EUA and CER contracts and the critical energy markets for Europe. Using an Autoregressive Distributed Lag Model, Kim and Koo (Zhu & Chevallier, 2017) examined whether price movements of fossil energy can significantly affect carbon price dynamics in short-run. Zhang & Sun (Zhang & Sun, 2016) analyzed both return and volatility spillovers (i.e., an unexpected repercussion) between carbon and energy markets using the Dynamic Conditional Correlation (DCC) threshold GARCH model and the full BEKK-GARCH model. They pointed out that there were significant and unidirectional volatility spillovers from the coal market to the carbon market, and from the carbon market to the natural gas market, whereas there exists no spillover between carbon and oil markets. Chevallier, et al. (Chevallier, et al., 2019) employed a conditional vine copula approach with a dataset covering both Phase two and three and provided novel insights in investigating the dependence structure between carbon and energy prices in Europe, taking fuel-switching mechanism into account. They found that carbon prices demonstrate a weak and negative link with both oil and natural gas prices. They also argued that inefficiency of fuel-switching mechanism in reducing carbon emissions and analyzed that the switch from coal-fired to natural gas-fired plants does not occur even if carbon prices remain at a high level. Kun et al. (Zhu & Chevallier, 2017) examined the interdependency of energy and carbon market by employing a Quantile-on-Quantile Regression approach using the data from Phase three. The paper found that a positive (negative) price change in carbon-consumed resources (oil, natural gas, coal) due to strong (weak) demand or weak (strong) supply could rise (decrease) of marginal production costs of installations using such energy as an input, lower (decrease) the installations outputs, and then depress (prompt) their future energy demand. They remarked that current energy price fluctuations are expected to exert negative impacts on future carbon price dynamics, while the intensity of the impact could be heterogeneous at different locations of the carbon-energy price distribution, due to idiosyncratic market characteristics and carbon emission volumes per tonne of different fossil energy.

In the above paragraphs, we have described the contemporary research papers that are available, which focused on the individual EU carbon market and also on the determinants of the market. The next few paragraphs of this section discuss some of the critical studies on the oil price shocks on the carbon market. Several studies have focused on the collective dynamics between West Texas Intermediate (WTI), Brent crude oil, and natural gas spot log returns. The dynamics have been explored by many statistical techniques such as copula, Monte Carlo simulations, and bootstrap based goodness-of-fit tests. The modelling of stochasticity in the energy, equity, commodity, and foreign exchange markets has become more common nowadays. Most of the studies assert that crude oil plays a significant role in many types of investments, including equity market, commodity market, and the foreign exchange market. Gr´egoire, et al. (Gr´egoire, et al., 2008) examined the dependence structure of log-returns of futures on crude oil and natural gas and implied that the dependence between the two prices is roughly constant with time.

A study by Accioly & Aiube (Accioly & Aiube, 2008) found conflicting results with Gr´egoire, et al. (Gr´egoire, et al., 2008). The authors found a change in price behaviour at different periods. The change was observed through different copula models, and the results were confirmed using bootstrap analysis. An interesting study was conducted by Reboredo (Reboredo, 2012) on the dependence structure between crude oil benchmark prices utilizing copulas using weekly data. The researcher wanted to assess whether markets were regionalized or globalized on the basis of upper and lower tail dependence. The study concluded that markets with well-developed forward and future markets exhibit conditional dependence and that globalization hypothesis holds as oil prices move together, independently of whether the market is booming or crashing. The contemporary literature on the relationship between oil price and emission allowance price is relatively scarce. The co-movements of EU ETS and energy prices are crucial for government planning since they affect the overall economy of both oil-consuming and producing countries. Benz & Trück (Benz & Trück, 2009) and Hammoudeh, et al. (Hammoudeh, et al., 2014) explored the relationship between oil price and emission allowance price by utilizing higher frequency (daily) data. The authors also created a model of potential asymmetries in oil price fluctuations. A related study by Dutta, et al. (Dutta, et al., 2018) employed a bivariate VAR-GARCH approach and concluded that volatility in the EUA prices affects positively on the renewable energy stock returns. However, the associated relationship was not statistically significant. Krokida, et al. (Krokida, et al., 2020) in their paper examined the effect of different oil price shocks on the price of emission allowances traded under the EU ETS; leading to changes in aggregate and sector-specific European equity returns. The paper reports that positive aggregate demand shocks have an immediate and persistent positive effect on carbon emission price, whereas an unexpected oil disruption has a positive but smaller effect. They also conducted a historical variance decomposition analysis reveals that the responses of the price of CO2 carbon emission allowance have been mainly driven by global economic activity and oil-specific demand shocks rather than oil-supply shocks which typically exert smaller effects. Lastly, Soliman & Nasir (Soliman & Nasir, 2019) examined the association between the Energy prices and EU ETS prices using a time-varying SJC copula model. The results indicate that there exists a proportionate correlation between ETS and crude oil spot price.

3 Theoretical and Empirical Approach

3.1 VAR and Cointegration

In our study, we will be implementing two econometric models that are closely related to each other, Vector Autoregression (VAR) and Cointegration and a Vector Error Correction form (VECM) for the estimated VAR. The actual analysis will be described in the Data analysis section, and the results will be discussed in the Discussion section.

In the first part of this section, we start by providing a theoretical framework for the methodology, i.e., VAR, Cointegration and VECM. We derive our model for analysis in the subsequent sections. We will start by describing the VAR model and derive the estimation technique, limiting distributions and significant equations that are used to estimate the model later in the analysis part. In a nutshell, we will describe how to estimate a VAR model, how the select the appropriate order for the VAR model, achieving a parsimonious model through model simplification, forecasting into the future with the available information, and finally the dynamic effect between the variables in the study.

In the second part, we start with the concept of unit-root, determining the order of integration, theoretical concepts of Cointegration along with the error correction form, cointegrating vectors, Johansen's trace statistic for Cointegration tests, and estimation of the Error-Correction model and their limiting distributions which is function of standard Brownian motions. The theoretical construct section draws heavily on the works of Hamilton (Hamilton, 1994), Juselius (Juselius, 2006), Johansen (Johansen, 1995), Pfaff (Pfaff, 2008), and Tsay (Tsay, 2014).

3.1.1 VAR:

One of the most commonly used multivariate time series models is the VAR model. The VAR model has become popular due to its relative ease of estimation techniques. A VAR can be estimated using the least-squares (LS) method, maximum-likelihood (ML) method or Bayesian method and all the three estimation methods have closed-form solutions. The multivariate time series z_t follows a VAR model of order p, VAR(p), if

$$z_t = \emptyset_0 + \sum_{i=1}^{p} \emptyset_i z_{t-i} + a_t$$

where $\emptyset_0$ is a k-dimensional constant vector and $\emptyset_i$ are $k \times k$ matrices for $i > 0$, $\emptyset_p \neq 0$, and a_t is a sequence of independent and identically distributed (iid) random vectors with mean zero and covariance matrix $\sum_a$ which is positive-definite.

3.1.1.1 Properties of VAR:

VAR(p) model has some unique properties that we will explore in this section. We will start with the stationarity conditions. For the above model, a necessary condition for the VAR(p) series to be stationary is that all eigenvalues of must be less than 1 in absolute value or equivalently, the solutions of the determinant equation are greater than 1 in absolute value. That is, the solutions of the determinant equation are outside the unit circle. A time series z_t is said to be invertible if it can be written as

$$z_t = c + a_t + \sum_{j=1}^{\infty} \pi_j z_{t-j}$$

where, c is a k-dimensional constant vector, a_t is a sequence of iid, and π_j are $k \times k$ constant matrices. For an invertible series z_t, $\pi_j \to 0$ as $i \to \infty$.

By definition, a VAR(p) time series is a linear combination of its lagged values, which makes the VAR(p) always invertible.

3.1.1.2 Estimation of VAR:

As stated before, a VAR(p) model can be estimated using the least-squares or maximum-likelihood method. We will briefly describe the maximum likelihood estimation of the VAR(p) model. Let us consider the below model

$$z_t = \emptyset_0 + \emptyset_1 z_{t-1} + \cdots + \emptyset_p z_{t-p} + a_t, \qquad t = p + 1, \dots, T$$

where the covariance matrix of a_t is $\sum_a$. We have $T - p$ data points for effective estimation. To facilitate the estimation, we rewrite the VAR(p) model as

$$z_t' = x_t'\beta + a_t'$$

where $x_t = (1, z'_{t-1}, ..., z'_{t-p})'$ is a $kp + 1$ -dimensional vector and $\beta' = [\emptyset_0, \emptyset_1, \dots, \emptyset_p]$ is a $k \times (kp+1)$ matrix. With this new format, we can write the data as

$$\boldsymbol{Z} = \boldsymbol{X}\beta + \boldsymbol{A},$$

where $\boldsymbol{Z}$ is a $(T-p) \times k$ matrix with ith row being z'_{p+i}, $\boldsymbol{X}$ is a $(T-p) \times (kp+1)$ design matrix with ith row being x'_{p+i}, and $\boldsymbol{A}$ is a $(T-p) \times k$ matrix with ith row being a'_{p+i}.

Given the data set $\{z_1, \dots, z_T\}$, the maximum likelihood of a VAR(p) model is

$$L(\hat{\beta}, \widehat{\Sigma_a} | z_{1:p}) = ([(2\pi)])^{-\frac{k(T-p)}{2}} |\widehat{\Sigma_a}|^{-\frac{T-p}{2}} exp\left[-\frac{k(T-p)}{2}\right]$$

Under the multivariate normality assumption, i.e., a_t follows a k-dimensional normal distribution, the ML estimates of a VAR(p) model are asymptotically equivalent to the LS estimates.

3.1.1.3 Model Building:

We now turn to model building where we follow the iterated procedure of Box and Jenkins (Box, et al., 2016) consisting of model specification, estimation and diagnostic checking. For VAR models, specification implies the order, p, selection. Various methods have been proposed in the literature to select the VAR order. We choose the information criteria approach.
Information criteria are useful in selecting a statistical model. All criteria are based on likelihood and consist of two components. The first component is the goodness of fit of the model to the data, and the second component penalizes more heavily complicated models. For the normal distribution, the maximized likelihood is equivalent to the determinant of the covariance matrix. This determinant is known as the generalized variance in multivariate analysis. The selection of the penalty is relatively subjective. Three criteria functions are commonly used to determine VAR order. Under the normality assumption, these three criteria for a VAR(l) model are

$$AIC(l) = ln|\widehat{\Sigma_{a,l}}| + \frac{2}{T}lk^2$$

$$BIC(l) = ln|\widehat{\Sigma_{a,l}}| + \frac{ln\ (T)}{T}lk^2$$

$$HQ(l) = ln|\widehat{\Sigma_{a,l}}| + \frac{2ln\ [ln(T)]}{T}lk^2$$

where T is the sample size, $\widehat{\Sigma_{a,l}}$ is the ML estimate of $\sum_a$. AIC was proposed Akaike (Akaike, 1981) and is abbreviated Akaike Information Criterion. BIC stands for Bayesian Information Criterion (Schwarz, 1978) and HQ is proposed by Hannan and Quinn (Quinn & Hannan, 1979). If z_t is indeed a Gaussian VAR(p) time series with $p < \infty$, then both BIC and HQ are consistent and will select the true VAR(p) model with the probability one as the total sample size T approaches towards infinity. To compute the information criteria for a given time series realization $\{z_1, \dots, z_T\}$, we use the data from $t = P + 1$ to T to evaluate the likelihood functions, where P is the maximum AR order.

Residual analysis is a crucial function of model building. The main objectives include to ensure that the fitted model is adequate and to suggest directions for further improvement if needed. Typically, a fitted model is said to be adequate if

- All fitted parameters are statistically significant (at a specified level),
- The residuals have no significant serial or cross-sectional correlations,
- There exist no structural changes or outliers,
- The residual does not violate the distributional assumption of multivariate normality.

We derive here the multivariate Portmanteau statistics for model checking. The test is used to detect the existence of linear dynamic dependence in the data. Let $\boldsymbol{R_l}$ be the theoretical lag l cross-correlation matrix of innovation a_t. The hypothesis of interest in model checking is

$$H_0: \boldsymbol{R_1} = \cdots = \boldsymbol{R_m} = \boldsymbol{0}$$

versus

$$H_0: \boldsymbol{R_j} \neq \boldsymbol{0}\ for\ some\ 1 \leq j \leq m$$

where m is a pre-specified positive integer.

For the residual series, the Portmanteau statistic becomes

$$Q_k(m) = T^2 \sum_{l=1}^{m} \frac{1}{T-l} tr\left(\widehat{R_l}' \widehat{R_0^{-1}} \widehat{R}_l \widehat{R_0^{-1}}\right)$$

where $tr(A)$ is the trace of the matrix A and T is the sample size and l is the lag size. The test statistic $Q_k(m)$ is asymptotically distributed as a chi-square distribution with $(m-p)k^2$ degrees of freedom. In practice, some of the AR parameters in a VAR(p) model are fixed to 0. In this case, the adjustment in the degrees of freedom of the chi-square distribution is set to the number of estimated AR parameters.

Multivariate time series models may contain many parameters if the dimension k is moderate or large. In practice, some of the parameters might not be statistically significant at a given significance level. So, it is advantageous to simplify the model by removing the insignificant parameters by the information criteria option. For instance, we can estimate the unconstrained VAR(p) model (under alternative hypothesis) and the constrained VAR(p) model (under the null hypothesis). If the constrained model has a smaller value for a selected criterion, then we accept the null hypothesis according to that criterion.

3.1.1.4 Forecasting:

After we have estimated the VAR model, we turn to forecasting. The minimum mean-squared error forecast of z_{h+l} is simply the conditional expectation of z_{h+l} given F_h, where h is the forecast origin and F_h is the information available at time h (inclusive). For the VAR(p) model, the general, l -step ahead forecast is

$$z_h = E(z_{h+l}|F_h) = \emptyset_0 + \sum_{i=1}^{p} \emptyset_i z_h(l-i)$$

which can be computed recursively. For a stationary VAR(p) model, all eigenvalues of $\emptyset$ are less than 1 in absolute value which leads to the relationship,

$$\emptyset^j \to 0, as\ j \to \infty$$

Consequently, we have

$$z_h(l) - \mu \to 0, as\ l \to \infty$$

In other words, the stationary VAR(p) process is mean-reverting. The speed of mean-reverting is determined by the magnitude of the largest eigenvalue, in modulus, of $\emptyset$.

It is most convenient to use the moving average (MA) representation of the VAR(p) model for the forecast error, which is

$$z_t = \mu + \sum_{i=0}^{\infty} \psi_i a_{t-i}$$

where $\mu = [\emptyset\ (1)]^{-1}\emptyset_0$, $\psi_0 = \boldsymbol{I}_k$, and

$$\psi_i = \sum_{j=1}^{\min(i,p)} \emptyset_j \psi_{i-j}, \qquad i = 1,2, \ldots,$$

which can be calculated recursively. Now we define the l-step ahead forecast error

$$e_h(l) = a_{h+l} + \psi_1 a_{h+l-1} + \cdots + \psi_{l-1} a_{h+1}$$

3.1.1.5 Impulse Response Functions:

For our analysis, we would like to know the effect of changes in carbon futures price on oil futures prices or vice versa. To figure out the effect of the changes we turn to the impulse response function analysis, also known as multiplier analysis. In the multiplier analysis, we assume that $E(z_t) = 0$ because the mean does not affect the pattern of the response of z_t to any shock. We would like to study the behaviour of z_t for $t > 0$ while z_{10} increases by 1. Using the MA representation of a VAR(p) model with coefficient matrix $\psi_l = [\psi_{l,ij}]$, we have,

$$z_0 = a_0 = [1\ 0 \ldots 0]', z_1 = \psi_1 a_0 = [\psi_{1,11}\ \ \psi_{1,21}\ \ldots\ \psi_{1,k1}]'$$

The results are the first columns of the coefficient matrices ψ_i. The coefficient matrix ψ_i of the MA representation of a VAR(p) model is referred to as the coefficient of impulse response functions. The summation $\underline{\psi}_n = \sum_{i=0}^{n} \psi_i$ denotes the accumulated responses over n periods to a unit shock to z_t. Elements of $\underline{\psi}_n$ are referred to as the nth interim multipliers. The total accumulated responses for all future periods can be stated as,

$$\underline{\psi}_\infty = \sum_{i=0}^{\infty} \psi_i$$

Often $\underline{\psi}_\infty$ is called the long-run effects. In practice, often the elements of a_t tend to be correlated. To overcome this difficulty, we can transform a_t such that components of the innovation become uncorrelated. We could use the Cholesky decomposition of $\sum_a$. Specifically, we have

$$\textstyle\sum_a = U'U$$

where $\boldsymbol{U}$ is an upper triangular matrix with positive diagonal elements. From the MA representation of z_t we have,

$$z_t = \psi(B)a_t = \psi(B)U'(U')^{-1}a_t = \left[\underline{\psi}_0 + \underline{\psi}_1 B + \underline{\psi}_2 B^2 + \cdots\right]\eta_t$$

where $\underline{\psi}_l = \psi_l U'$ for $l \geq 0$, $\eta_t = (U')^{-1}a_t$.

Let $[\underline{\psi}_{l,ij}] = \underline{\psi}_l$, which is the impulse response coefficients of z_t with orthogonal innovations. The plot of $\underline{\psi}_{l,ij}$ against l is called the impulse response function of z_t with orthogonal innovations. $\underline{\psi}_{l,ij}$ denotes the impact of a shock with size being 'one standard deviation' of the jth innovation at time t on the future value of $z_{i,t+l}$. The (i,j) th element of the transformation matrix $(U')^{-1}$ denotes the instantaneous effect of the shock η_{jt} on z_{it}. As before, The summation

$$\underline{\psi}_n = \sum_{i=0}^{n} \psi_i$$

denotes the accumulated responses over n periods to a unit shock to z_t.

3.1.2 Cointegration and Error Correction Model:

We discuss here some theoretical methodologies for Cointegration and VECM. We will start this section by defining Cointegration and its usage and derive the VECM from the VAR(p) model that we described in the previous section.

The simplest unit-root nonstationary time series is the univariate random walk, which we write as

$$z_t = \pi z_{t-1} + a_t$$

where $\pi = 1$.

The characteristic equation of this model is $1 - x = 0$, which has a solution $x = 1$. Consequently, the random walk process z_t is called a unit-root process. The solution $x = 1$ is on the unit circle which makes z_t nonstationary. We are considering the hypothesis $H_0: \pi = 1$ versus $H_1: \pi < 1$. This testing problem is called unit-root testing.

Below we summarize the framework of unit-root tests commonly employed in the literature known as the Augmented Dickey-Fuller (ADF) (Dickey, 1979) tests. It takes account of the serial correlation that may exists in the error process. Three types of model are often employed in the test. They are listed below:

- **No constant**: $\Delta z_t = \beta z_{t-1} + \sum_{i=1}^{p-1} \emptyset_i^* \Delta z_{t-1} + a_t$
- **With constant**: $\Delta z_t = \alpha + \beta z_{t-1} + \sum_{i=1}^{p-1} \emptyset_i^* \Delta z_{t-1} + a_t$
- **With constant and time trend**: $\Delta z_t = \omega_0 + \omega_1 t + \beta z_{t-1} + \sum_{i=1}^{p-1} \emptyset_i^* \Delta z_{t-1} + a_t$

where, $\beta = (\pi - 1)$. For an AR(p) process, $\emptyset(B) z_t = a_t$ with $p > 1$, such that $\emptyset(B) = \emptyset^*(B)(1 - B)$, where $\emptyset^*(B)$ is a stationary AR polynomial. Let $\emptyset^*(B) = 1 - \sum_{i=1}^{p-1} \emptyset_i^* B^i$.

The null hypothesis of interest then becomes $H_0: \beta = 0$ and the alternative hypothesis is $H_a: \beta < 0$. The test statistic is the t-ratio of the least squares estimate(LSE) of β. The usual t-ratio for testing the null hypothesis is given by

$$t_\pi = \left(\sum_{t=1}^{T} z_{t-1}^2\right)^{\frac{1}{2}} \frac{\hat{\pi} - 1}{s} = \frac{\sum_{t=1}^{T} z_{t-1} a_t}{s\sqrt{\sum_{t=1}^{T} z_{t-1}^2}}$$

where $s = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(z_t - \hat{\pi} z_{t-1})^2}$ is the residual variance.

Next, we turn to Cointegration. In econometric literature, a time series z_t is said to integrated process of order d, i.e., $I\ (d)$ process, if $(1-B)^d z_t$ is stationary and invertible, where $d > 0$. The order d is referred to as the order of integration or the multiplicity of a unit root. A stationary and invertible time series is said to be an $I\ (0)$ process.

Let us consider a multivariate process z_t. If z_{it} are $I\ (1)$ processes, but a nontrivial linear combination $\beta' z_t$ is an $I\ (0)$ series, then z_t is said to be cointegrated of order 1. In general, if z_{it} are $I\ (d)$ nonstationary and $\beta' z_t$ is $I\ (h)$ with $h < d$, then z_t is cointegrated. Cointegration often means that a linear combination of individually unit-root nonstationary time series becomes a stationary and invertible series. The linear combination vector β is called a cointegrating vector. Below we define Cointegration more formally by adhering the definition of Johansen (Johansen, 1995): Assume $\mathrm{Z_t}$ is an integrated series of order 1. We can call $\mathrm{Z_t}$ cointegrated with vector $\beta \neq 0$ if $\beta' Z_t$ can be made stationary by choosing a suitable initial distribution. The number of linearly independent cointegrating relations is the number of cointegrating rank, and the cointegrating space is the space spanned by the cointegrating relations.

Suppose that z_t is unit-root nonstationary such that the marginal models for z_{it} have a unit root. If β is a $k \times m$ matrix of full rank m, where $m < k$, such that $w_t = \beta' z_t$ is $I\ (0)$, then z_t is cointegrated series with m cointegrating vectors, which are the columns of β. This implies that there are $k - m$ unit roots in z_t. For the given full-rank $k \times m$ matrix of β with $m < k$, let $\beta_\perp$ be a $k \times (k-m)$ full rank matrix such that $\beta' \beta_\perp = \mathbf{0}$. Then $n_t = \beta'_\perp z_t$ is unit-root nonstationary. The components $n_{it}[i = 1, \dots, (k-m)]$ are referred to as the common trends of z_t. Johansen's (Johansen, 1995) method is the most popular and best-known approach to Cointegration tests for VAR model. Let the VAR(p) model for our test be:

$$\Delta z_t = c_0 + c_1 t + \boldsymbol{\Pi} z_{t-1} + \sum_{i=1}^{p-1} \boldsymbol{\Phi}_i^* \Delta z_{t-i} + a_t$$

Let m be the rank of $\mathbf{\Pi}$. There are two instances of interest.

1. Rank $(\boldsymbol{\Pi}) = 0$: Implies that $\boldsymbol{\Pi} = 0$. Thus, there is no cointegrating vector. In this case, z_t has k unit roots and we can work directly on the differenced series Δz_t, which is a VAR$(p-1)$ process.
2. Rank $(\boldsymbol{\Pi}) = m > 0$: In this case, Rank z_t has m cointegrating vectors and $k -$ m unit roots. There are $k\ \times$ m full-rank matrices α and β such that $\boldsymbol{\Pi} = \alpha\, \beta'$. The vector series $w_t = \beta' z_t$ is an I (0) process which is referred to as the cointegrating series, and α denotes the impact of the cointegrating series on Δz_t.

For simplicity, we concentrate out the effects of $c(t)$ and Δz_{t-i} from the above equation before estimating $\boldsymbol{\Pi}$. We break the equation into the following to linear regressions:

$$\Delta z_t = c(t) + \sum_{i=1}^{p-1} \varpi_i\, \Delta z_{t-i} + u_t$$

$$z_{t-1} = c(t) + \sum_{i=1}^{p-1} \varpi_i^*\, \Delta z_{t-i} + v_t$$

where, $c(t)$ is the deterministic function such as $c(t) = c_0 + c_1 t$, and u_t and v_t denote the error terms. We can estimate these regression with least-squares method. Let $\widehat{u_t}$ and $\hat{v}_t$ are the residuals of the above equations. Then we have the following regression:

$$\widehat{u_t} = \boldsymbol{\Pi}\hat{v}_t + e_t$$

where e_t denotes the error term. Let the nested hypotheses:

$$H_0\!: m = m_0 \qquad versus \quad H_a\!: m > m_0;$$

where $m = Rank(\boldsymbol{\Pi})$ and m_0 is, a given integer between $0\ and\ k-1$ with k being the dimension of z_t. Then, Johansen's (Johansen, 1995) trace statistic is defined as

$$L_{tr}(m_0) = -(T - kp) \sum_{i=m_0+1}^{k} ln\,(1 - \lambda_i)$$

where λ_i are the eigenvalues of the positive-definite covariance matrix $\hat{\Sigma}_{uu}, \hat{\Sigma}_{vv}, \hat{\Sigma}_{vu}$. If $Rank(\boldsymbol{\Pi}) = m_0$, then the m_0 smallest eigenvalues should be 0, and the test statistic should be small. On the contrary, if $Rank(\boldsymbol{\Pi}) > m_0$, then some of the eigenvalues in $\{\lambda_i\}_{i=m_0+1}^{k}$ are nonzero and the test statistic should be large.

3.1.2.1 Vector Error Correction Model:

We could give different parametrizations without imposing any binding restrictions on the model parameters of the unrestricted VAR model, i.e., without changing the value of the likelihood function. This formulation is called the Vector Error Correction Model (VECM). There are several advantages of this formulation (Juselius, 2006):

(1) The multicollinearity effect which is typically persistent in time-series data is significantly reduced in the error-correction form.
(2) The long-run effects are summarized in the levels matrix (π).
(3) To avoid the non-invertibility in the VAR model. The error-correction form for the model has an invertible MA structure, but uses z_{t-i} in the right-hand side of the model. The term z_{t-i} is referred to as the error-correction term.

3.1.2.2 Estimation of Error-Correction Models (ECM):

We illustrate two cases here. In the first case, the cointegrating matrix β is known so that the cointegrating process $w_t = \beta' z_t$ is available. In this case, our model for ECM becomes

$$\Delta z_t = \alpha w_{t-1} + c(t) + \sum_{i=1}^{p-1} \boldsymbol{\Phi}_i^* \Delta z_{t-i} + a_t$$

which can be estimated by the ordinary least-squares method. The estimates have the usual asymptotic normal distribution and the conventional approach can be used to make statistical inference. In the second case, the β is unknown. Here the model becomes

$$\Delta z_t = \alpha \beta' w_{t-1} + c(t) + \sum_{i=1}^{p-1} \boldsymbol{\Phi}_i^* \Delta z_{t-i} + a_t$$

which involves products of parameters and requires nonlinear estimation. Let us consider rewriting the cointegrating matrix β such as

$$\beta = \begin{bmatrix} \boldsymbol{I}_m \\ \beta_1 \end{bmatrix}$$

where β_1 is an arbitrary $(k - m) \times m$ matrix. We can use the Quasi Maximum Likelihood Estimation to estimate the model. We could use the initial estimate of β from Cointegration tests and the results of the previous case can be used to start the nonlinear estimation. With the presence of z_{t-1}, the limiting distribution of the estimate of $\boldsymbol{\Pi}$ involves functions of Brownian motion discussed previously.

Though Cointegration is an interesting concept there are few drawbacks of this methodology. Firstly, it does not address the rate of achieving long-term equilibrium. For example, if the cointegrating series $w_t = \beta' z_t$ has a characteristic root that is close to unit circle, then the Cointegration relationship may take a long time to achieve. Second, Cointegration tests are scale invariant.

4 Data Collection

For our paper, we have collected the data from the Intercontinental Exchange (ICE). We will concisely review the data collection technique in this section of the paper.

The European Union Allowance (EUA) Futures contract listed on the ICE is deliverable. Each Clearing Member is obligated to make or take the delivery of the Emission Allowances. The delivery is organized on or from the Union Registry upon the termination of the contract. The unit of trading is one lot which contains 1,000 Carbon Emission Allowances (EUA). Each EUA has the entitlement to emit one tonne of carbon dioxide equivalent gas. The contract trades in Euro and Euro cent per metric tonne. For the EUA futures contract, we have collected data from January second of 2008 till August seventh, 2020. For complete synchronization of our analysis, we have also taken the oil futures contract from ICE. The ICE Brent crude futures composes of North Sea crudes. The Brent crude is waterborne, which makes it easy to access on different global shipping, ports, and storage capacity around the world. The contract size is 1,000 barrels and is settled in cash.

For both futures price, we have confined to the returns instead of the futures price. Campbell et al. (Campbell, et al., 1997) provided two justification for using returns, (i) return of an asset is a complete and scale-free summary of the investment opportunity, (ii) return series are easier to handle than price series and the former has more attractive statistical properties. The primary reason for taking the returns is, prices tend to be more volatile than returns which could distort the analysis. For example, around the end of phase one for EU ETS, the prices were almost zero, which could skew the total dataset giving us biased results. Similarly, during the 2008 Financial crisis, oil prices plummeted.

5 Data Analysis

After collecting the data from the Intercontinental Exchange, we converted the daily price change into natural logarithmic returns so that all the data are on the same scale. A snapshot of the data after conversion is given below. The full dataset can be accessed here.

Date	carbonReturn	brent1mReturn	brent2mReturn	brent3mReturn
2008-01-02	↑ 2.25	↑ 4.16	↑ 3.96	↑ 2.89
2008-01-03	↑ 2.67	↓ -0.25	↓ -0.14	↑ 0.48
2008-01-04	↑ 0.04	↓ -0.83	↓ -0.9	↓ -0.12
2008-01-07	↑ 0.47	↓ -2.51	↓ -2.36	↓ -1.93
2008-01-08	↑ 0.17	↑ 1.21	↑ 1.12	↑ 0.74
2008-01-09	↓ -1.19	↓ -1.23	↓ -1.61	↓ -2.01
2008-01-10	↓ -1.33	↓ -2.3	↓ -2.07	↓ -1.28
2008-01-11	↓ 0	↓ -1.25	↓ -1.1	↓ -0.72
2008-01-14	↑ 1.29	↑ 2.01	↑ 1.91	↑ 1.67
2008-01-15	↓ -1.03	↓ -2.11	↓ -1.86	↓ -1.27
2008-01-16	↓ -1.83	↓ -1.46	↓ -1.44	↓ -0.84
2008-01-17	↓ -2.31	↓ -0.84	↓ -0.88	↓ -0.74
2008-01-18	↑ 0.22	↑ 0.54	↑ 0.32	↑ 0.08
2008-01-21	↓ -6.68	↓ -1.95	↓ -1.79	↓ -1.05
2008-01-22	↓ -2.58	↑ 1.07	↑ 1.01	↑ 0.77
2008-01-23	↓ -1.39	↓ -2.09	↓ -2.17	↓ -1.75
2008-01-24	↓ -1.36	↑ 2.79	↑ 2.71	↑ 2.05
2008-01-25	↑ 6.28	↑ 2.03	↑ 2.12	↑ 1.98
2008-01-28	↓ -1.87	↑ 0.53	↑ 0.52	↑ 0.72
2008-01-29	↑ 0.24	↑ 0.68	↑ 0.54	↑ 0.18

Figure I Return Series

The data has been collected from February of 2008 till August of 2020. The first column is the Date column. The next columns are daily carbon returns, one month Brent crude returns, two month Brent crude returns and three month Brent crude returns. The green colour signifies that the returns are positive for that month and the red colour signifies that the commodity incurred a negative return. However, we cannot interpret the true property of the data until we plot the data. Below we depict the returns individually.

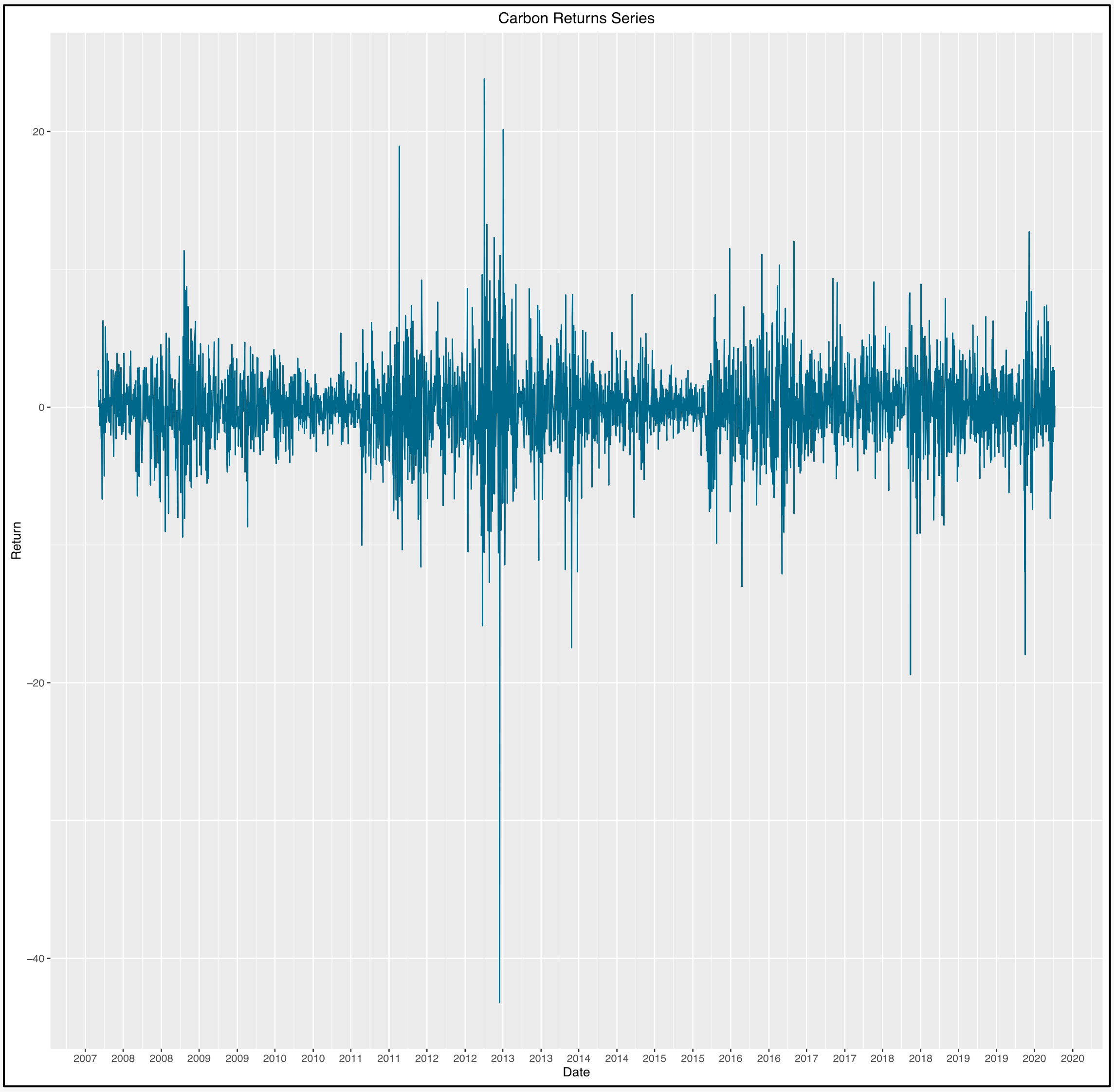

Figure II Carbon Return Series

After plotting the returns, we can see that the data looks quite stationary, however, we visualize some outliers which can be thought of the various economic downturn that carbon futures price went through its timeline. For example, the most significant outlier is the drop of almost 40% which can be attributed to the fact that at the end of phase 2, the cumulative surplus in the allowances increased to more than 2.1 billion (European Commission, 2014). Due to coronavirus, many factories have stopped production temporarily and it affected the price of EU ETS. The price of allowance fell to EUR 15 from EUR 25. When companies sell emission allowances on a large scale, the emission price drops and a surplus may arise. It is important to be aware of the measures offered by the ETS rules to avoid a surplus of allowances. These measures result in a decrease in the number of allowances in circulation, as a result of which the CO2 price is expected to remain relatively high (Angeren, et al., 2020).

Next, we plot the Brent crude one month return series.

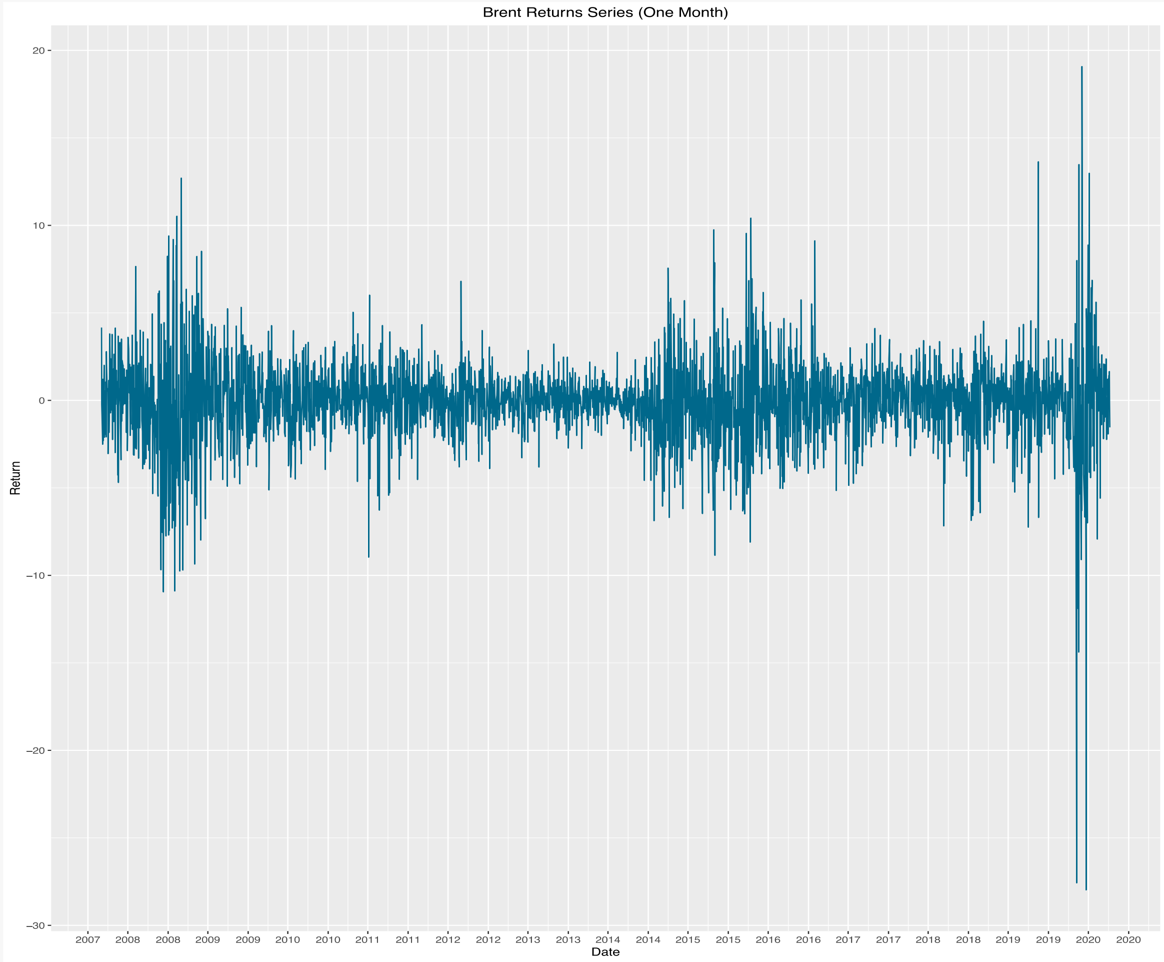

Figure III Brent Crude Returns (One Month)

As we can see from the plot, the series looks visually stationary except the fact that there might be some outliers. Such as we can see the anomalous spike around the financial crisis of 2008. We can also clearly see the impact of recent economic turmoil due to coronavirus on the oil price. In our analysis, we will also include the Brent Crude two months and three months return to discover the dynamic relationship between the futures contract of one, two and three month. The three returns series depicts similar behaviour which can be seen from the plots.

5.1 VAR Analysis

As mentioned in the estimation of VAR in our paper, there are primarily three criteria to select VAR order for further analysis. All the criteria are based on likelihood and consist of two components. The first component is concerned with the goodness of fit of the model to the data, whereas the second component penalizes more heavily complicated models. The order is selected based on the sequential M-statistic given by:

$$M(l) = -(T - P - 1.5 - kl)\ln\left(\frac{|\widehat{\Sigma}_{a,l}|}{|\widehat{\Sigma}_{a,l-1}|}\right)$$

for $l = 1, \ldots, P$, $where\ \widehat{\Sigma}_{a,l}$ is the residual covariance matrix. However, these are estimates and is a good starting point to start our initial analysis. After computing the statistics, we looked at the p-values and select an initial VAR order for our model. If z_t is indeed a Gaussian VAR(p) time series with $p < \infty$, then both BIC and HQ are consistent in the sense they will select VAR(p) model with probability 1 as $T \to \infty$. After conducting our order selection analysis with Carbon Return series and Brent Crude Return series, we see that AIC selected an order of 13, BIC selected an order of 1 and HQ selected an order of 2. For our paper, we will initialize our VAR model with VAR (2).

5.1.1 Model Estimation

With our selected VAR order of 2 estimated by HQ, we start our VAR analysis. From the output, the VAR (2) model for the daily returns of Brent Crude and Carbon EUAs is:

$$\textbf{Carbon Returns (one month):}$$

$$z_{1t} = 0.551z_{3,t-1} - 0.653z_{4,t-1} - 0.0684z_{1,t-2} - 0.419z_{3,t-2} + 0.471z_{4,t-2} + a_{1t}$$

$$\textbf{Brent Returns (one month):}$$

$$z_{2t} = 0.292z_{2,t-1} - 0.391z_{4,t-1} + a_{2t}$$

where, $\mathrm{z_{1t}} = \text{Carbon Returns}$, $\mathrm{z_{2t}} = \text{Brent Returns(one month)}$,

$\mathrm{z_{3t}} = \text{Brent Returns(two month), and } \mathrm{z_{4t}} = \text{Brent Returns(three months)}$.

The correlation matrix of the residuals is:

$$R_0 = \begin{bmatrix} 1.00 & 0.214 & 0.214 & 0.207 \\ 0.214 & 1.00 & 0.988 & 0.969 \\ 0.214 & 0.988 & 1.00 & 0.990 \\ 0.207 & 0.969 & 0.990 & 1.00 \end{bmatrix}$$

We start with the correlation matrix of the residuals. It is evident that the correlation between carbon returns and Brent Crude returns is low. However, we can clearly see that the Brent Crude Futures are instantaneously correlated with each other and have a high correlation of 0.9. Therefore, we can say that the futures contract of Brent Crude has a dynamic interdependence on each other.

Now we move to the model interpretation. All the estimates are significant at the usual 5% level. The fitted four-dimensional model shows that the returns for carbon futures depend on the lagged Brent Crude two-month futures contract positively and negatively dependent on the Brent Crude three-month futures contract. Though, the Carbon Futures returns are not contemporaneously related with Brent Crude one-month futures contract, the Carbon Futures returns are dependent on its lagged value -0.0684. One of the reason that we can attribute to the above-mentioned behaviour could be due to hedging tactics deployed by the futures contract holder. There has been no evidence of correlation or dynamic interaction between the Brent Crude futures contract and Carbon Futures contract. However, the relationship between these two contracts might be long-term and can be found by Cointegration or Error-Correction model that we deploy in the next section of our analysis. Furthermore, the Brent Crude one-month returns are dependent on its lagged value and negatively related with the Brent Crude three-month returns.

5.1.2 Residual Analysis

Residual analysis is an extremely important part of data analysis. We start with the residual cross-correlation matrices. The dashed lines of the plots indicate the approximate 2 standard-error limits of the cross-correlations, that is $\pm 2/\sqrt{T}$. Based on the plots, the residuals of the model have some strong cross-correlations.

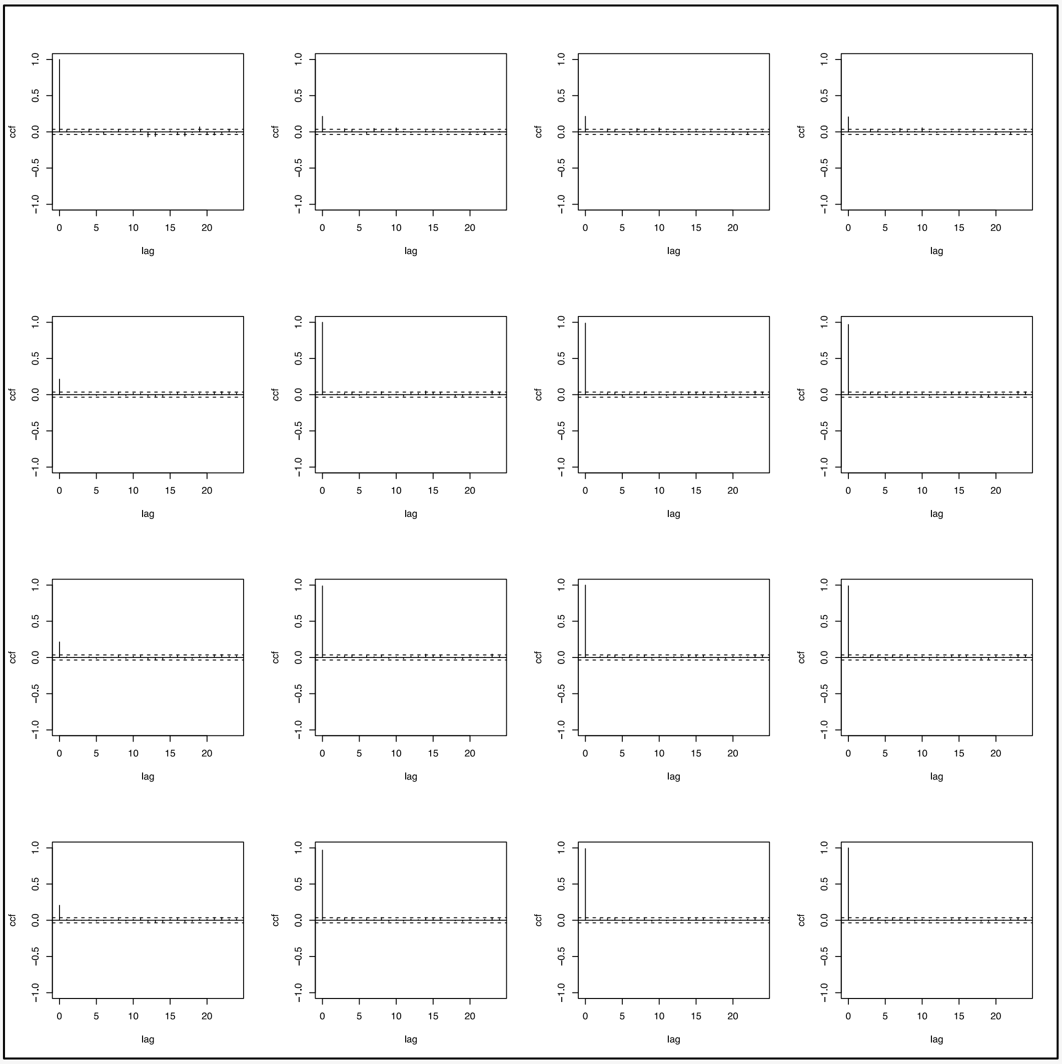

Figure IV Residual Analysis of VAR

Next, we plot the multivariate Portmanteau test to check the residual cross-correlations. The below figure plots the p-values of the $Q_4(m)$ statistics applied to the residuals of the VAR (2) model. Since there are 11 parameters, the degree of freedom of the chi-square distribution for $Q_4(m)$ is 11.

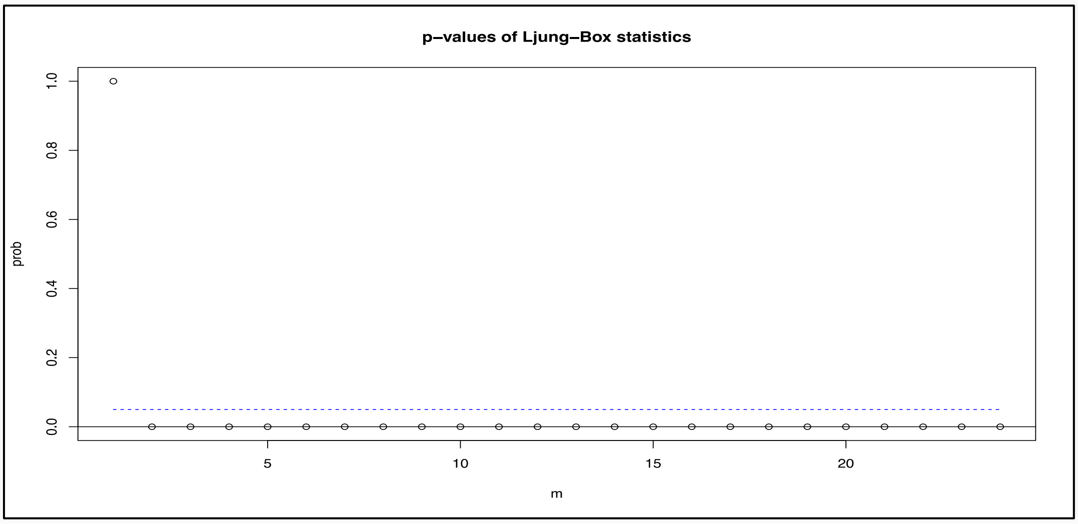

Figure V Portmanteau Statistic

There is a strong indication of serial correlations in the residuals of the VAR (2) model. The reason behind it might be that the oil futures contract is dynamically dependent on each other and influence each other in both negative and positive way. We have also tried differencing the series and the serial correlation tends to pertain.

5.1.3 Forecasting

Previously in our analysis, we fitted a VAR (2) model on the return series data. Using this model, we consider one-step to five-step ahead forecasts of the returns at the forecast origin seventh August of 2020. We also provide the standard errors and root mean-squared errors of the predictions. The root mean-squared errors include the uncertainty due to the estimated parameters. The results are given in the figure below:

	Forecasts				Standard Errors				Root MSE			
Step	Carbon Return	Brent Crude One Month	Brent Crude Two Month	Brent Crude Three Month	Carbon Return	Brent Crude 1M	Brent Crude 2M	Brent Crude 3M	Carbon Return	Brent Crude 1M	Brent Crude 2M	Brent Crude 3M
1	0.2469	1.682e-01	1.594e-01	1.341e-01	3.107	2.384	2.243	2.065	3.111	2.387	2.246	2.068
2	(-0.1122)	(-3.238e-03)	(-2.522e-03)	(-2.973e-03)	3.115	2.393	2.253	2.072	3.115	2.394	2.253	2.072
3	(-0.0199)	2.157e-04	1.993e-04	1.755e-04	3.125	2.393	2.253	2.072	3.125	2.393	2.253	2.072
4	0.0073	(-5.546e-06)	(-4.605e-06)	(-4.887e-06)	3.125	2.393	2.253	2.072	3.125	2.393	2.253	2.072
5	0.0013	2.892e-07	2.626e-07	2.387e-07	3.125	2.393	2.253	2.072	3.125	2.393	2.253	2.072

Figure VI Forecast Analysis

From the figure, we can make the following observations. First, the point forecasts of the four series move closer to the sample means of the data as the forecast horizon increases, showing the evidence of mean reverting. Second, the standard errors and root mean-squared errors of forecasts increase with the forecast horizon. The standard errors should converge to the standard errors of the time series as the forecast horizon increases. Third, the effect of using estimated parameters is evident when the forecast horizon is small. The effect vanishes quickly as the forecast horizon increases which is a reasonable explanation because a stationary VAR model is mean reverting. The standard errors and mean-squared errors of prediction converges to the standard error of the series. An interesting thing would be to forecast the distribution for the next day future contract price which itself can be a further research topic.

5.1.4 Impulse Response Function

The below figure shows the impulse response functions of the fitted four-dimensional model. From the plots, the impulse response functions decay to 0 quickly. This is expected for a stationary series.

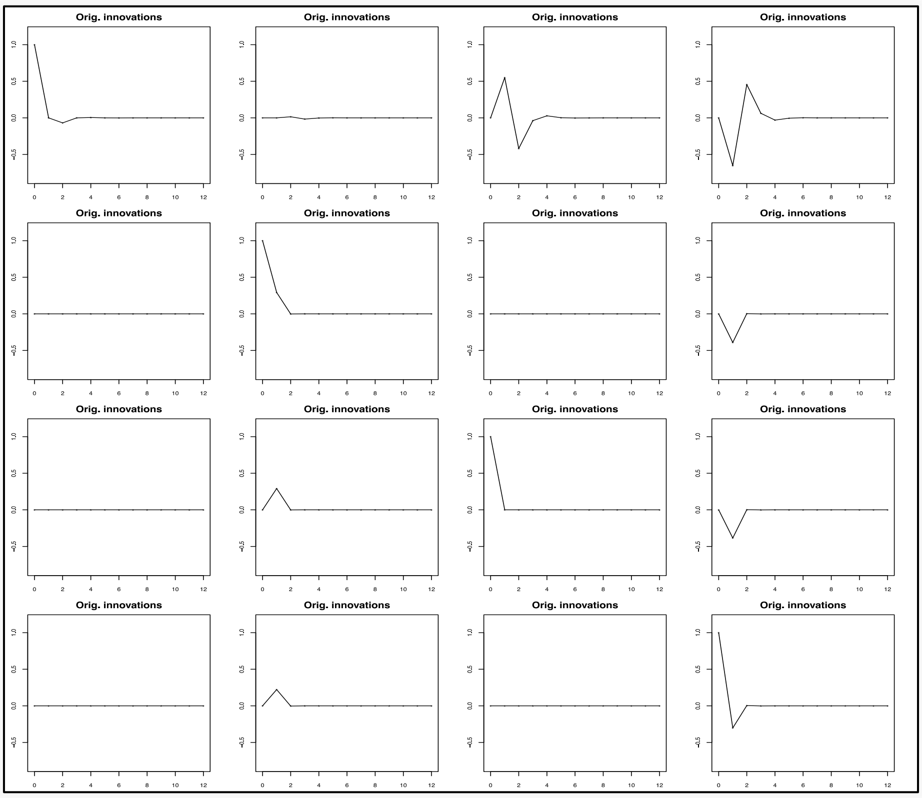

Figure VII Impulse Response Function

We are essentially interested in the first row of plots. The farthest left plot is the impulse on Carbon Returns. As per the equation (i), we see a response from the two-month Brent Crude futures and the three-month Brent Crude futures. The delayed effect on the Carbon Return is due to the fact that a change in Carbon Returns at time t affects the Brent Crude two-month return at both $t + 1$ and $t + 2$. The impulse also effects Brent Crude three-month return at $t + 1$ and $t + 2$. However, the impulse response functions show the marginal effects, not the conditional effects.

5.2 Cointegrating Price Relationship

Cointegration tests measures whether the difference in means between two variables remains constant. When testing for Cointegration, we use prices rather than returns since we are more interested in the trend between the variables' means over time than in the individual price movements. We will start our Cointegration analysis by plotting the price series of Brent Futures and Carbon Futures. The time frame for both the series is from January of 2008 till August seventh of 2020. The price series has been transformed into natural logarithm to ensure scalability of the two variables.

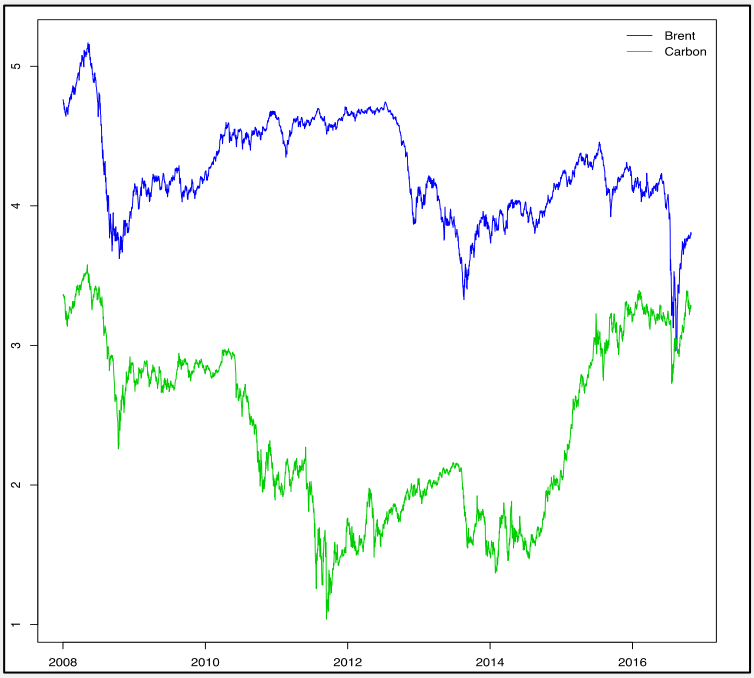

Figure VIII Brent Crude and Carbon Price Series

From the above figure, we can see that the two-price series has some co-movements between the variables, however, it is not that evident. We can also see some structural breaks around the time after 2008, before 2014 and around 2020. These structural breaks can be attributed to the facts of financial crisis, and coronavirus.

5.2.1 Estimation of the model

The VAR analysis of our paper was conducted based on the returns computed on the price series used for the Cointegration analysis here. However, using returns for Cointegration analysis might yield spurious results. For this reason, we are using the price series to identify whether Brent Futures and Carbon Futures share a common stochastic trend. Furthermore, the primary idea behind Cointegration is

$$X_t - \theta Y_t = I(0)$$

where X_t is the Carbon Futures price series integrated of order $I\ (1)$,
Y_t is the Brent Futures price series integrated of order $I\ (1)$,
and θ is the cointegrated vector.

5.2.2 Tests for Cointegration

There are primarily two different tests for Cointegration. We will employ both test here to make sure that both test results yield similar results. We will start with Engle-Granger ADF tests of Cointegration. Then, we will move on to the Johansen procedure for Cointegration. For both tests, we start by selecting the correct lag order. Next, we employ the Cointegration tests to check for the equation $X_t - \theta Y_t = I(0)$. If there is a cointegrating vector, we move on to the analysis of the long-term relationship between the variables. However, if we do not find any cointegrating vector, we conclude our result by stating the fact that the price series are not cointegrated.

5.2.2.1 VAR Order

From our analysis, we can see that according to the AIC the selected lag order is 5, according to BIC and HQ the selected lag order is 2. As previously discussed, BIC and HQ are more consistent than AIC. We will consider the lag order of 2 for our analysis.

```
selected order: aic =  5
selected order: bic =  2
selected order: hq =  2
Summary table:
       p      AIC      BIC       HQ       M(p) p-value
 [1,]  0  -3.0352  -3.0352  -3.0352     0.0000  0.0000
 [2,]  1 -14.3685 -14.3610 -14.3658 36336.8712  0.0000
 [3,]  2 -14.3805 -14.3654 -14.3751    46.3948  0.0000
 [4,]  3 -14.3832 -14.3605 -14.3750    16.4390  0.0025
 [5,]  4 -14.3843 -14.3541 -14.3735    11.5453  0.0211
 [6,]  5 -14.3852 -14.3474 -14.3716    10.7482  0.0295
 [7,]  6 -14.3830 -14.3377 -14.3668     0.9640  0.9152
 [8,]  7 -14.3813 -14.3285 -14.3623     2.4730  0.6495
 [9,]  8 -14.3808 -14.3205 -14.3592     6.5308  0.1629
[10,]  9 -14.3807 -14.3127 -14.3563     7.3475  0.1186
[11,] 10 -14.3793 -14.3039 -14.3523     3.6795  0.4511
[12,] 11 -14.3786 -14.2956 -14.3489     5.7274  0.2205
[13,] 12 -14.3787 -14.2882 -14.3463     8.1587  0.0859
[14,] 13 -14.3837 -14.2856 -14.3485    23.5900  0.0001
```

Figure IX VAR Order for Cointegration Analysis

5.2.2.2 Unit-Root Testing

With the VAR order, we obtained in the previous page, we perform the ADF test here to determine whether the financial variables follow a random walk. If the series has unit root, then it is said to follow a random walk i.e., implying a non-stationarity condition. For our analysis, we deploy the Augmented Dicky-Fuller (ADF) Test for checking unit root in time series. We perform ADF tests for each of our variable. As we can see from figure, the value of our test statistic is -0.8719 and the critical values are, $-2.58, -1.95, -1.62$ for the 1%, 5% and 10% significance level.

```
###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression none


Call:
lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)

Residuals:
      Min        1Q    Median        3Q       Max
-0.283475 -0.010211  0.000842  0.010954  0.186547

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
z.lag.1     -8.758e-05  1.005e-04  -0.872   0.3833
z.diff.lag1 -4.140e-02  1.763e-02  -2.348   0.0189 *
z.diff.lag2  1.296e-02  1.763e-02   0.735   0.4625
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.02431 on 3216 degrees of freedom
Multiple R-squared:  0.002154,  Adjusted R-squared:  0.001224
F-statistic: 2.315 on 3 and 3216 DF,  p-value: 0.07393


Value of test-statistic is: -0.8719

Critical values for test statistics:
      1pct  5pct 10pct
tau1 -2.58 -1.95 -1.62
```

Figure X ADF Test 1

In the next test, we considered whether the variable is integrated of order 1.

we got a test statistic of -31.9171 with the critical values of $-2.58, -1.95, -1.62$ for the 1%, 5% and 10% significance level respectively. Clearly, we can see that the null hypothesis is rejected, unit root is not present. Thus, it is evident that the Brent price series is integrated of the order 1.

```
###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression none


Call:
lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)

Residuals:
      Min        1Q    Median        3Q       Max
-0.283949 -0.010666  0.000544  0.010578  0.188821

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
z.lag.1     -0.99691    0.03123 -31.917   <2e-16 ***
z.diff.lag1 -0.04486    0.02545  -1.763   0.0780 .
z.diff.lag2 -0.03052    0.01763  -1.732   0.0834 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.02431 on 3215 degrees of freedom
Multiple R-squared:  0.5215,	Adjusted R-squared:  0.5211
F-statistic:  1168 on 3 and 3215 DF,  p-value: < 2.2e-16


Value of test-statistic is: -31.9171

Critical values for test statistics:
      1pct  5pct 10pct
tau1 -2.58 -1.95 -1.62
```

Figure XI ADF Test 2

Similar test results are yielded when we perform unit root tests for Carbon Futures price. First, we perform ADF test to check whether the price series is a random walk. Our test statistic is -0.4115 and corresponding critical values are $-2.58, -1.95, -1.62$ for the 1%, 5%, and 10% significance level. Clearly the series is unit-root non-stationary.

```
###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression none


Call:
lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)

Residuals:
     Min       1Q   Median       3Q      Max
-0.42576 -0.01437  0.00067  0.01592  0.23665

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
z.lag.1     -9.178e-05  2.231e-04  -0.411 0.680762
z.diff.lag1  1.440e-02  1.760e-02   0.818 0.413185
z.diff.lag2 -6.578e-02  1.760e-02  -3.738 0.000189 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.0313 on 3216 degrees of freedom
Multiple R-squared:  0.004565,	Adjusted R-squared:  0.003636
F-statistic: 4.916 on 3 and 3216 DF,  p-value: 0.002076


Value of test-statistic is: -0.4115

Critical values for test statistics:
      1pct  5pct 10pct
tau1 -2.58 -1.95 -1.62
```

Figure XII ADF Test 3

Next, we check for whether the price series is of $I\,(1)$. The value of our test statistic is -34.499 and the corresponding 1%, 5%, and 10% critical values are $-2.58, -1.95, -1.62$ respectively.

Thus, we conclude that both the price series are integrated of order 1. We now move on to checking whether the price series are cointegrated or not.

```
###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression none


Call:
lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)

Residuals:
     Min       1Q   Median       3Q      Max
-0.42577 -0.01468  0.00049  0.01570  0.23580

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
z.lag.1     -1.06599    0.03090 -34.499  < 2e-16 ***
z.diff.lag1  0.07944    0.02473   3.212  0.00133 **
z.diff.lag2  0.01383    0.01764   0.784  0.43307
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.0313 on 3215 degrees of freedom
Multiple R-squared:  0.4956,    Adjusted R-squared:  0.4951
F-statistic:  1053 on 3 and 3215 DF,  p-value: < 2.2e-16


Value of test-statistic is: -34.499

Critical values for test statistics:
      1pct  5pct 10pct
tau1 -2.58 -1.95 -1.62
```

Figure XIII ADF Test 4

5.2.2.3 Engle-Granger ADF test

Since there are no theory suggesting the value of θ, we first compute the θ using the first-stage OLS regression with the following equation:

$$CarbonFutures, X_t = \beta_0 + \beta_1 BrentFutures + z_t$$

The result of the regression is given in the following figure. Our $\theta = 0.0491$ which is not even at 10% level.

```
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   2.1852     0.1331  16.412   <2e-16 ***
brent         0.0491     0.0312   1.573    0.116
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6245 on 3220 degrees of freedom
Multiple R-squared:  0.0007682, Adjusted R-squared:  0.0004579
F-statistic: 2.476 on 1 and 3220 DF,  p-value: 0.1157
```

Figure XV EG-ADF Test

```
Residuals:
     Min       1Q   Median       3Q      Max
-1.36936 -0.57059 -0.05462  0.51454  1.14173
```

Figure XIV Residual of EG-ADF Test

However, we continue our Cointegration with residuals from the analysis given in the next figure.

The result of our Cointegration analysis is the given figure. Here we can see that the test statistic is -1.3816 and the corresponding 1%, 5%, and 10% critical values are $-2.58, -1.95, -1.62$ respectively. Thus, we conclude our test for Cointegration by stating that the price series of Brent Futures and Carbon Futures are not cointegrated.

```
###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression none


Call:
lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)

Residuals:
     Min       1Q   Median       3Q      Max
-0.42563 -0.01469  0.00047  0.01576  0.23475

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
z.lag.1     -0.0012171  0.0008809  -1.382 0.167185
z.diff.lag1  0.0140589  0.0175935   0.799 0.424296
z.diff.lag2 -0.0666705  0.0175945  -3.789 0.000154 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.03116 on 3216 degrees of freedom
Multiple R-squared:  0.005275,  Adjusted R-squared:  0.004347
F-statistic: 5.685 on 3 and 3216 DF,  p-value: 0.0007026


Value of test-statistic is: -1.3816

Critical values for test statistics:
      1pct  5pct 10pct
tau1 -2.58 -1.95 -1.62
```

Figure XVI ADF Test 5

5.2.2.4 Johansen Cointegration Test

In our theoretical construct section, we have discussed the theoretical concept behind the Johansen Cointegration Test. In the previous section, we performed an Engle-Granger Test for Cointegration and concluded that the price series of Carbon Futures and Brent Futures are not cointegrated. To verify our result, we will conduct the Johansen Cointegration test on the price series and check the result with the Engle-Granger Test for Cointegration.

The VAR order selection and the Unit Root Testing is same as the previous section. Our VAR order was 2 according to the HQ and BIC criterion and both the price series are integrated of order 1. The figure below is our output of the analysis. In the figure r is the rank of the coefficient matrix for the first lag. When the matrix $A = 0$ the series are not cointegrated. We perform an eigenvalue decomposition on A. The Johansen Test checks if $r = 0$ or 1. In our analysis, the test statistic for r is 7.09 and the corresponding 1%, 5%, and 10% critical values are $23.52, 17.95, 15.66$ respectively.

Clearly, we cannot reject the rank of r and conclude that the price series are not cointegrated. The result is consistent with Engle-Granger Cointegration Test.

```
######################
# Johansen-Procedure #
######################

Test type: trace statistic , with linear trend

Eigenvalues (lambda):
[1] 0.0018434939 0.0003557847

Values of teststatistic and critical values of test:

          test 10pct  5pct  1pct
r <= 1 | 1.15  6.50  8.18 11.65
r = 0  | 7.09 15.66 17.95 23.52

Eigenvectors, normalised to first column:
(These are the cointegration relations)

            CarbonP.l2 BrentP.l2
CarbonP.l2    1.000000  1.000000
BrentP.l2     1.831935 -1.716163

Weights W:
(This is the loading matrix)

              CarbonP.l2     BrentP.l2
CarbonP.d -0.0008062526 -0.0005767923
BrentP.d  -0.0010221801  0.0002369326
```

Figure XVII Johansen Cointegration Test

5.3 Structural Breaks Analysis

Structural break can be caused by new legislation that affects the economy or by a redefinition of the policy affect the time series or any significant external effects. A structural break or change can have a long-lasting effect on the time series of $I\ (1)$ characteristics. In our paper, both Carbon Futures prices and Brent Crude Futures prices are of $I\ (1)$ i.e., integrated of order 1. Our research hypotheses and literature review indicated that there might be a cointegrated relationship between the two-price series, however, the analysis indicated that the series are not cointegrated. Such unexpected result led us to the structural break analysis. The figure displays the result for the presence of structural breaks in the Carbon Futures price dataset. As we can see from the figure, there are five structural breaks, starting at $2009, 2010, 2012, 2013,\ 2015$.

The next figure displays the structural breaks in the Carbon Futures price series. In the Discussion section, we will identify some suggestive reasoning behind the price behaviour.

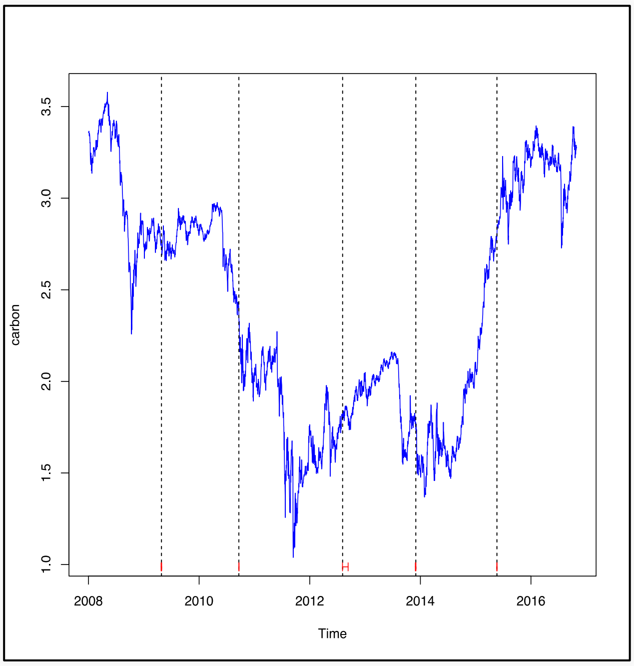

Figure XVIII Structural Breaks in the Carbon Price Series

We also conducted a Cointegration analysis with structural breaks however, we did not found any significant result. We plotted the Carbon price series along with the regression line considering five structural breaks. The figure is illustrated below:

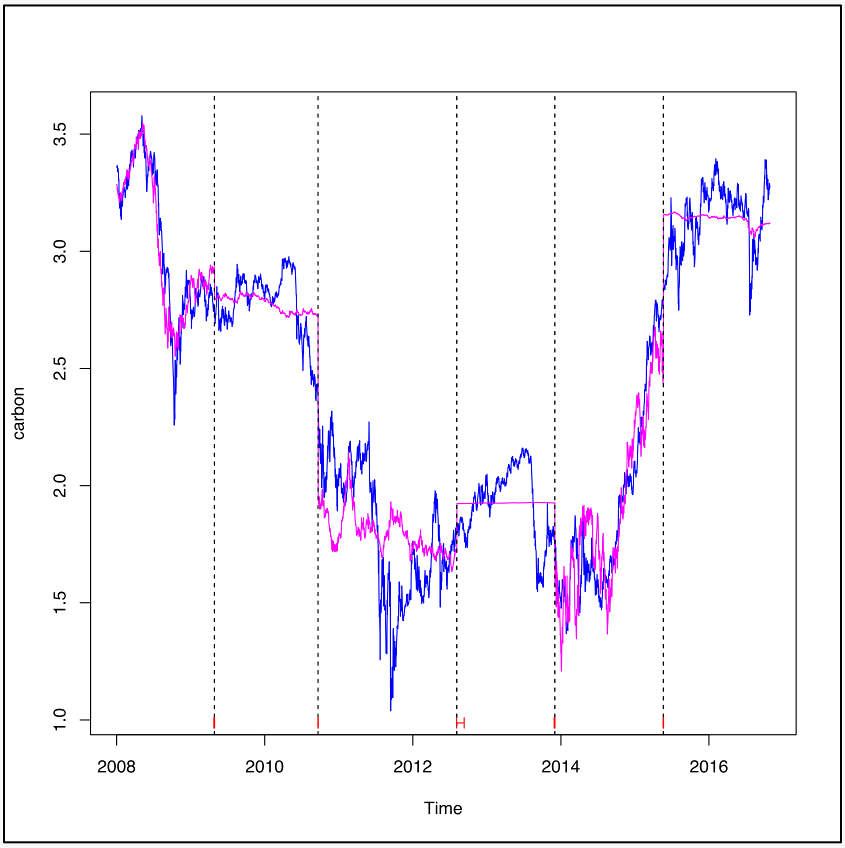

Figure XIX Changes in Carbon Price Series

As we can see from the figure, the aftershock of 2008 financial crisis changed the relationship between the Carbon price series and Brent Crude price series. The relationship returned to somewhat normalized position after 2014 and before 2016. From the above figure, we can assume that due to several macroeconomic policies and external influence the dynamic relationship between the Carbon price and Brent Crude price has changed significantly.

6 Results and Discussion

In the previous section, we conducted several analyses on the Carbon Futures and Brent Crude Futures return and prices. We deployed a VAR model on the returns and we checked whether the price-series (Carbon and Brent) are cointegrated. We also checked for structural breaks in the series. The final results found on the previous section is summarized here.

Brent Crude Futures returns have some significant effects on the Carbon Futures returns, however, the residuals are non-stationary. The price-series of Carbon Futures and Brent Crude Futures are not cointegrated. There are five structural breaks in the Carbon Futures price series. The break periods are $2009, 2010, 2012, 2013, 2015$. The breaks in the price series might be the primary reason behind the reasoning of no Cointegration. We also conducted a Cointegration analysis with five structural breaks and found out that the relationship between the Carbon price series and Brent Crude price series has changed after the shock of 2008 financial crisis drastically.

The implications for our research work can be manifold in various situations. Firstly, the third phase of the EU ETS will be ending by 2020. The policymakers can focus on strategies that excludes oil as a primary driver of CO2 emissions and design policy plans regarding coal and natural gas based energy sources. Secondly, dynamics of the oil market is more complex than it seems which would lead further researchers to investigate on the mechanism of the oil market by including other relevant factors such as political influence, demand and supply relationship. The CO2 emission can only be a small part of the dynamics. Thirdly, further research between the dynamic relationship of fossil fuel (coal, natural gas) and EU ETS might lead to an increase in the marginal cost of production for energy which in turn could affect on the price of the product. These research works could lead to the increased dependency on the renewable energy sources.

In our paper, we attempted to identify the dynamic relationship between the Carbon Futures and Brent Crude Futures. There is some effect of Brent Crude Futures return on the Carbon Futures return, however, the price series is not cointegrated. Our suggestive reasoning behind the behaviour is most industries uses gasoline or coal as an energy input rather than oil. There might be some plausible connection between the gasoline or coal prices and Carbon prices if we deploy a Cointegration model for these commodities. The volatility of the Carbon and Oil might be cointegrated however, we cannot state it as a fact. Furthermore, there are several structural breaks in the Carbon Futures price series which might be another reason for the above-mentioned results. The first break date is in 2009 which corresponds to the after-shock of the financial crisis happened in 2008. Structural breaks can have long-lasting effect on time series that are of integrated of order 1. The European Union Emissions Trading Scheme was launched around 2006 to control the effect of Fossil Fuel on our environment and economy. The scheme was designed towards the decrease of hazardous gas on our atmosphere. From a logical reasoning perspective, it would make sense that the increase and decrease in the price of Oil would eventually affect the increase and decrease in price of Carbon. However, as we have studied in our paper, the logical reasoning does not hold. The means between the two-price series is not constant. According to a press release by the European Commission, the EU ETS emissions fell 11.6% in 2009 compared to 2008 (European Commission, 2010). The structural breaks primarily refer to the price drops that happened during that period. There are three commonly identified factors that affects the low EUA price: economic recession, policies regarding renewables, and the usage of international credits (Skeptical Science, 2016). However, the price variation and the breaks in the series is largely unexplained due to the time and resource constraint of our research. Further research is required to identify the imperative reason behind the breaks.

As we have seen from our analysis, the Brent Crude Futures and Carbon Futures are not cointegrated. Carbon pricing is a penalty to the usage of Fossil Fuel. However, due to myriad reasons, it may be wise to associate other energy factors such as gasoline and coal with Carbon rather than Oil. Most industry uses gasoline and coal as an input in the energy factor. Brent Crude might be imperative to transportation however, it is not than imperative when it comes to industry usage. Economist and policy researcher should take it in consideration while designing renewables policies. Further research can shed light on the matter of creating renewables policies. It would also be interesting to identify the change in volatility given the two-price series, Carbon Futures and Brent Crude. The change in volatility could be designed as a density function and the changes in it can be measured through the impulses given to it. For example, given a high price change at time t, how would the density plot react at time $t + 1$.

Another important improvement over our paper would be to employ the Gregory-Hansen Cointegration test which is superior to Engle-Granger test. The Gregory-Hansen test involves testing for Cointegration with regime shift at an unknown date. The test would help us identify the cointegrating relationship between the Brent Crude Futures and Carbon Futures all along the time-period from 2008 to 2020. Further research work on this topic might yield some better insight on our assumption that there used to be a cointegrating relationship between the two commodities, however, it changed due to some specific structural regime change.

7 Conclusion

The relationship between the fossil fuel and carbon is significant to researchers and policy makers. The identity of the relationship could help them make decisions that would lead to the betterment for the society and environment. In our paper, we found out that the Carbon Futures Return and Brent Crude Futures Return (one month) does not have an implied or dynamic relationship, however, the Brent Crude Futures Return for two and three months have some effect on the Carbon Futures Return. The result could not be generalized immediately and should go through some other extensive tests that we discussed in the Results and Discussion section of our paper. Furthermore, there is no apparent cointegrating relationship between Carbon Futures and Brent Crude Futures price series, however, there are several structural shifts in the Carbon Futures price series, which can lead to spurious results for Engle-Granger and Johansen Cointegration test results that we conducted. A further improvement over those techniques would be to deploy the Gregory-Hansen Cointegration test that captures the cointegrating relationship with structural shifts. The results of our paper can help other researchers to further investigate the relationship between other types of fossil fuel such as natural gas or coal to EUAs. The implications for our paper could help future researchers and policymakers focus on the dynamic relationship between coal based and natural gas based energy sources and EU ETS excluding the oil based energy sources.

8 Bibliography

- Accioly, R. d. M. e. S. & Aiube, F. A. L., 2008. Analysis of Crude Oil and Gasoline Prices through Copulas. *Cadernos do IME – Série Estatística* , Volume 24, pp. 15-28.
- Akaike, H., 1981. Likelihood of a model and information criteria. *Journal of Econometrics*, 16(1), pp. 3-14.
- Alberola, E., Chevallier, J. & Chèze, B., 2008. Price drivers and structural breaks in European carbon prices 2005–2007. *Energy Policy*, February, 36(2), pp. 787-797 .
- American Chemical Society National Historic Chemical Landmarks, 2009. *Development of the Pennsylvania Oil Industry.* [Online]
  Available at: https://bit.ly/2ZTdVgd
  [Accessed 09 05 2020].
- Angeren, J. R. v., Lam, V. v. '. & Putting, S., 2020. *The effects of the coronavirus crisis on the European Emissions Trading System.* [Online]
  Available at: https://www.lexology.com/library/detail.aspx?g=593b6ff6-9290-4d44-b6d5-bdbfae3874d8
  [Accessed 16 07 2020].
- Aoghs.org Editors, 2019. *First American Oil Well.* [Online]
  Available at: https://bit.ly/3ffNUOB
  [Accessed 08 05 2020].
- Arrhenius, S., 1896. On the Influence of Carbonic Acid in the Air upon the Temperature of the Ground. *Philosophical Magazine and Journal of Science,* 41(251), pp. 237-276.
- Bamberg, J. H., 1994. *The History of the British Petroleum Company.*. 1st ed. Cambridge: Cambridge University Press.
- Bayly, L., 2020. *U.S. crude oil futures for May plummet to minus $37 — lowest price in history.* [Online]
  Available at: https://www.nbcnews.com/business/markets/oil-prices-tumble-lowest-level-1980s-n1187716
  [Accessed 30 05 2020].
- Benz, E. & Trück, S., 2009. Modeling the price dynamics of CO2 emission allowances. 31(1), pp. 4-15.
- Biddle, F. M., 1985. The Saudi strategy in cutting oil prices. [Online]
  Available at: https://www.chicagotribune.com/news/ct-xpm-1985-09-22-8503040428-

story.html
[Accessed 28 08 2020].

- Bird, P. J. W. N., 1987. Futures Trading and the European Oil Market. *The Energy Journal*, 8(3), pp. 149-155.
- Box, G. E., Jenkins, G. M., Reinsel, G. C. & Ljung, G. M., 2016. *Time Series Analysis Forecasting and Control.* Fifth ed. New Jersey: John Wiley & Sons, Inc..
- BP, n.d. *First oil – 1901-1908.* [Online]
  Available at: https://www.bp.com/en/global/corporate/who-we-are/our-history/first-oil.html
  [Accessed 18 05 2020].
- Britannica, 2011. *Whale oil chemical compound.* [Online]
  Available at: https://www.britannica.com/technology/whale-oil
  [Accessed 12 04 2020].
- British Petroleum, 2019. *BP Statistical Review of World Energy.* [Online]
  Available at: https://on.bp.com/2CmuGIw
  [Accessed 03 March 2020].
- Brohé, A., Eyre, N. & Howarth, N., 2009. *Carbon Markets An International Business Guide.* 1st Edition ed. London: Earthscan.
- Brueck, H., 2018. *This week in 1912, a newspaper printed a spot-on warning about our warming world. We're living in the future it predicted..* [Online]
  Available at: https://bit.ly/3iP2azY
  [Accessed 25 January 2020].
- Buehler, R., Griffin, D. & Ross, M., 1994. Exploring the "Planning Fallacy": Why People Underestimate Their Task Completion Times. *Journal of Personality and Social Psychology*, 67(3), pp. 366-381.
- Buis, A., 2019. *The Atmosphere: Getting a Handle on Carbon Dioxide.* [Online]
  Available at: https://go.nasa.gov/307VF35
  [Accessed 11 January 2020].
- Campbell, J. Y., Lo, A. W. & MacKinlay, A. C., 1997. *The Econometrics of Financial Markets.* 1st ed. New Jersey: Princeton University Press.
- Chevallier, J., Nguyen, D. K. & Reboredo, J. C., 2019. A conditional dependence approach to CO2-energy price relationships. *Energy Economics,* Volume 81, pp. 812-821.

- Coase, R. H., 1960. The Problem of Social Cost. *Journal of Law and Economics,* October, Volume 3, pp. 1-44.
- Constable, S., 2020. *What Is Contango and Backwardation?.* [Online] Available at: https://www.wsj.com/articles/what-is-contango-and-backwardation-11599491694
[Accessed 27 09 2020].
- Convery, F. J. & Redmond, L., 2007. Market and Price Developments in the European Union Emissions Trading Scheme. *Review of Environmental Economics and Policy,* 01 January, 1(1), pp. 88-111.
- Cooper, N. R. & Cramton, P. eds., 2017. *Global Carbon Pricing - The Path to Climate Cooperation.* N/A ed. London: The MIT Press.
- Cooper, R. N., 2001. The Kyoto Protocol: A Flawed Concept. 07.
- CPI Inflation Calculator, n.d. *$18 in 1860 → 2020 | Inflation Calculator.* [Online] Available at: https://bit.ly/322b4nX
[Accessed 19 June 2020].
- Creti, A., Joëts, M. & Mignon, V., 2013. On the links between stock and commodity markets' volatility. *Energy Economics,* Volume 37, pp. 16-28.
- Crocker, T. D., 1966. The structuring of atmospheric pollution control systems. *The economics of air pollution,* Volume 61, pp. 81-84.
- Dales, J. H., 1968. *Pollution, Property and Prices.* 1st Edition ed. Cheltenham: Edward Elgar Publishing.
- Daskalakis, G., Psychoyios, D. & Markellos, R. N., 2009. Modeling CO2 emission allowance prices and derivatives: Evidence from the European trading scheme. *Journal of Banking & Finance,* 33(7), pp. 1230-1241 .
- Davis, L. E., Gallman, R. E. & Hutchins, T. D., 1988. The Decline of U.S. Whaling: Was the Stock of Whales Running Out?. *The Business History Review,* 62(4), pp. 569-595.
- Dechezleprêtre, A. D. N. & Venmans, F., 2018. *The joint impact of the European Union emissions trading system on carbon emissions and economic performance,* Paris: OECD Economics Department Working Papers.
- Dickey, D. A., 1979. Distribution of the Estimators for Autoregressive Time Series With a Unit Root. *Journal of the American Statistical Association,* 74(366), pp. 427-431.
- Downey, M., 2009. *Oil 101.* 1st Edition ed. New York: Wooden Table Press LLC.

- Duffy, C. & Disis, J., 2020. *OPEC+ reaches deal to cut oil production by 9.7 million barrels per day.* [Online]
  Available at: https://edition.cnn.com/2020/04/12/energy/opec-deal-production-cut/index.html
  [Accessed 16 08 2020].
- Dutta, A., Bouri, E. & Noor, M. H., 2018. Return and volatility linkages between CO2 emission and clean energy stock prices. *Energy,* Volume 164, pp. 803-810 .
- Ederington, L. & Lee, J. H., 2002. Who Trades Futures and How: Evidence from the Heating Oil Futures Market. *The Journal of Business,* 75(2), pp. 353-373.
- Ellerman, A., Convery, F. J. & Perthuis, C. D., 2010. *Pricing Carbon.* 1st Edition ed. New York: Cambridge University Press.
- ESI Africa, 2019. *African countries tout their oil and gas investment opportunities.* [Online]
  Available at: https://bit.ly/2Chm8Tx
  [Accessed 9 July 2020].
- European Commission, 2010. *Emissions trading: EU ETS emissions fall more than 11% in 2009.* [Online]
  Available at: https://ec.europa.eu/commission/presscorner/detail/en/IP_10_576
  [Accessed 9 11 2020].
- European Commission, 2012. on the monitoring and reporting of greenhouse gas emissions pursuant to Directive 2003/87/EC of the European Parliament and of the Council. *Official Journal of the European Union* , 12 07, Volume 009, pp. 308 - 382.
- European Commission, 2014. *EU ETS emissions estimated down at least 3% in 2013.* [Online]
  Available at: https://ec.europa.eu/clima/news/articles/news_2014051401_en
  [Accessed 28 08 2020].
- European Commission, 2015. *Climate Action.* [Online]
  Available at: https://bit.ly/3iQBOOq
  [Accessed 16 January 2020].
- Federal Reserve History, 2013. *Oil Shock of 1978–79.* [Online]
  Available at: https://www.federalreservehistory.org/essays/oil-shock-of-1978-79
  [Accessed 26 08 2020].
- Fezzi, C. & Bunn, D., 2010. Structural Analysis of Electricity Demand and Supply Interactions. *Oxford Bulletin of Economics and Statistics,* 72(6), pp. 827-856.

- Foss, M. M., 2020. *U.S. Shale Goes Viral.* [Online]
  Available at: https://bit.ly/2O99vwl
  [Accessed 21 March 2020].
- Graham, S., 1999. *John Tyndall.* [Online]
  Available at: https://go.nasa.gov/2ObOJfC
  [Accessed 12 February 2020].
- Gr´egoire, V., Genest, C. & Gendron, M., 2008. Using copulas tomodel price dependencies in energy markets. *Energy Risk,* 5(5), p. 58–64.
- Hamilton, J. D., 1994. *Time Series Analysis.* 1st Edition ed. Princeton: Princeton University Press.
- Hammoudeh, S., Nguyen, D. K. & Sousa, R., 2014. Energy prices and CO2 emission allowance prices: A quantile regression approach. *Energy Policy,* 70(C), pp. 201-206.
- Hintermann, B., 2010. Allowance price drivers in the first phase of the EU ETS. *Journal of Environmental Economics and Management,* 59(1), pp. 43-56.
- Intercontinental Exchange, n.d.Ice Crude Oil. [Online]
  Available at: https://www.theice.com/publicdocs/ICE_Crude_Oil.pdf
  [Accessed 17 03 2020].
- International Association of Oil Transporters, n.d. *History of oil transportation.* [Online]
  Available at: https://www.iaot.eu/en/oil-transport/history-of-oil-transportation
  [Accessed 12 05 2020].
- International Energy Agency, 2019. *From oil security to steering the world toward secure and sustainable energy transitions.* [Online]
  Available at: https://www.iea.org/about/history
  [Accessed 22 08 2020].
- International Energy Agency, 2020. *Global Energy Review 2020.* [Online]
  Available at: https://bit.ly/2AKvRRR
  [Accessed 01 March 2020].
- Johansen, S., 1995. *Likelihood-Based Inference in Cointegrated Vector Autoregressive Models.* First ed. New York: Oxford University Press.
- Johnson, A. M., 1966. The Early Texas Oil Industry: Pipelines and the Birth of an Integrated Oil Industry, 1901-1911. *The Journal of Southern History,* 32(4), pp. 516-528.

- Juselius, K., 2006. *The Cointegrated VAR model Methodology and Applications.* First ed. New York: Oxford University Press.
- Kanen, J. L. M., 2006. *Carbon Trading and Pricing.* 1st Edition ed. London: Environmental Finance Publications.
- Keppler, J. H. & Mansanet-Bataller, M., 2010. Causalities between CO2, electricity, and other energy variables during phase I and phase II of the EU ETS. *Energy Policy,* 38(7), pp. 3329-3341.
- Krokida, S.-I., Lambertides, N., Savva, C. S. & Tsouknidis, D. A., 2020. The effects of oil price shocks on the prices of EU emission trading system and European stock returns. *The European Journal of Finance,* 26(1), pp. 1-13.
- Lantero, A., 2015. *History of the Strategic Petroleum Reserve.* [Online]
  Available at: https://www.energy.gov/articles/history-strategic-petroleum-reserve
  [Accessed 24 07 2020].
- Leahy, S., 2019. *National Geographic.* [Online]
  Available at: https://www.nationalgeographic.com/science/2019/11/nations-miss-paris-targets-climate-driven-weather-events-cost-billions/
  [Accessed 6 June 2020].
- Lynch, P., 2019. *How Joseph Fourier discovered the greenhouse effect.* [Online]
  Available at: https://bit.ly/3fg7ESr
  [Accessed 08 February 2020].
- MacKay JC, D., Cramton, P., Ockenfels, A. & Stoft, S., 2017. *Global Carbon Pricing.* 1st Edition ed. London: The MIT Press.
- Mansanet Bataller, M., Tornero Pardo, Á. & Valor, E., 2006. *CO2 Prices, Energy and Weather.* [Online]
  Available at: http://dx.doi.org/10.2139/ssrn.913964
  [Accessed 01 June 2020].
- Mathur, A., 2013. Reassessing the Brent Benchmark for Crude Oil. *Economic and Political Weekly,* 48(51), pp. 14-17.
- McNally, R., 2017. *Crude Volatility The History and The Future of Boom-Bust Oil Prices.* 1st Edition ed. New York: Columbia University Press.
- Milunovich, G. & Nazifi, F., 2010. Measuring the Impact of Carbon Allowance Trading on Energy Prices. *Energy & Environment,* 21(5), p. 367–383.
- Mir-Babayev, M. Y., 2002. *Azerbaijan's Oil History A Chronology Leading up to the Soviet Era.* [Online]

Available at:
https://www.azer.com/aiweb/categories/magazine/ai102_folder/102_articles/102_oil_chronology.html
[Accessed 17 05 2020].

- Montgomery, W., 1972. Markets in licenses and efficient pollution control programs. *Journal of Economic Theory,* 5(3), pp. 395-418 .
- Napoli, C., 2012. Understanding Kyoto's Failure. *SAIS Review of International Affairs,* 32(2), pp. 183-196.
- Oberndorfer, U., 2009. Energy prices, volatility, and the stock market: Evidence from the Eurozone. *Energy Policy,* 37(12), pp. 5787-5795.
- Oil Price, 2009. *A Detailed Guide on the Many Different Types of Crude Oil.* [Online]
  Available at: https://bit.ly/3flsyQc
  [Accessed 01 July 2020].
- Oxford Reference, 2020. *Definition of the term Business-as-Usual Scenario,* London: Oxford University Press.
- Pfaff, B., 2008. *Analysis of Integrated and Cointegrated Time Series with R.* 1st Edition ed. Kronberg: Springer Science+Business Media, LLC.
- Philpott, T., 2006. *How the world got addicted to oil, and where biofuels will take us.* [Online]
  Available at: https://bit.ly/3iLlSwB
  [Accessed 10 June 2020].
- Quinn, B. G. & Hannan, E. J., 1979. The Determination of the Order of an Autoregression. *Journal of the Royal Statistical Society,* 41(2), pp. 190-195.
- Reboredo, J., 2012. Modelling oil price and exchange rate co-movements. *Journal of Policy Modeling,* 34(3), pp. 419-440.
- Reserve Bank of Australia, 2019. *The Changing Global Market for Australian Coal.* [Online]
  Available at: https://bit.ly/3iOYRJ4
  [Accessed 1 July 2020].
- Reuters Staff , 2020. *Shale producer Whiting Petroleum emerges from bankruptcy.* [Online]
  Available at: https://www.reuters.com/article/us-whiting-petrol-bankruptcy-urgent-idUSKBN25S5WO
  [Accessed 23 10 2020].

- Reuters Staff, 2009. Factbox: NYMEX and ICE's *long-standing rivalry.* [Online] Available at: https://www.reuters.com/article/us-ice-nymex-factbox-idUSTRE5AT3GF20091130 [Accessed 21 05 2020].
- Ritchie, H. & Roser, M., 2014. *Energy.* [Online] Available at: https://ourworldindata.org/energy#citation [Accessed 16 09 2020].
- Ritchie, H. & Roser, M., 2019. *CO_2 and Greenhouse Gas Emissions.* [Online] Available at: https://bit.ly/2AK7rI1 [Accessed 13 March 2020].
- Roser, M., 2013. *Economic Growth.* [Online] Available at: https://bit.ly/3204yy7 [Accessed 14 April 2020].
- Roser, M., Ritchie, H. & Ortiz-Ospina, E., 2019. *World Population Growth.* [Online] Available at: https://bit.ly/2Zeue8s [Accessed 16 April 2020].
- Roske, R. J., 1963. The World Impact of the California Gold Rush 1849-1857. *Arizona and the West*, 5(3), pp. 187-232.
- Royal Dutch Shell, n.d. *History of Shell In Indonesia.* [Online] Available at: https://www.shell.co.id/en_id/about-us/who-we-are/history-of-shell-in-indonesia.html [Accessed 19 05 2020].
- Sampson, A., 1985. *The Seven Sisters.* 7th ed. London: Hodder & Stoughton.
- Schwarz, G., 1978. Estimating the Dimension of a Model. *The Annals of Statistics,* 6(2), pp. 461-464.
- Skeptical Science, 2016. *The economic impacts of Carbon Pricing.* [Online] Available at: https://www.skepticalscience.com/co2-limits-economy-intermediate.htm [Accessed 1 11 2020].
- Soliman, A. M. & Nasir, M. A., 2019. Association between the energy and emission prices: An analysis of EU emission trading system. *Resources Policy,* Volume 61, pp. 369-374.
- Stevens, P., 2005. Oil Markets. *Oxford Review of Economic Policy,* 21(1), pp. 19-42.
- Stevens, P., 2020. *Oil jumps nearly 90% in May to $35, registering best month on record.* [Online]

Available at: https://www.cnbc.com/2020/05/29/oil-is-on-track-for-its-best-month-ever.html
[Accessed 30 05 2020].

- Sullivan, C., 2016. *Characterizing Interglacial Periods over the Past 800,000 Years.* [Online]
Available at: https://bit.ly/2Octvhv
[Accessed 25 June 2020].
- Sullivan, W., 1991. *Roger Revelle, 82, Early Theorist In Global Warming and Geology.* [Online]
Available at: https://nyti.ms/2W2zSbs
[Accessed 12 May 2020].
- Tarbell, I. M., 1904. *The History of the Standard Oil Company.* 1st Edition ed. New York: McClure, Phillips & Co..
- T. Corneliussen, S., 2015. *"Climate Science, 50 Years Later".* [Online]
Available at: https://bit.ly/3flj5bC
[Accessed 23 April 2020].
- Tsay, R. S., 2014. *Multivariate Time Series Analysis.* First ed. Chicago: John Wiley & Sons, Inc.,.
- U.S. Energy Information Administration , 2020. Short-Term Energy Outlook. [Online]
Available at: https://www.eia.gov/outlooks/steo/report/global_oil.php
[Accessed 14 11 2020].
- Union of Concerned Scientists, 2008. *The Hidden Costs of Fossil Fuels.* [Online]
Available at: https://www.ucsusa.org/resources/hidden-costs-fossil-fuels#:~:text=Coal%20is%20known%20for%20being,heavy%20metals%20and%20other%20chemicals.
[Accessed 13 06 2020].
- United Nations, 1992. *United Nations Framework Convention on Climate Change.* New York: United Nations.
- United States Environmental Protection Agency, 2020. *Acid Rain Program.* [Online]
Available at: https://www.epa.gov/acidrain/acid-rain-program
[Accessed 08 07 2020].
- Wei, Y., Wang, Y. & Huang, D., 2010. Forecasting crude oil market volatility: Further evidence using GARCH-class models. *Energy Economics,* 32(6), pp. 1477-1484.

- Yamani, A. Z., 1975. The Oil Industry in Transition. *Natural Resources Lawyer*, 8(3), pp. 391-398.
- York, R., 2017. Why Petroleum Did Not Save the Whales. *Socius,* 3(1).
- Yousef, N. A., 2011. The Prominent Role of Saudia Arabia in the Oil Market from 1997 to 2011. *The Journal of Energy and Development,* 36(1/2), pp. 63-84.
- Zhang, Y.-J. & Sun, Y.-F., 2016. The dynamic volatility spillover between European carbon trading market and fossil energy market. *Journal of Cleaner Production*, 112(4), pp. 2654-2663 .
- Zhu, B. & Chevallier, J., 2017. *Pricing and Forecasting Carbon Markets.* 1st Edition ed. Cham: Springer International Publishing AG.

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