IMPACT OF ENVIRONMENTAL ANNOUNCEMENTS ON THE FINANCIAL MARKETS OF EUROPEAN CRUDE OIL EXPORTERS AND IMPORTERS

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Abstract

Climate change poses a severe threat to the world as we know it. Over the last decades, governments and intergovernmental organisations have introduced regulations and policies to limit greenhouse gas emissions. Several studies have found that announcements of environmental regulations and policies affect financial markets worldwide. Our thesis examines whether the main stock market indices of exporters of crude oil are affected differently than importers by environmental announcements. We consider the Russian MOEX, the Norwegian OSEBX and the British FTSE 100 as proxies for exporters, while the German DAX, Spanish IBEX 35 and Italian FTSE MIB represent importers. We employ the event study methodology to investigate whether indices display significant cumulative abnormal returns around environmental announcements. In addition, we estimate the same period volatility using a GJR-GARCH model, where we introduce dummy variables for the event period. We find significant negative cumulative abnormal returns for the Russian MOEX around the announcement of the Glasgow climate pact. We also find significant increases in volatility for both importers and exporters around two events. Overall, our findings do not indicate that the financial markets of exporters of crude oil behave differently from importers around environmental announcements.

Keywords: Climate change, capital markets, abnormal returns, volatility

JEL Classification: C12, C22, G14, G15

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1. Introduction

Climate change poses a severe threat to the world as we know it. To battle the ever-increasing risks of permanent environmental damage from high climate gas emissions, the United Nations (UN) and European Union (EU) have for the past decades, urged countries to come together to develop solutions. The announcement of the Kyoto Protocol (1997) was a turning point for climate change policies in line with the first global and legally binding Paris Agreement (2015). The Paris Agreement set a max target to limit global warming to below 2 degrees Celsius compared to pre-industrial levels. The EU is also highly committed to battle climate change by introducing numerous regulations and strategies in recent years. Some notable announcements are the action plan for the planet (2017), a clean planet for all strategy plan (2018) and the European Green Deal (2019).

Several scholars have highlighted the urgency for action and a change of course in economic development to halt and reverse climate change. Will Steffen et al. (2015) introduced the planetary boundaries framework in which they defined a "*safe operating zone for humanity*." The framework revolves around nine different processes which impact the earth's systems, and if the boundary is breached, it may cause irreversible damage. The framework aims to influence policymakers to act against the increasing risk of human-caused planetary changes. The paper argues that we are in the zone of uncertainty when it comes to climate change, which means an increased risk of doing irreversible damage.

In 2015, the United Nations (UN) introduced the sustainable development goals (SDGs) to address a number of issues related to the term sustainable development (Van Tulder, 2018, p. 12). Introduced by the Brundtland commission in 1987, the term Sustainable development is defined as: "*Meeting the needs of the present without compromising the ability of future generations to meet their own needs*" (Harris & Roach, 2018, p. 10). Van Tulder (2018, p. 73) argues that the SDGs might be an opportunity for private companies to increase profits, which could lead to a greener economy. A green economy is related to sustainable development and is defined as: "*An economy that improves human well-being and social equity while reducing environmental impacts*" (Harris & Roach, 2018, p. 375).

Modern economics is often linked to capitalism, which is built on the belief that chasing profits also benefits society (Core, 2017). This belief has come under scrutiny over the years, with Becker (2019, p. 68) arguing that a capitalistic market economy fails to face the challenges of the 21st century, including decoupling the economy from environmental harm. Becker (2019, p. 70) links human economic activities to several planetary boundaries and raises concerns that economic growth is expected to continue.

Schoenmaker (2017, p. 11-12) claims that continued economic growth without accounting for negative environmental externalities could push the limits of the planetary boundaries. Ecological economists support this claim and advocate that the world needs an optimal macroeconomic scale, where economic growth needs to stop (Harris & Roach, 2018, p. 214). They argue that because of the link between higher energy usage and economic growth, while most of the world's energy still comes from fossil fuels, economic growth cannot continue (Harris & Roach, 2018, p. 217; Becker, 2019, p. 70). Hickel and & Kallis (2020, p. 480-483) agree and state that no nations or companies would sacrifice economic growth and profits to stop climate change. Therefore, ecological economists believe that governments and intergovernmental organizations should enforce strict climate policies and regulations (Harris & Roach, 2018, p. 225).

On the other hand, some economists believe that it is possible to adopt a green economy without stopping economic growth (Harris & Roach, 2018, p. 13). Bowen & Hepburn (2015) argue that achieving a green economy while continuing economic growth will require a substantial transformation of today's economy. They claim that ensuring economic growth without hurting natural capital requires governmental intervention. On the other hand, environmental economists believe in market-based solutions to environmental problems by providing incentives or taxation (Harris & Roach 2018, p. 13). This is similar to the ideas of Becker (2019, p. 60), who argues that the optimal way of dealing with a public good, like climate change, is trough taxation. A commonly used hypothesis in papers about environmental policies and the financial markets is the Porter hypothesis. In short, it assumes that environmental regulations and policies may be beneficial for firms due to fostering innovations and ultimately saving costs (Harris & Roach, 2018, p. 380).

Green assets and Environmental, Social and Governance (ESG) investing have become increasingly popular among investors (Piu, 2020). A report by Cowell, Kelly, & Rajan (2021) written for KPMG underlines that financial markets are essential in combatting climate change, especially when it comes to directing capital towards sustainable energy. Bose (2019, p. 111) states that one of the most important roles of the financial market is to signal scarcity and abundance. It is argued that the price of a material, or in this case, an asset, should reflect the asset's scarcity. Considering the state of the planetary boundaries (Steffen et al., 2015), the stock return and market value of a polluting firm should reflect its impact on the environment. Even though this may be true in theory, Cowell et al.'s (2021) report show that experts find that climate risks are not reflected in a security's stock price. An interview quote from the same report states: "*Capital markets can't easily detect risks and opportunities, until they are clear on how governmental actions will create incentives as well as sanctions*" (Cowell et al., 2021).

As financial markets will not adapt to resolve climate change on their own, it is crucial to study how environmental policies affect financial markets. There has been extensive research on how environmental announcements affect the risk and returns of industries worldwide, although most papers focus on one country (Gangemi, Morris, Moosa, Pucian & Ramiah, 2016; Moosa, Pichelli & Ramiah, 2015; Moosa, Mudalige, Nguyen, Pham & Ramiah, 2019a; Qian, Suryani & Xing, 2020). Research with an international focus has also been conducted (Aleksovski, Mozetič & Schütze, 2020; De Angelis & Monatrolo, 2020). Findings have not been univocal for financial markets, but high-polluting industries frequently display negative returns and higher risk in response to environmental announcements. For this reason, we thought it would be interesting to examine the largest importers and exporters of crude oil in Europe to investigate whether a fossil fuel production-based economy will impact the overall economy of that country. Six countries are included, divided into exporters and importers and represented by their main stock market index. We have thus developed the following research question:

Are the financial markets of crude oil exporters more impacted than importers by environmental announcements?

To answer this research question, we have created two hypotheses that will be investigated further by employing the event study methodology and a GARCH volatility analysis. Our hypotheses are presented below, where the first hypothesis is related to the event study and the second to the GARCH model. Note that the term "environmental announcements" will be used throughout this thesis to denote our events.

Hypothesis 1:

> **H0**: The main indices of European exporters and importers of crude oil will have a similar reaction to environmental announcements.
>
> **H1**: The main indices of European exporters will react more negatively than importers of crude oil to environmental announcements.

Hypothesis 2:

> **H0**: The main indices of European exporters and importers of crude oil will have the same volatility around environmental announcements.
>
> **H1**: The main indices of European exporters of crude oil will have more volatile markets than importers around environmental announcements.

This thesis is organised as follows: Chapter 2 provides an overview of existing literature regarding environmental announcements, climate change, and financial markets. In chapter 3, we present the efficient market hypothesis. Chapter 4 gives a detailed description of the data used by providing descriptive statistics and describing the events and indices. In Chapter 5, the methodology is presented, along with the employed estimation techniques. Chapter 6 presents and interprets the results, both numerical and visual. Chapter 7 provides a discussion organized event by event and interprets the findings considering the event expectations and previous literature before presenting and explaining the thesis limitations. Chapter 8 summarizes the thesis, from methodology to discussion, and suggests future research.

2. Literature review

This part of the thesis will present existing literature that focuses on the relationship between environmental regulations and financial markets. The event study methods introduced by Brown & Warner (1985) and Mackinlay (1997) are widely used in the current literature. Event studies require the estimation of abnormal returns for some given securities over a relevant period. Numerous papers have analysed the effects of environmental announcements on financial markets worldwide, both in terms of risk and return. We look at the papers by dividing them into different geographic areas.

2.1 North America

Moosa et al. (2015) investigated how “green policy announcements” and the election of President Barack Obama affected both the risk and return of the United States (US) and international financial markets. Using the Brown & Warner (1985) methodology, they applied the market model, a Capital Asset Pricing Model (CAPM), and different factor models to identify possible abnormal returns around 133 announcements from 1997 to 2011. By employing a t-test, the researchers find that environmental announcements impact both US and international market returns. Additionally, findings suggest that the biggest polluters experience more negative abnormal returns than those more environmentally friendly. As for the “Obama effect,” the tests showed significant reactions in the US and international markets.

Gehricke, Rainet, Roberts & Zhang (2021) also investigated the election of a US president by looking at the election of Obama’s successor, Donald Trump. As Trump was a supporter of the US oil and gas industry, researchers wished to examine whether the stock returns and implied volatility of US oil and gas firms were affected differently by the election of Trump than by the signing of the Paris Agreement. Researchers employ the event study methodology, using the Fama-French five-factor model to calculate abnormal returns and the Black Scholes option pricing model with a GARCH (1,1) error term to estimate implied volatility. The paper found that the signing of the Paris Agreement led to the US oil and gas firms experiencing large negative abnormal returns and an increase in implied volatility. As for the Trump effect, oil and gas firms surprisingly experienced negative abnormal returns around the election, with the same being the case for the US exit of the Paris Agreement.

2.2 Asia

Fan, Fang, Hua & Zhao (2018) examined how the stock market returns of fossil-fuel energy companies listed on the Shanghai stock exchange reacted to the announcement of four different types of environmental regulations. Using the market model by Mackinlay (1997), the paper looks for abnormal returns around 20 different Chinese environmental policies. Fan et al. (2018) used EGARCH to calculate the estimated parameters and J-statistic to test the significance of the cumulative average abnormal returns. The paper finds that the returns of the energy companies are negative shortly after the policies are announced. Additionally, the researchers found that energy companies in the oil and gas sector do not show significant abnormal returns, while coal and electricity firms do.

A paper published by Moosa et al. (2019a) investigates how environmental regulations and carbon tax affected the risk and return of the Singapore stock market between 2006-2018. Building on the event study methodology by Brown & Warner (1985), the paper uses the CAPM approach with dummy variables and a Fama-French five-factor model to examine the potential abnormal returns and changes in systematic risk. Using both parametric t-test and non-parametric Corrado (1989) test, Moosa et al. (2019a) found that many big polluters experienced negative returns, while the more environmentally friendly firms experienced positive returns. Moosa et al. (2019a) conclude that the environmental regulations achieved their desired effects on the Singapore stock market.

Guo, Kuai & Lio (2020) applies the event study methodology to inspect how the Chinese stock market reacts to announcements of environmental regulations and laws while also focusing on investor attention. Specifically, Guo et al. (2020) use the market model to calculate cumulative average abnormal returns and employed a multivariate regression approach to investigate how investor attention affects the stock market. T-tests and several robustness tests are used to determine the significance of the abnormal returns. Results from the paper show that carbon-intensive firms react more negatively to strict laws than regulations.

Additionally, Guo et al.'s (2020) research indicate that investor attention helps anticipate the stock markets' response to environmental announcements.

China has had an increasing focus on environmental issues while aiming to sustain economic growth. Therefore Dong, Wang, Li, & Luan (2020) investigates how Chinese environmental regulations affect the stock market returns. Researchers consider 16 highly polluting industries and employs the event study methodology with the standard market model, a Fama-French 3 factor model, and a multivariate regression model with dummy variables for pollution. In order to determine significance, Dong et al. (2020) use both a t-test and the Wilcoxon test. The tests find that the stock markets do not show any clear reactions to the announcement of environmental regulations. However, the research indicates that low-polluting firms perform better than high-polluting firms in the post-event period.

Qu, Zhang & Zhao (2021) also investigate the financial markets in China. They examine whether ESG investing has yielded higher returns after China launched "guidelines for establishing a green financial system." The researchers use ESG performance to group the returns of the Chinese stock market into five portfolios. Performing Fama-Macbeth cross-sectional regressions using multiple risk factors, Qu et al. (2021) find that "high ESG" portfolios experience significantly higher abnormal returns than "low-ESG" portfolios after 2016.

Dahal & Das (2022) investigate how several green policies announced between 2014-2020 affected the stock returns of the Bombay Stock Exchange (BSE) industrial index. After grouping the securities as the BSE India proposes, Dahal & Das (2022) use the market model to calculate abnormal returns. After employing parametric t-tests and non-parametric Wilcoxon tests, the researchers found that green policies that do not directly impact the firm, such as the announcement of international agreements, positively affect returns. However, agreements and policies which are supposed to be achieved within a certain amount of time, seems to have a negative impact on stock market returns.

2.3 Oceania

Martin, Moosa & Ramiah (2013) investigates how the Australian stock market reacts to 19 different environmental regulation announcements. The researchers employ the event study methodology from Brown & Warner (1985) and use the CAPM to obtain the abnormal returns aggregated over industries. Using a parametric t-test and Corrado (1989) non-parametric test, Martin et al. (2013) find that the announcements heavily impact most industries. Interestingly, the biggest polluters are not significantly affected, with the low polluting industries showing the most negative abnormal returns.

Australia had three major shifts in climate policy between 2008-2014, where the government shifted from fossil-fuel friendly to environmentally friendly focus, then back to fossil-fuel friendly. Qian et al. (2020) investigated whether the environmental performance of firms affected their stock return when the climate policies changed. Qian et al. (2020) use the market model from Mackinlay (1997) to calculate the abnormal returns while also applying Fama-French 3 factor regression models and controlling for the environmental sensitivity of the firms, where a parametric t-test is used to measure significance. The paper finds that the events intended to reward environmentally friendly companies did not provide any difference in the return. However, the repeal of the carbon tax, which should favour the polluters, led to environmentally friendly firms experiencing higher returns, while polluters experienced negative returns.

2.4 Europe

Gangemi et al. (2016) studies the financial market in the United Kingdom to assess whether 75 different announcements of green policies impact the stock returns. Organising the stocks into 41 different industries, Gangemi et al. (2016) follow Brown & Warner's (1985) event study methodology, where the abnormal returns are estimated using a CAPM with dummy variables. The paper uses a t-test and Corrado non-parametric tests to check for significance. Findings report that the announcement of green policies had a large impact on the stock returns in the UK, with 19 of 42 industries displaying abnormal returns. Most abnormal returns were positive, with international policies having the biggest impact, followed by domestic and nuclear announcements.

To check whether the Paris Agreement affected the German stock market, Moosa, Nguyen, Pham, Ramiah & Saleem (2019b) analyse 20 announcements related to the agreement. Employing the Brown & Warner (1985) event study methodology, Moosa et al. (2019b) use CAPM to calculate the cumulative abnormal returns and CAPM with dummy variables to measure the changes in systematic risk. They apply a t-test and Corrado's (1989) non-parametric tests to determine the significance of the abnormal returns. The paper also includes several ARCH models as a robustness check. Out of the 17 industries analysed, 16 were affected by at least one of the announcements. Additionally, Moosa et al. (2019, b) note that some polluters experience negative abnormal returns around the announcement of the Paris Agreement. Findings also identify a diamond risk structure, which they explain by investors being unsure of the effects of the Paris Agreement.

Moosa, Nguyen, Pham & Ramiah (2020) explore whether the French stock markets' risk and return are influenced by the announcement of national, European, and international environmental regulations. The researchers follow Brown & Warner's (1985) event study methodology, where abnormal returns are calculated using a CAPM. A CAPM with dummy variables is also used to identify increases in systematic risk. Dividing into industries and using parametric t-tests and non-parametric Corrado (1989) tests, they find that the EU trading system affects the French stock market. Oil and gas firms experience negative abnormal returns, while other polluters like industrial transportation experience positive abnormal returns. Some industries also show increases in systematic risk around events.

Birindelli & Chiappini (2020) examine whether some of the many climate policies announced by the EU have affected stock returns. The paper looks at the sectors in which a firm operates, as well as the environmental commitment of the firms. Using eight different announcements and dividing them into 11 industries, the researchers apply Brown & Warner's (1985) and Mackinlay's (1997) event study methodology to identify potential abnormal returns. The exact model used to calculate the abnormal returns is Mackinlay's (1997) market model. To check the abnormal returns for significance, a cross-sectional t-test and a non-parametric GRANK t-test is used. Birindelli & Chiappini (2020) find that some of the announcements seem to provide positive returns, while others provide negative ones. They imply that the Paris Agreement looks like a turning point as many sectors start experiencing negative abnormal returns after its announcement. The environmental score analysis reconfirms the former, as high-scoring firms have a positive reaction before the Paris agreement, yet negative afterward. The authors claim that a firm's sector seems to be more important than its environmental commitment.

2.5 Global

Aleksovski et al. (2020) investigated the short-term effect of international climate negotiations on large "brown" and "green" companies globally. The researchers studied all international climate negotiations from 2009 to 2016 and the US exit from the Paris Agreement in 2017. The "brown" companies are taken from the CDP 500 report, while the green companies stem from Clean 200. Using the event study methodology by Mackinlay (1997), the researchers employ the market model to estimate the abnormal returns and use a parametric t-test to check for significance. Aleksovski et al. (2020) find that climate negotiations significantly impact the global financial market. Specifically, the "green" companies have positive abnormal returns before 2013, while "brown" companies show negative abnormal returns after 2013.

De Angelis & Monatrolo (2020) also examine the effects of the Paris Agreement on the global financial market. By looking at low-carbon investments before and after the Paris Agreement, the researchers employ the Fama-French five-factor model to estimate the abnormal returns, as well as the Markowitz portfolio optimisation. The researchers found that the optimum weighting of low-carbon firms in a portfolio is higher after the Paris Agreement than before, implying that low-carbon firms are rewarded after the announcement.

El Ouadghiri, Guesmi, Peillex & Ziegler (2021) look at whether public attention to environmental issues affects financial markets. Using a pooled linear panel model, the researchers examine whether media coverage of environmental issues, public attention to keywords of environmental issues, or natural weather disasters affect the stock market. Findings report that sustainable indices experience significantly lower returns when there are no events. However, when there are natural disasters, and the public attention is high, sustainable indices outperform others.

Pastor, Stambaugh & Taylor (2022) construct their own "green" factor to examine why green assets have outperformed brown when climate concerns increase. They employ time series analysis and Fama-French-factor models, including their own green factor. The paper finds that the recent outperformance of green assets is due to the green factor and can be explained by increasing climate concerns.

3. Theory

3.1 The Efficient Market Hypothesis

Fama (1970) argues that the ideal financial market is one where proper resource allocation is achieved through asset price signals, which represents an efficient market. The efficient market hypothesis envisions a capital market where asset prices reflect all available information at any time. According to this hypothesis, security prices will only change as new information becomes available. As new information is primarily unpredictable for investors, security prices evolve randomly.

Fama (1970) presents three possible subsets of information states for asset prices in his empirical literature review. He also tests how efficiently each category adapts to the newly available information. The first category is the weak form which only considers historical prices, assumed to be independent of future price movements. This implies that trading strategies based on past prices cannot give consistent excess returns when new information becomes available. In the semi-strong form, clearly, publicly accessible information is also available to investors in addition to historical prices. Lastly, the strong form includes both weak and semi-form assumptions as well as any information only available for one individual, resulting in that person gaining a higher expected profit than other investors. The last state of efficiency is hard to test and best serves as a benchmark.

When events such as environmental announcements occur, new information is brought to the market. Thus, analysing the effects of these events in line with the efficient market hypothesis is relevant. This research paper targets the semi-strong form of market efficiency. If the market is efficient, investors will not be able to generate abnormal returns in the time window surrounding the event.

4. Data and Events

This paper will investigate whether the main indices of selected importers and exporters of crude oil react differently to the environmental announcements. Indices from six countries will be considered in total, as well as one regional market index to be used as a market portfolio in the event study. The following sections will explain how the specific countries were selected and how data was collected and pre-processed, as well as providing descriptive statistics for two sample periods. The different index compositions will also be presented in addition to the main content of the considered environmental announcements.

4.1 Data Introduction

To address the research question, countries are divided into importers and exporters of crude oil. Countries represent the largest importers and exporters of crude oil in Europe. Crude oil is the main metric because it is a raw product extracted from oil drilling and serves as a global commodity. Natural gas is also a critical part of energy production in Europe. However, the EU recently stated that natural gas could be beneficial in mitigating future climate risk as the carbon emissions are lower than those of other fossil fuels. Thus, natural gas will not count toward this study's importer or exporter status (Yadav, 2022; European Commission, 2021).

Tables 1 and 2 lists the countries included in the study and the annual amount of average imported or exported crude oil, denoted in thousand tonnes between 2015-2020. The total average amount of either exported or imported crude oil in Europe is also reported. The dataset provided by Eurostat (2022a) does not include Russia, however the international trade centre (ITC) (2022) shows that the Russian Federation exported 239 170 tons of crude oil in 2020. This constitutes 11.9% of total world exports and makes Russia the second largest exporter of crude oil in the world.

Table 1: Largest exporters of crude oil in Europe

Exporters	Average exports (2015-2020) of crude oil (tons)	Index notation
Russia	239 170*	IMOEX.ME
Norway	66 463	OSEBX.OL
United Kingdom	35 263	FTSE
Europe	107 353	-

Data on crude oil exporters in thousand tonnes provided by Eurostat, 2022a. * The Russian export is not the average, but from 2020.

Table 2: Largest importers of crude oil in Europe

Importers	Average imports (2015-2020) of crude oil (tons)	Index notation
Germany	87 864	GDAXI
Spain	63 933	IBEX
Italy	60 873	FTSEMIB.MI
Europe	575 015	

Data on crude oil importers in thousand tonnes provided by Eurostat (2022b).

4.2 Acquiring data

All exporter and importer countries are represented by their main stock market index and are listed in table 1 and 2. These indices are composed of different large national companies, that operate in separate sectors of the economy. In addition to the six country indices, a regional market index is used to represent the overall market portfolio in the event study. The composition of some indices has changed over time such as the German DAX index being increased from 30 to 40 constituents in 2021 (Deutsche Börse Group, 2021).

All index data is downloaded from Yahoo Finance, except for Norway (OSEBX.OL) which is downloaded from Euronext live. Data is downloaded manually and imported into R. Downloaded data are daily adjusted close prices ranging from 4th of August 2015 till 31st of December 2021 for all indices. MacKinlay (1997) argues that using daily data is most beneficial for detecting abnormal performance. This is due to the larger number of observations over the estimation period, hence increasing the power of the estimations. When downloaded, the data is pre-processed in R by merging a single country index with the market index. Because each country has their own specific trading days, merging the indices is necessary in order to align dates properly. After merging is done, all ''no amount'' (NA) values are replaced by the value on the last trading day.

4.3 Index composition

This subsection will provide an overview of the various indices examined in this paper by looking at their methodology and composition. The chosen market portfolio is the STOXX Europe 600 Index. Other indices like MSCI Global were also explored to represent the market portfolio, but the STOXX Europe 600 consistently returned a higher R^2 in the market model estimations. The STOXX Europe 600 Index is also well known and commonly used in academic research. As for the methodology, the index is composed of the 600 largest securities in Europe, measured by free-float market capitalisation. The highest represented sectors per March 31st, 2022, are health care at 15.6%, industrial goods & services at 12.3% and food, beverage & tobacco with 8.2%. Since the market portfolio is regional, country weights are also reported. Great Britain is the top constituent at 24.2% followed by France at 16.5% and Switzerland at 15.3% (Qontigo, 2022b).

4.3.1 Exporters

Russia, Norway and United Kingdom are selected as the exporters in this study. They are represented by MOEX, OSEBX and the FTSE 100 index respectively. The largest exporter is Russia, who's MOEX index is capitalisation weighted and a composite of the largest and most liquid stocks listed on the Moscow Exchange. According to Eurostat (2020) Russia supplied 29% of the total crude oil imports and 54% of solid fuel to the EU in 2020. This is reflected by the included securities representing MOEX as of March 2021 where energy (oil & gas) amount to 40.2% of the total asset allocation. Other highly represented sectors are financials with 20.7% and metals & mining with 18.5% (Moscow Exchange, 2022).

Norway is also a large supplier of crude oil, with 8% of EUs crude oil being imported from Norway in 2020 (Eurostat, 2020). The Oslo Børs Benchmark Index - OSEBX includes the largest and most traded securities listed on Oslo Børs weighted based on free float market capitalisation. Energy is the top sector on OSEBX with 28.7% a share followed by financials and consumer staples with 18.2% and 14% respectively. Sector shares were published on March 31st, 2022 (Euronext, 2022).

The final exporter considered is the United Kingdom and the FTSE 100 Index. In 2020 they supplied 7% of EUs crude oil (Eurostat, 2020). The FTSE 100 Index measures the performance of the 100 largest firms listed on the London Stock Exchange. Firms included are blue chip companies weighted based on market capitalisation. Breaking down sector sizes, the largest sector as of April 29th, 2022, is health care representing 10.92% followed by financial services at 10.85%, industrial goods and services at 10.61% and then energy with 9.92% (FTSE Russel, 2022a).

4.3.2 Importers

The importers in this study are Germany, Spain and Italy. Their respective main stock market indices are DAX, IBEX 35 and the FTSE MIB Index. In 2020, Germany was the eighth largest importer of crude oil in the world (OEC, 2022). DAX includes the 40 largest companies traded on the Frankfurt Stock Exchange. The index comes in several different versions and the one used in this paper is the DAX EUR Gross Return denoted by GDAXI. Selection of firms is based on free float market capitalisation and only tracks the performance of firms that meets certain profitability and quality requirements. As of March 31st, 2022, DAX's largest sectors are chemicals at 15.91%, industrials at 15.26% and pharma & healthcare with 11.60% (Qontigo, 2022a).

Spain's IBEX 35 index reflects the performance of the 35 largest companies listed on the Spanish Stock Market and securities are weighted based on free float market capitalisation. The largest sector of IBEX 35 as of March 2022 is oil and energy which accounts for 23.8%. Oil and energy are followed by basic materials, industry & construction at 11.98%, and the third largest sector is consumer goods with 11.04% (BME Market Data, 2022).

FTSE MIB Index is the main benchmark index in Italy and consists of the 40 most liquid securities listed on Borsa Italiana. Included stocks are free float weighted and captures approximately 80% of the market capitalisation. As of March 2022, the largest security sectors making up the FTSE MIB are banks, utilities and automobiles & parts with 17.59%, 16.17% and 13.98% respectively. Following these sectors is energy at 12.66% and industrial goods and services at 11.73% (FTSE Russel, 2022b).

4.4 Descriptive statistics

Descriptive statistics are estimated for all indices including the market portfolio. The first step in calculating the descriptive statistics is to estimate the daily returns which was done by taking the difference of log transformed daily adjusted closing prices. Table 3 reports the descriptive statistics for all included indices in the period 4th of August 2014 till 31st of December 2021.

Table 3: Descriptive statistics for the event study

	MEAN RETURN	STANDARD DEVIATION	MAX VALUE	MIN VALUE	KURTOSIS	SKEWNESS	ADF	JB
MARKET	0.02	1.08	8.07	-12.19	17.22	-1.24	-30.03 (0.0000)	38710.8 (0,0000)
GERMANY	0.03	1.26	10.41	-13.05	14.19	-0.75	-29.64 (0.0000)	9994.6 (0,0000)
SPAIN	-0.01	1.32	8.23	-15.15	20.46	-1.46	-29.38 (0.0000)	24752 (0,0000)
ITALY	0.02	1.49	8.55	-18.55	22.50	-1.71	-30.185 (0.0000)	30824 (0,0000)
UK	0.01	1.05	8.67	-11.51	16.79	-0.93	-31.03 (0.0000)	15313 (0,0000)
NORWAY	0.04	1.11	5.46	-9.18	9.75	-0.81	-31.57 (0.0000)	3773.7 (0,0000)
RUSSIA	0.05	1.12	9.37	-8.71	13.43	-0.37	-30.55 (0.0000)	8710.8 (0,0000)

Descriptive statistics, augmented Dickey-Fueller and Jarque & Bera test for all included indices. For ADF and JB p-values are also reported.

Looking at the mean returns, Spain is the only country to report a negative mean return over the 6-year period, while Russia has the highest daily return of 0.05%. Furthermore, all indices exhibit positive maximum values and negative minimum values. The large range between the maximum and minimum values are reflected by the reported standard deviation. The skewness value reflects that each index has a negatively skewed distribution, where a value lower than -1 is considered highly negatively skewed. Moreover, the kurtosis for all indices is greater than three, which entails that extreme values will be observed more often than under a Gaussian distribution. It is worth mentioning that the period of estimation includes the Covid 19 pandemic and thus, these statistics will reflect the impact of that event on financial markets. This can be considered a structural break that has the potential to cause problems for the modelling approach implemented subsequently. However, none of our models use data from March and April 2020, meaning that the Covid-19 structural break will not affect our OLS estimations. In addition, all market models will be tested to see if they fulfil 2 underlying OLS assumptions. The augmented Dickey-Fuller test (1979) confirms that the returns on all indices are stationary, which is an important criterion for the validity of later estimations. Lastly, the Jarque & Bera (1980) test was performed to test the returns for Gaussianity. As we can see from the sample used in table 3 deviates from Gaussianity.

As mentioned earlier, this thesis will also include an analysis of the volatility of the indices. The structural break related to the Covid 19 pandemic has greatly impacted the volatility of indices in March and April 2020, which is why the GARCH model will exclude the period after the 31st of December 2019. Table 4 reports the descriptive statistics in the period the 1st of August 2014 till the 31st of December 2019.

Table 4: Descriptive statistics for the GARCH estimation period

	MEAN RETURN	STANDARD DEVIATION	MAX VALUE	MIN VALUE	KURTOSIS	SKEWNESS	ADF	JB
GERMANY	0.027	1.11	4,85	-7,07	5,42	-0.36	-29.64 (0.0000)	366,33 (0,0000)
SPAIN	-0.007	1.16	3,80	-13,19	16,03	-1.24	-29.38 (0.0000)	10152 (0,0000)
ITALY	0.01	1.38	5,70	-13,33	10,45	-0,75	-30.185 (0.0000)	3307,8 (0,0000)
UK	0.009	0,86	3,51	-4,78	5,59	-0.23	-31.03 (0.0000)	406,87 (0,0000)
NORWAY	0.03	1.00	4,17	-5,32	5,42	-0.20	-31.57 (0.0000)	339,97 (0,0000)
RUSSIA	0.06	1.03	9.37	-8.71	12,22	0,07	-30.55 (0.0000)	4829,5 (0,0000)

Descriptive statistics, augmented Dickey-Fueller test and Jarque & Bera test for all included indices.

Compared to the period that include the structural break, one can see that the observed values are similar, though less extreme. This includes smaller max values, higher min values and smaller standard deviations. These differences point towards the Covid-19 pandemic influencing the volatility of all indices, hence the sample period from 4th of August till 31st of December will be used to model the volatility. It can also be seen through the Skewness, Kurtosis and Jarque & Bera (1980) test that all indices deviate from the Gaussian distribution, as well as the results for the Dickey-Fuller test (1979) showing clear signs of stationarity.

4.5 Events

Five events are considered in this research paper where an event is defined as: "… *a point in time when a company makes an announcement or when a significant market event occurs*"

(Benninga, 2008, p. 372). Using this definition, the environmental announcements count as a significant market event which can impact financial markets in Europe. We focus on events that originate from United Nations and the European Commission. Every event is substantial since it seeks to guide the world economy towards a sustainable future. Table 5 summarises all events and is followed by a short description of each event.

Table 5: Environmental policy events

Number	Date	Policy announcements	Provider
1	12/12/2015	The Paris Agreement was announced at the COP21 in Paris	United Nations
2	12/12/2017	Action plan for the planet was published	European commission
3	11/28/2018	A clean planet for all was published	European commission
4	12/11/2019	European Green deal was announced	European Commission
5	11/13/2021	Glasgow climate pact signed on COP26	United Nations

Looking at the literature review, index compositions and the events, we can indicate how the indices will react to each environmental announcement. Our research question implies that we expect the importers to be less affected than the exporters overall. However, this does not have to be the case with every announcement. Thus, we will formulate a short expectation of how the indices will react to the events after introducing each event below. Using Google Trends, we will also consider the number of “climate change” searches to check whether the announcements lead to a spike in activity.

4.5.1 The Paris Agreement

On the 12th of December 2015, the United Nations announced the Paris Agreement at the 21st Conference of the Parties (COP21). The historic agreement is a legally binding international treaty signed by 195 parties where they pledged to reduce emissions and take joint action on climate change. It also represents the first time a binding agreement on battling climate change has been reached under which all countries are expected to contribute to reduce carbon emissions. Limiting global warming to below 2 degrees Celsius compared to pre-industrial levels, ideally, 1.5 degrees, is the main goal of the Paris Agreement. To achieve this goal and for the world to be climate neutral by 2050, the peak of global greenhouse gas emissions must be reached as soon as possible. To ensure gradually lower greenhouse gas emissions, a social and economic shift through ambitious nationally determined contributions (NDCs) is required (United Nations, 2015, 2022).

Several researchers have found the Paris Agreement to generate negative abnormal returns and increased volatility for polluting industries Moosa et al. (2019b); De Angelis (2020); Gehricke et al. (2021). The Paris Agreement is also identified as a turning point where several sectors experience negative abnormal returns after the announcement (Birindelli & Chiappini, 2020). This gives us an expectation that the exporters with a large share of oil and energy companies, such as the Russian MOEX, Norwegian OSEBX, and maybe Spain's IBEX 35, might be negatively impacted by the announcement of the Paris Agreement. For the other indices with a large share of chemicals and industry (DAX), banks and utilities (FTSE MIB) and health care (FTSE 100), it is more difficult to assume a reaction to the Paris Agreement. Additionally, Investor attention is assumed to be high, as the google trends show a spike in interest for climate change around the event (Google, 2022a). Guo et al. (2020) found that investor attention helps foresee stock market response to environmental announcements. El Ouadghiri et al. (2021) also found that public attention to climate change influences the stock market by sustainable assets experiencing higher returns.

4.5.2 Action plan for the planet

The action plan for the planet was announced at the One Planet Summit in Paris on the 12th of December 2017. The plan contains ten transformative initiatives to help guide and accelerate the way towards the targets of the 2015 Paris Agreement, and the European Union's own goal of reducing the CO^2 emissions by 40% in all sectors in Europe by 2030. All initiatives are aimed at creating a fair society and a modern economy built on innovative technologies and renewable energy sources (European Commission, 2018a). One of the initiatives is targeted at the financial sector - increasing its role in the green transition. By introducing reforms, the European Commission is committed to shift private investments away from carbon-intensive assets and rather incentivise investments in low-carbon securities. To achieve this, future initiatives will aim for better sustainability reporting and considerations of ESG factors. A new classification system defining sustainable investments known as the European taxonomy was also mentioned (European Commission, 2018a).

Action plan for the planet further enforces the goals set at the 2015 Paris Agreement. New initiatives to accelerate the shift towards a sustainable economy could have implications for our indices. Especially the initiative enabling future reforms targeted at lowering investments in carbon-intensive assets could be bad news for the exporters of crude oil, and maybe for Spain's IBEX 35 due to the large oil and energy sector. Birindelli & Chiappini (2020) also analysed the action plan for the planet announcement and found significant negative CAARs for the consumer discretionary, industrials and utilities sector. All our importers have a sizable industry sector and Italy's FTSE MIB also have a large utility sector. Despite a low number of searches on "climate change" surrounding the event, previous findings make us expect a mild or negative reaction for all exporters and importers to the announcement of action plan for the planet (Google, 2022b).

4.5.3 A clean planet for all

Announced on the 28th of November 2018, a clean planet for all is a long-term vision for the European economy to be climate neutral by 2050. A clean planet for all will be achieved through following a strategy based on cost efficiency implemented as a socially fair transition. The European Commission (2018b) states that the strategy does not include new policies or revised 2030 emissions targets. It intends to set the direction of EUs climate policy to achieve the temperature goals of the Paris Agreement and the UN Sustainable Development Goals. The strategy's main purpose is to spark a debate between EU citizens and decision makers to decide how Europe should move towards the 2050 emission goals and agree on a long-term plan to submit to the UN Framework Convention for Climate Change in 2020 (European Commission, 2018b).

A clean planet for all does not include any new policies or emissions targets but is still an important step in achieving a climate neutral economy. Gou et al. (2020) analysed the Chinese financial market and found that strict laws generate more negative reactions from carbon-intensive firms than regulations. These findings may indicate that we do not expect large movement in the indices around the announcement of a clean planet for all. Despite no new regulations, the clean planet for all generated much attention when looking at Google Trends around the announcement (Google, 2022c). A high investor attention could have negative consequences for our exporters, in line with Guo et al.'s (2020) findings. In addition, Italy's FTSE MIB has a large utility sector which was the industry found by Birindelli & Chiappini (2020) to have the worst reaction to the announcement of a clean planet for all in the EU. Mainly due to the content of a clean planet for all, we do not expect large movements for our exporters, but we could see a negative effect on Italy's FTSE MIB index.

4.5.4 European Green Deal

Announced on the 11th of December 2019, the European Green Deal represents a new growth strategy with the goal of no net greenhouse gas emissions in the European Union (EU) in 2050. The goal is achieved by transforming the EU into a modern and resource-efficient economy, enabling a fair and prosperous society. An important factor is to decouple the economic growth from resource use. To achieve the goals of European Green Deal, new policies are required in all sectors of the economy. Another important factor is to provide incentives for upholding and restoring natural ecosystems and making better use of resources sustainably. Reaching these goals also requires a significant amount of investment. The EU taxonomy - a classifying tool for sustainable investments and better sustainability reporting by companies are important factors. It is highlighted by the Commission that one single measure will not be enough to achieve the objectives and that trade-offs between social, environmental and economic objectives require careful attention when new policies are drafted (European Commission, 2019).

The European Green deal proposes new policies to reach net zero greenhouse gas emissions in 2050. Although not introducing any new laws at the time of the announcement, the Green Deal lists several proposed regulations that will be discussed and come into force later. One of which is the potential revision of the energy taxation directive and the potential for stricter emissions trading schemes and carbon tax. The European Green Deal includes a time limit for when the EU must be net zero in greenhouse gas emissions, which, according to Dahal & Das (2022), could negatively affect the stock market. Although the policy suggestions are comprehensive, they are not in line with the strict regulations which Guo et al. (2020) found to affect the stock market. Additionally, looking at investor attention, Google Trends shows that the public was not particularly interested in the event, meaning that El Ouadghiri et al.'s (2021) findings do not support that the Green Deal will impact exporters more than importers (Google, 2022d). Therefore, we expect small reactions to this event from all indices.

4.5.5 Glasgow climate pact

The 2021 United Nations Climate Change Conference in Glasgow (COP26) resulted in the Glasgow climate pact. Almost 200 countries were present, and the agreement means that there are still hopes of reaching the 1.5-degree Celsius goal from the Paris Agreement (United Nations, 2021). The climate pact is built on four main action points: mitigation, adaptation, finance, and collaboration. Mitigation is concerned with reducing emissions, focusing on moving away from coal power, reversing deforestation, lower methane emissions, and accelerating the move to electric vehicles. Delivering on climate goals requires big financial resources and all nations agreed to mobilise significant investments directed towards global net zero emissions. Most nations attending the COP26 pledged even more ambitious targets across the four action points than before the conference (United Nations, 2021).

Aleksovski et al. (2020) showed that climate negotiations negatively affected "brown" firms after 2013. These findings could mean exporters of crude oil and perhaps the Spanish IBEX 35 index could experience negative returns surrounding the Glasgow climate pact. Furthermore, Dahal & Das (2022) showed that international agreements tend to affect the stock market positively. However, time-specific goals like those proposed in the Glasgow climate pact had negative effects. Given that the public attention to climate change around the event is high, more sustainable companies could react better than polluters (El Ouadghiri et al. 2021; Google, 2022e). Therefore, we expect this event to have a mild or positive effect on importers, while exporters are expected to react negatively.

5. Empirical Methods

This section presents the empirical methodology applied in this paper. The chapter is made up of two main parts, the introduction of event studies and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. This thesis applies event study methodology described by MacKinlay (1997), as it is useful in measuring the effect of events on financial markets. As mentioned in the literature review, there are numerous event study approaches, however, Brooks (2019, p. 724) explains that Mackinlay (1997), and Armitage (1995), are easy to interpret. Given the number of literature review papers that used the Mackinlay (1997) method, we will also use his approach. A GARCH model measures the volatility of an asset in the stock market. Thus, it can capture the volatility effects surrounding the same events examined in the event study. Together they will provide insights into how environmental announcements affect the financial markets of different countries in Europe.

5.1 Estimation Methods

Before the two main methodologies are explained, some key estimation methods applied in the event study and the GARCH model are introduced.

5.1.1 Ordinary Least Squares Estimation

Mackinlay (1997) and Brown & Warner (1985) suggest using Ordinary Least Squares (OLS) to estimate the market model parameters, which in turn is used to calculate the abnormal returns. It can be argued that the OLS technique might be the most influential estimation method in econometrics (Verbeek, 2004, P.7). The OLS estimation procedure estimates a linear relationship between two or more variables through a linear regression model. Typically, one explains the linear regression model by the following equation: (Brooks, 2019, P. 147-150)

$$y_t = \alpha + \beta x_t + \varepsilon_t \tag{5.1}$$

Brooks (2019, P. 152) mentions different ways of estimating the linear regressions model, with the OLS approach being the most common. The OLS method builds on minimizing the squared distance between the observed value y_t and the predicted value $\hat{y}$ (Verbeek, 2004, P. 8). Brooks (2019, P. 154) explains it by using the following equation:

$$L = \sum_{t=1}^{T} (y_t - \hat{y})^2 = \sum_{t=1}^{T} \left(y_t - \hat{\alpha} + \hat{\beta} x_t\right)^2 \tag{5.2}$$

Minimizing the equation L gives the values of $\hat{\alpha}$ and $\hat{\beta}$ with the lowest variance, and therefore the best estimated regression line.

However, the OLS technique comes with some assumptions which could affect the reliability of the estimated parameters if the given assumptions are not fulfilled (Zdaniuk, 2014). Verbeek (2004, P. 16) divides the assumptions into sets, with the first four being the Gauss-Markov assumptions.

$$E\{\varepsilon_i\} = 0 \quad \text{(A1)}$$

$$\{\varepsilon_i, \dots, \varepsilon_N\} and \{x_1, \dots, x_N\} \text{ Are independent (A2)}$$

$$V\{\varepsilon_i\} = \sigma^2 \quad \text{(A3)}$$

$$cov\{\varepsilon_i, \varepsilon_j\} = 0 \quad \text{(A4)}$$

The first assumption (A1) explains that one expects the error terms to be equal to 0. This tells us that even though some of the estimated residuals do not match the observations, the errors go either way and on average, the estimated regression line is accurate. A2 can be explained by saying that the error terms ε are independent of the deterministic variables X, which means that the value of X does not tell us anything about the value of ε . Assumption 3 (A3) can be explained by homoskedasticity in the error terms, which tells us that the error terms have a constant variance. Assumption 4 (A4) states that there is no correlation between the error terms and, therefore no autocorrelation. If all the Gauss-Markov assumptions are fulfilled, OLS is described as the Best Linear Unbiased Estimator (BLUE) of β (Verbeek, 2004, P. 18). However, Verbeek (2004, p. 16) states that one does not need to fulfil all the assumptions to use the OLS estimator.

Another key question to ask when one estimates a regression model is how good the model represents the actual observations. A way of measuring this is to use a goodness of fit statistic. A popular and very common way of measuring said fit is known as R^2, Brooks (2019, p. 226) explains it as follows:

$$R^2 = \frac{ESS}{TSS} \tag{5.3}$$

where

$$TSS = ESS + RSS \tag{5.4}$$

$$TSS = \sum (y_t - \overline{y})^2 \tag{5.5}$$

$$ESS = \sum (\hat{y}_t - \overline{y})^2 \tag{5.6}$$

$$RSS = \sum \hat{e}_t^2 \tag{5.7}$$

RSS means residual sum of squares and can be explained as the part of the variation that is not explained by the model. ESS means explained sum of squares, which is the part of the variation that is explained by the model. TSS is the total sum of squares and is also the total variation of the dependent variable y. R^2 will have a value somewhere between 0 and 1, with a value of 0 not explaining anything more than the mean of y, and a value of 1 explaining all of the variance, where all the residuals e will be equal to zero.

5.1.2 Maximum likelihood estimation

The GARCH model builds on conditional variance and heteroskedasticity (Brooks, 2019, P. 512). However, the OLS estimation technique assumes a homoscedastic and constant variance and is therefore not applicable for estimating the parameters in the GARCH model (Verbeek, 2004, P. 18). Therefore, one uses a method known as maximum likelihood to estimate GARCH models (Brooks, 2019, P. 515). The maximum likelihood method attempts to find the most likely parameters that caused the observed data that has been put into to model (Brooks, 2019, P. 516).

When using maximum likelihood to estimate a model, one needs to form a likelihood function. We look at the example provided in Sengabo & Øverby's (2021) thesis, where they refer to Dendukuri's (2020) interpretation of the likelihood function:

$$L(\theta) = L(\theta | \chi_1, \chi_2, .., \chi_n) = f(\chi_1, \chi_2, .., \chi_n | \theta) \tag{5.8}$$

In this equation the observed data $X_1, X_2, .., X_n$ follow the joint density function $f(X_1, X_2, .., X_n)$ if $X_1 = \chi_1$, $X_2 = \chi_2, .., X_n = \chi_n$. This means that the observations follow the same density function if the estimated parameters are equal to the real parameters. Brooks (2019, p. 516) argues that one should form a log-likelihood function, because working with the real data may make it hard to maximize $L(\theta)$. Taboga (2017) explains why researchers tend to use the logarithmic transformation of the likelihood function. He argues that it becomes less complicated to analyse the asymptotic properties like the central limit theorem and law of large numbers when using the logarithmic transformation. Jungeilges (2021a) also argue for the convenience of using log-likelihood by implying that it is more straightforward to calculate the partial derivatives for the mean and variance.

A key assumption when dealing with maximum likelihood estimation is that the sample data needs to come from the same distribution and be independent. This is usually referred to as i.i.d. which means identically and independently distributed and refers to that any two random points in the sample are independent from each other, and stems from the same distribution (Jungeilges, 2021a). According to Jakobsen (2018) one usually assumes that the sample comes from a Gaussian distribution and is therefore i.i.d. N(0,1).

Brooks (2019, P. 515) shows how a simple GARCH (1,1) with an AR(1) process is estimated through maximum likelihood:

$$y_t = \mu - \phi y_{t-1} + u_t,\ u_t \sim N(0, \sigma_t^2) \tag{5.9}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{5.10}$$

Where the following log-likelihood function for the error term is maximized:

$$L = -\frac{T}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\ln(\sigma_t^2) - \frac{1}{2}\sum_{t=1}^{T}\frac{(y_t - \mu - \phi y_{t-1})^2}{\sigma_t^2} \tag{5.11}$$

Comparing the equation above to the log-likelihood function given by Jakobsen (2018) which is as follows:

$$L(\theta) = \sum_{t=1}^{T}\frac{1}{2}\left(-\ln 2\,\pi - \ln(\sigma_t^2) - \frac{\varepsilon_t^2}{\sigma_t^2}\right) \tag{5.12}$$

The equations are the same, but with different notation for the error term, with ε replacing u . Given that they represent the same log-likelihood function, we can say that the likelihood function follows the same steps when estimating a GJR GARCH model, with only the σ_t^2 being different due to the leverage effect (Jakobsen, 2018).

5.1.3 Information Criteria

As explained earlier, when selecting a specific statistical model, one often performs a goodness of fit test. When dealing with ARIMA models, one typically uses something called information criteria, and not just the simple R^2. An information criterion aims to find the optimal trade-off between minimizing the residual sum of squares (RSS) and applies a penalty for adding new parameters (Brooks, 2019, p. 360). Javed & Mantalos (2013) state that researchers use information criterion to fit the best model, as a model with more lags than needed reduces the RSS. There are different information criteria, but typically one uses either Akaike's information criterion (AIC), or Schwarz Bayesian Information Criterion (SBIC) (Verbeek, 2004, p. 58). According to Brooks (2019, p. 360), these criteria are expressed as follows:

$$AIC(k) = \hat{\sigma}_y^2(1 - R^2)e^{\frac{2k}{n}}$$

$$SBIC(k) = \hat{\sigma}_y^2(1 - R^2)n^{\frac{k}{n}}$$

Where $\hat{\sigma}^2$ is the estimated variance of the residuals, and k is the number of parameters p+q+1. The main difference between these two is that they apply different penalties for adding new parameters. SBIC penalizes the addition of new parameters more than AIC does, but there is no criterion that dominates the other (Brooks, 2019, p. 361). The model which provides the lowest AIC or SBIC is the model that should be preferred (Verbeek, 2004, p. 58). Jungeilges (2021b) explains that SBIC usually chooses the smaller model, and if one builds a predictor, AIC is preferred, while SBIC is used when one wants the true model. It is rare to observe another GARCH model than the GARCH (1,1) in literature, however, Javad & Mantalos (2013) showed that this might not always be the best model and could result in "*high prediction errors*".

5.2 Event study

This section will introduce the event study methodology. As this study aims to look at the effects of environmental announcements on stock market indices in Europe, the event study methodology presented by Mackinlay (1997) will be used. Event studies are frequently used in research on capital markets to detect possible abnormal returns surrounding an event. The methodology has advanced and spread across different disciplines over the last decades, but the fundamental statistical tools remain mostly unchanged (Corrado, 2010).

5.2.1 Event study introduction

Event studies applies stock market data to measure the effects of an identifiable event on firms or other securities in the market. There are some underlying assumptions of the event study in detecting abnormal returns, namely the efficient market hypotheses introduced in section 3.1, that market participants are rational and that there are no confounding effects resulting from separate events to those in question (McWilliams & Siegel, 1997).

In general event studies follow the same steps, although there are several research design choices to consider. Firstly, the event(s) that are to be examined needs to be identified. Here, it can be useful to set some criteria for which securities and events to include in the analysis. Inclusion criteria, securities and events are elaborated in the chapter 4. When the relevant events are determined, the estimation window, event window and post-event window must be established. Furthermore, a model for measuring normal returns must be chosen as well as the method of calculating abnormal returns (MacKinlay, 1997). Capturing the impact of an event requires estimation of abnormal returns in the event window. Abnormal returns in the event window with event day τ is the actual ex post return of asset i minus normal return during the event window. Consequently, normal return is the expected return over the event window conditioned to the event not taking place. This is illustrated by equation (5.15)

$$AR_{i\tau} = R_{i\tau} - E(R_{i\tau}|X_\tau) \tag{5.15}$$

where abnormal return is given by $AR_{i\tau}$, actual return $R_{i\tau}$ and normal return is $E(R_{i\tau}|X_\tau)$.

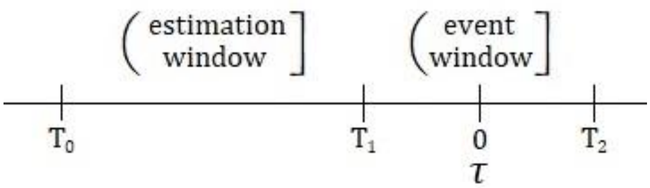
The next sections will address the respective time windows, model selection, abnormal return estimation and significance test.

5.2.2 Time windows

Figure 1 illustrates the event study time windows, displayed as a timeline. $\tau = 0$ is defined as the event date. The separate time periods can be stated as $\tau = T_0 + 1$ to T_1 which is the estimation window while $\tau = T_1 + 1$ to T_2 is the event window. Furthermore, let the length of the estimation window be $L_1 = T_1 - T_0$ and the event window $L_2 = T_2 - T_1$. Sometimes a post-event window is included in the period after the event window. Including a post-event window combined with the estimation window could increase robustness in the normal market return estimations (MacKinlay, 1997). In general, the estimation window and event window do not overlap. As this methodology is based on a measure of normal returns in the estimation period and abnormal returns in the event period, any overlap would be problematic for the results. This would cause the potential event driven returns to be included in the calculations of the normal returns.

In this thesis the estimation window is set to one year or 252 trading days. The event window is set to a total of 21 trading days $[-10,10]$, ten days prior to the event day, the day of the event and ten days after the event. A large event window allows for detection of early and delayed announcement effects on securities. The post-event window will not be applied in this study as the estimation window is sufficiently long to ensure robust calculations (MacKinlay, 1997).

Figure 1: Event study timeline



Inspired by MacKinlay (1997)

5.2.3 Normal return model selection

When the respective time windows are determined, choosing the appropriate normal return model is the next step. There are several options available when selecting a model. The models can be categorised as statistical and economic models. The statistical models adhere to statistical assumptions regarding security returns. On the other hand, economic models include assumptions on investor behaviour rather than statistical assumptions alone. MacKinlay (1997) presents four models or categories of models which are further elaborated below.

Constant Mean Return Model

The constant mean return model defines the normal return as the mean of the real returns over the estimation window. While being considered a simple measure of normal returns the mean return model is often as accurate as more sophisticated models (Brown & Warner, 1980; 1985). The statistical properties of the constant mean return model is given by

$$R_{it} = \mu_i + \zeta_{it} \tag{5.16}$$

$$E(\zeta_{it}) = 0 \qquad var(\zeta_{it}) = \sigma^2_{\zeta_i}$$

where R_{it} is the asset i return in period t , μ_i the mean return and ζ_{it} the disturbance term with an expected value of zero and variance $\sigma^2_{\zeta_i}$. It is not necessarily the case that a more intricate model will result in a lower variance in the abnormal returns (MacKinlay, 1997).

Market Model

The market model applies the actual returns of a market portfolio used as a benchmark for the return of a given security. It is a linear model with the underlying assumption of joint normality between the market portfolio returns and security returns. The market models' statistical properties for any asset i are given by

$$R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it} \tag{5.17}$$

$$E(\epsilon_{it}) = 0 \qquad var(\epsilon_{it}) = \sigma^2_{\epsilon_i}$$

where R_{it} is the i^{th} security return during time t and R_{mt} the market portfolio returns over the same period. Parameters are given by α_i, β_i and $\sigma^2_{\epsilon_i}$. To represent the market portfolio, it is common to use a broad market index such as a world index or other regional indices (MacKinlay, 1997).

Compared to the constant mean return model, the market model is a possible improvement. This comes from eliminating the variance variable in the normal return estimation which in turn lowers the abnormal return variance. The benefit can be seen from a higher R^2 returned by the market model regression. A lower variance in the abnormal returns is beneficial in identifying event effects on the market (MacKinlay, 1997).

The estimated model parameters $\hat{\beta}_i$ and $\hat{\alpha}_i$ can be estimated by using the ordinary least squares (OLS) method. Given the assumptions about the market model, OLS will be a consistent and efficient estimator. From MacKinlay (1997) the parameters are calculated as follows

$$\hat{\beta}_i = \frac{\sum_{\tau=T_0+1}^{T_1}(R_{i\tau} - \hat{\mu}_i)(R_{m\tau} - \hat{\mu}_m)}{\sum_{\tau=T_0+1}^{T_1}(R_{m\tau} - \hat{\mu}_m)^2} \tag{5.18}$$

$$\hat{\alpha}_i = \hat{\mu}_i - \hat{\beta}_i\hat{\mu}_m \tag{5.19}$$

$$\hat{\sigma}_{\epsilon_i}^2 = \frac{1}{L_1 - 2}\sum_{\tau=T_0+1}^{T_1}(R_{i\tau} - \hat{\alpha}_i - \hat{\beta}_i R_{m\tau})^2 \tag{5.20}$$

where

$$\hat{\mu}_i = \frac{1}{L_1}\sum_{\tau=T_0+1}^{T_1} R_{i\tau} \tag{5.21}$$

and

$$\hat{\mu}_m = \frac{1}{L_1}\sum_{\tau=T_0+1}^{T_1} R_{m\tau} \tag{5.22}$$

Other Statistical Models and Economic Models

MacKinlay (1997) also reviews other statistical models such as multifactor models and economic models being the Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory (APT). Multifactor models could be useful in lowering the variance of the abnormal returns by explaining the variation in the normal returns more sufficiently. The economic models can provide stricter normal return models by imposing restrictions on the statistical models. Although, the use of statistical factor and economic models over the market model have been found to add limited value to the estimations (Brown & Weinstein, 1985; MacKinlay, 1997). Thus, this thesis and the remainder of this section will focus on the market model.

5.2.4 Abnormal returns

Given the estimated market model parameters $\hat{\beta}_i$ and $\hat{\alpha}_i$ from 5.18 and 5.19 the abnormal returns during the event window can be calculated using

$$AR_{i\tau} = R_{i\tau} - \hat{\alpha}_i - \hat{\beta}_i R_{m\tau} \tag{5.23}$$

where $AR_{i\tau}$, $\tau = T_1 + 1, \dots, T_2$ is the sample of L_2 abnormal returns for security i in the event window. The associated conditional variance is given by

$$\sigma^2(AR_{i\tau}) = \hat{\sigma}^2_{\epsilon_i} + \frac{1}{L_1}\left[1 + \frac{(R_{m\tau} - \hat{\mu}_m)^2}{\hat{\sigma}^2_m}\right] \tag{5.24}$$

which has two main components. The first component from the market model (5.17) and the second one from sampling error in α_i and β_i. Even though the true errors are independent in time, the sampling error causes serial correlation in the abnormal returns. Although, a longer estimation window L_1 will reduce the sampling error to the point where the second component almost vanishes completely (MacKinlay, 1997).

The abnormal returns estimation tests the null hypotheses of no effect from the event on the security returns during the event window. MacKinlay (1997) states that for a given observation under the null hypotheses, the sample abnormal returns distribution is

$$AR_{i\tau} \backsim N\big(0, \sigma^2(AR_{i\tau})\big) \tag{5.25}$$

5.2.5 Aggregation of abnormal returns

The aggregation of abnormal returns is necessary in order to detect event effects during the event window. It is possible to aggregate both in time and across assets. As the data sample in this study is indices, and we want to investigate the single index response to an event, the aggregation across time in the event window is most relevant. The cumulative abnormal returns (CAR) $CAR_i(\tau_1, \tau_2)$ time-window is defined as τ_1 to τ_2 where $T_1 < \tau_1 \leq \tau_2 \leq T_2$ and is the sum of the abnormal returns in the event-time period (MacKinlay, 1997). The CAR for asset i from τ_1 to τ_2 is given by

$$CAR_i\,(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_1} AR_{i\tau} \tag{5.26}$$

5.2.6 Significance test

The abnormal returns in the event window must be tested to determine if they are significantly different from zero. This is done by applying a two-sided parametric t-test to the CARs for a single security. The t-statistic for the null hypotheses is given by

$$t_{CAR} = \frac{CAR_i\,(\tau_1, \tau_2)}{sd(CAR_i(\tau_1, \tau_2))} \tag{5.27}$$

where

$$sd\big(CAR_i(\tau_1, \tau_2)\big) = \sqrt{L_2}\sqrt{var(AR_{i\tau})}. \tag{5.28}$$

The corresponding null and alternative hypothesis are given by

$$\begin{aligned} H_0 &= E(CAR_i) = 0 \\ H_1 &= E(CAR_i) \neq 0 \end{aligned} \tag{5.29}$$

where the null hypothesis is rejected at a 5% level with a t-statistic larger than $\pm$ 1.96 or a p-value less than 0.05. The outcome of the hypothesis tests is presented in the results section.

5.3 GARCH Model

The last section regarding the event study and abnormal returns helps us get an overview of the effect of environmental announcements on a sample of stock market indices. However, as shown by the estimation of the variance of the abnormal returns, it is calculated during the estimation window. According to Brooks (2019, P. 732), this measure of variance might not be able to reflect the actual volatility in the period leading up to the event. He argues that it is likely that there will be an increase in volatility, due to investors not being sure of the announcements effect. Mackinlay (1997) supports this view, by suggesting that one could allow for changes in variance when conducting an event study. An additional view is provided by Brown & Warner (1985) who states that announcements increase stock return variance in the period surrounding the event. A way of operationalising this problem is to use a GARCH model. The market model used to calculate the abnormal returns assumes a linear relationship, and can be known as a homoscedastic model, with a constant variance. The heteroskedastic GARCH model however has a conditional variance which depends on its own lag, and therefore evolve over time (Brooks, 2019, P. 512). Using a variation of this model would give an indication of a possible risk increase around the event.

The GARCH model builds on the ARCH concept from Engle's (1982) paper, where he introduced the stochastic ARCH process were the observations from the past, tells us something about the future variance. Brooks (2019, P. 507) argues that this may useful due to "volatility clustering", which tells us that large changes in volatility follows other large changes, while the same is the case for small volatility changes. However, the number of drawbacks for the ARCH model has seen its use in financial papers decrease over time. It is therefore natural to consider using a GARCH model, as these are very often used in financial papers (Brooks. 2019, P. 511-512).

As mentioned earlier the GARCH model allows the researcher to model the conditional variance and analyse how the variance evolves over time. This conditional variance in a GARCH (1,1) model looks like this:

$$\sigma_t^2 = \omega_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{5.30}$$

α_1 in this model represents the ARCH effects, which as explained is the effect of the volatility in the last period on the conditional variance, while β tells us something about the duration of the ARCH effects, or in other words, how long it takes for the ARCH effect to fade out. It is possible to extend the GARCH model to a GARCH (q, p), but Brooks (2019, P. 514) states that a GARCH (1,1) model usually is sufficient, and that it is rare to observe any higher order models in literature.

There are also several versions of the GARCH model, which are designed to remove some of the drawbacks of the basic GARCH model. One of the restrictions that exist in the basic model is that of symmetry in the shocks. This means that the model does not take the sign of the shock into account, and it therefore suggests that a positive change in stock return causes the same volatility as a negative one. However, this is not believed to be the case, as a negative shock is likely to have a bigger effect on the volatility than a positive one (Brooks, 2019, P. 521). This thesis examines the effects of a number of different environmental announcements that are meant or believed to have an impact on the financial market. On that note, a model which follows the assumption that negative shocks are more influential than positive ones could be beneficial for the thesis. These models are called asymmetric GARCH models.

Brooks (2019, p. 521) suggest that the GJR- GARCH is an uncomplicated extension of the basic GARCH, which addresses the asymmetry. The reason why it is uncomplicated is that it only adds one term to the equation of the conditional variance. Which in the GJR-GARCH is given by:

$$\sigma_t^2 = \omega_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} \tag{5.31}$$

As can be seen by the model, the only difference is the last term I_{t-1}, which is called the leverage effect. It is a dummy variable which is equal to 1 if the last innovation were negative, and equal to zero if it was positive. In this way the model considers that negative shocks are more influential on the conditional variance than the positive ones.

Given the topic of the thesis, we are especially interested in looking at the risk in the event period, to determine if there is an effect of the announcements on the indices. As we will use a GJR-GARCH to look at the conditional variance we can build on the work by Sengabo & Øverby (2021), who examined the impact of Covid-19 on some indices. They added a dummy variable that represented the time of the pandemic and evaluated if it had an effect. We can do the same, but with different events. Our model would therefore look like this:

$$\sigma_t^2 = \omega_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} + \delta EVENT_t \tag{5.32}$$

This model will give us an indication if the different events influence the conditional variance of the indices. We could look at the significance of our own added dummy variable to see if there was an effect in any of the indices. Comparing the event coefficient of the different indices over the different events could help us see whether the exporters are more affected than the importers by these environmental announcements.

6. Results

In the following sections, we will present the results from the methodology described in section 5. Starting with section 6.1, we present the results from the event study, following the approach of Mackinlay (1997) to answer the first hypothesis. For the second hypothesis, we performed a volatility analysis using a GJR-GARCH model, where the results will be shown in section 6.2. Section 6.3 will show some implications of the choice of research design. Firstly, we perform some tests to see whether the OLS assumptions are fulfilled. Secondly, we provide results of an event study using a constant mean return as the normal performance. Lastly, we perform a volatility analysis using a "Vanilla GARCH (1,1)" model.

6.1 Event Study

This section will present the results of the event study. The main stock market index of the six largest importers and exporters of crude oil in Europe are examined to see how they react to environmental announcements. Abnormal returns are estimated surrounding every event for each individual index. Furthermore, CARs are calculated by summarising the abnormal returns over the event window. Table 6 reports the CARs starting from 10 days prior to the event until 10 days after the event.

Our event study tests the following hypothesis

> **H_0:** The main indices of European exporters and importers of crude oil will have a similar reaction to environmental announcements.
>
> **H_1:** The main indices of European exporters will react more negatively than importers of crude oil to environmental announcements.

Table 6: Event window cumulative abnormal returns [-10,10]

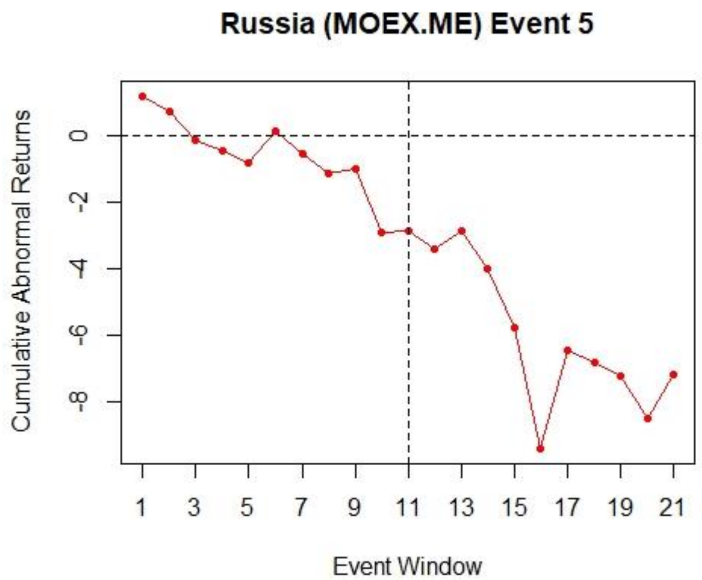
Country	Event 1	Event 2	Event 3	Event 4	Event 5
Germany	0.02 0.0073 (0.9942)	-2.09 -1.3480 (0.1920)	0.46 0.2838 (0.7793)	-2.06 -1.3653 (0.1867)	-0.23 -0.1472 (0.8884)
Spain	-1.60 -0.5450 (0.4915)	-1.18 -0.4389 (0.6651)	0.96 0.4713 (0.6423)	2.19 1.1314 (0.2706)	-4.41 -1.4654 (0.1577)
Italy	-0.33 -0.0968 (0.9244)	-2.62 -0.8697 (0.3947)	3.81 1.1534 (0.2617)	-2.72 -1.1677 (0.2563)	-1.34 -0.6323 (0.5342)

UK	3.07	2.31	1.01	1.37	0.20
	1.3816	1.2880	0.5585	0.70474	0.0915
	(0.1816)	(0.2118)	(0.5824)	(0.4887)	(0.9280)
Norway	0.40	-1.53	-3.20	-0.73	-0.96
	0.1063	-0.5983	-1.2000	-0.2833	-0.3432
	(0.9164)	(0.5562)	(0.2435)	(0.7799)	(0.7350)
Russia	-2.50	-2.51	1.01	1.36	-7.20
	-0.4233	-0.6991	0.2250	0.2295	-2.1392
	(0.6766)	(0.4922)	(0.8242)	(0.8202)	(0.0443)

Table of CARs and corresponding t-statistic and p-value.

From the event study results, we can see that the signing of the Glasgow climate pact in November 2021 is the only period that produces significant CARs in the [-10,10] event window. During the event window, the Russian MOEX index fell 7.20%, indicating a substantial reaction to the outcome of the announcement of the Glasgow climate pact. Day by day CARs for MOEX during event five is illustrated in figure 2, where the dotted vertical line on day 11 represents the event day. We can see a steady decline during the whole event window, with a sharp drop in CARs between two and five days after the announcement.

Figure 2: Cumulative abnormal returns for Russia during the Glasgow Climate Pact



Russia's MOEX is the only index with significant CARs in our event study. Although, some indices did experience large movements around certain events. Spain's IBEX 35 index dropped 4.41% during the time of the Glasgow climate pact signing. Furthermore, Italy's FTSE MIB and

Norway's OSEBX had large opposite CARs during the announcement of a clean planet for all in late November 2018, where Italy rose 3.81% and Norway fell 3.20%. It is also interesting to note that there seem to be small differences in being a large importer or exporter of crude oil. For instance, UK's FTSE 100 index did not react negatively to any of the events considered in the event study. The overall reaction to environmental announcements seems relatively mild.

Despite few significant CARs, it could be interesting to illustrate the overall index reactions to each announcement by aggregating the CARs for all importers and exporters and plotting them against each other. The graph for each event is presented in the figures below where the day-by-day change in the event window can be followed. The red line illustrates the exporters, and the blue line represents the importers.

Figure 3: Cumulative abnormal returns for importer and exporters during the Paris Agreement

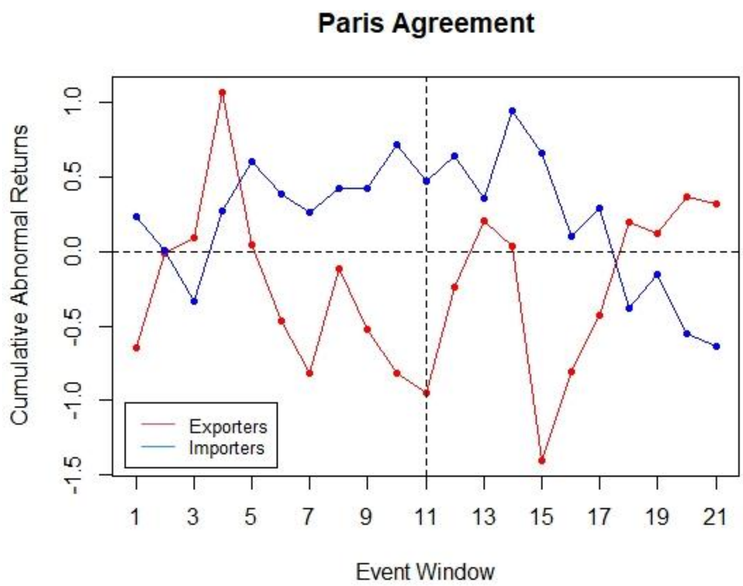


Figure 4: Cumulative abnormal returns for importer and exporters during Action Plan for the Planet

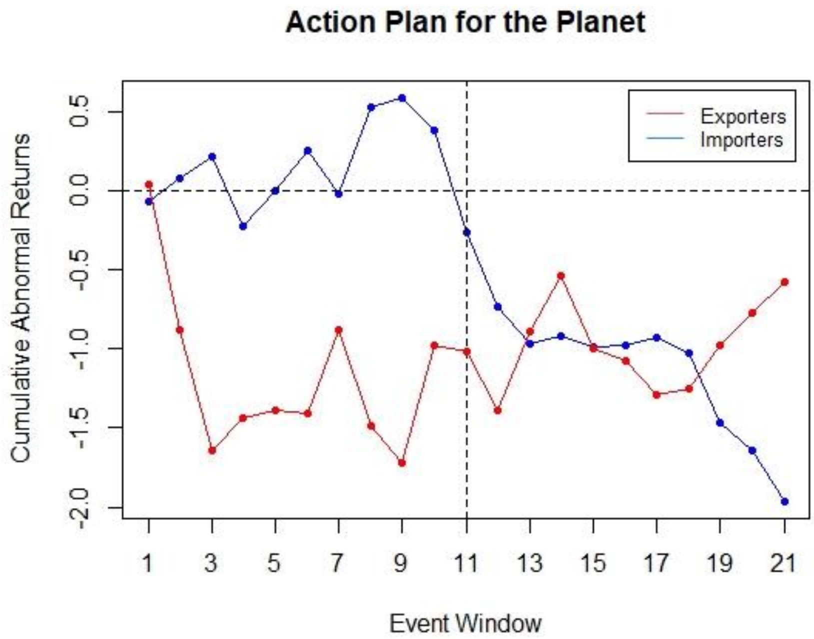


Figure 5: Cumulative abnormal returns for importer and exporters during A Clean Planet for All

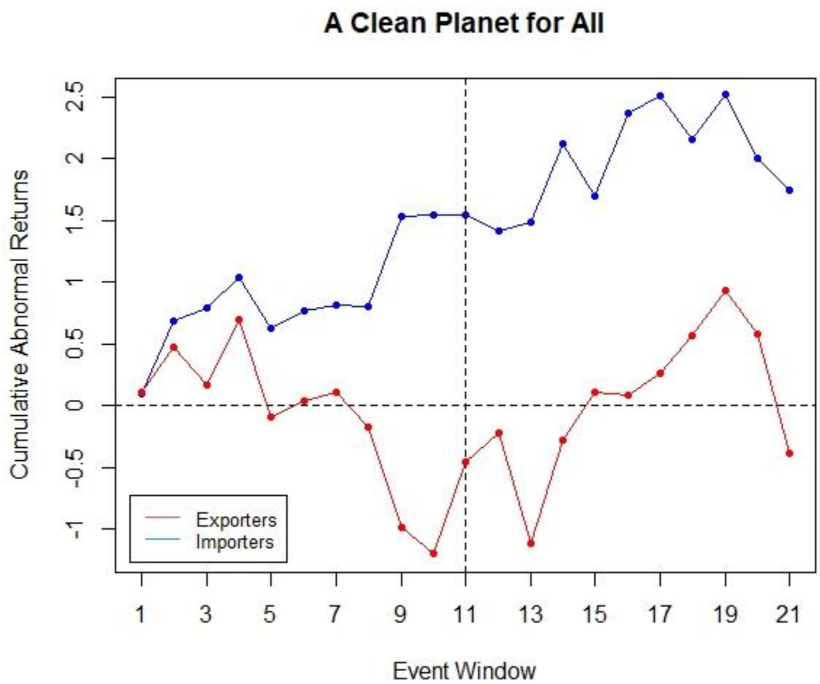


Figure 6: Cumulative abnormal returns for importer and exporters during the European Green Deal

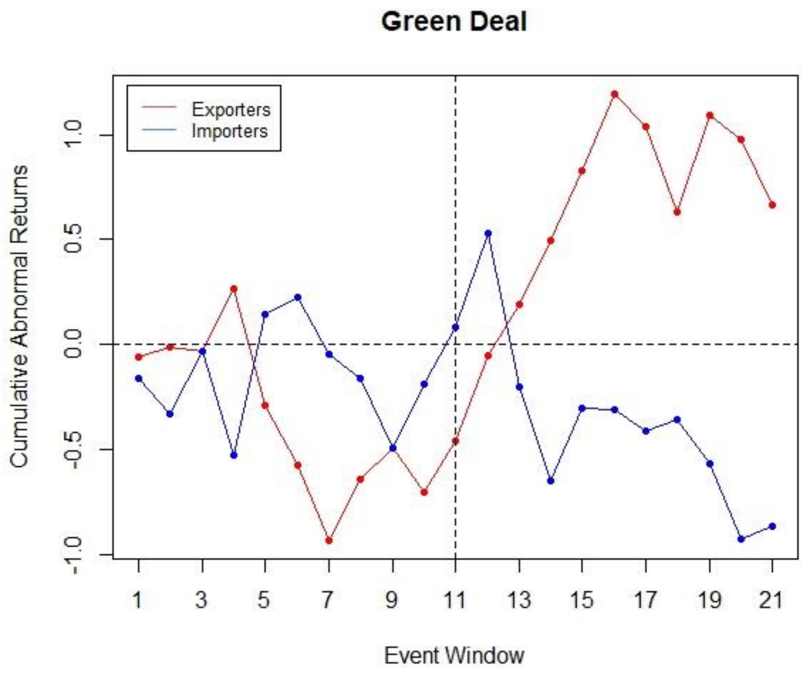
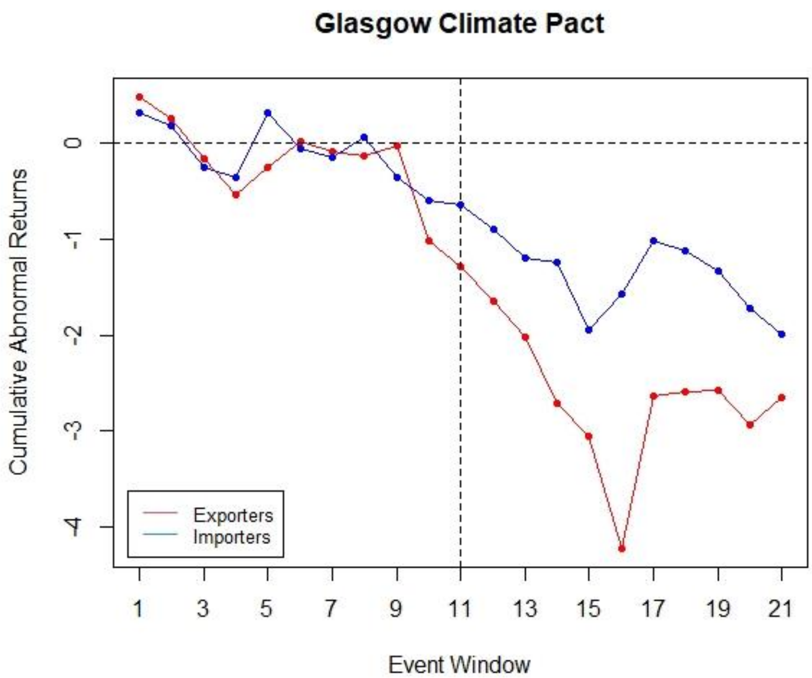


Figure 7: Cumulative abnormal returns for importer and exporters during the Glasgow Climate Pact



Around the announcement of the Paris Agreement, we can see exporters having a period of negative CARs before the event date but ending up with positive CARs towards the end of the event window. On the other hand, the importers are steady through the event date and then experience a drop a few days after the signing of the Paris Agreement. Another interesting observation is the inverse index reaction prior to the action plan for the planet publication. On the event date itself and in the following days, importers see a sharp drop and eventually end up at lower CARs than the exporters at the end of the event window, similar to what we see during the Paris Agreement. During the clean planet for all announcement, we see exporters experience lower CARs than importers. This is despite the exporters having a positive reaction to the event day itself and a general upward trend afterward. However, the importers seem to have a positive reaction throughout the entire event window. The European Green Deal is another event where the exporters achieve higher CARs than importers. Despite having similar pre-event day movements, and a positive reaction to the announcement of the European Green Deal, the CARs split off in different directions in the following days. Importers fell sharply post-event day while exporters reacted positively to the European Green Deal. Lastly, we observe the largest index movements around the announcement of the Glasgow climate pact. A stable trend can be observed in the days leading up to the signing of the Glasgow climate pact, but a drop is experienced for both exporters and importers a couple of days before the announcement. CARs continue to fall through the event day and the following days, with both importers and exporters ending the event window with large negative CARs.

6.2 GARCH

Results from the GARCH model estimations are summarised in table 7. The GARCH analysis tests the following hypothesis

> **H_0:** The main indices of European exporters and importers of crude oil have the same volatility around environmental announcements.
> **H_1:** The main indices of European exporters of crude oil have more volatile markets than importers around environmental announcements.

Table 7: GJR-GARCH model estimations

Parameter	Germany	Spain	Italy	Norway	UK	Russia

ARMA Order (p,q)	(1,0)	(1,0)	(1,0)	(1,1)	(1,1)	(1,1)
GARCH Order(p,q)	(1,1)	(3,1)	(1,2)	(1,2)	(1,2)	(2,2)
$\hat{\omega}$	0,000003 (0,0000)	0,000005 (0,0492)	0,000007 (0,0064)	0,000006 (0,0000)	0,000006 (0,0000)	0,000001 (0,0160)
$\hat{\alpha}$	0,006455 (0,1521)	0,070657 (0,0000)	0,052331 (0,2733)	0,004053 (0,5044)	0,000081 (0,9605)	0,010214 (0,0000)
$\hat{\beta}$	0,894551 (0,0000)	0,838748 (0,0000)	0,532152 (0,0000)	0,729181 (0,0000)	0,3927778 (0,0000)	0,498593 (0,0000)
$\hat{\gamma}$	0,173656 (0,0000)	0,10671 (0,0000)	0,204778 (0,0000)	0,261732 (0,0000)	0,339686 (0,0000)	0,114691 (0,0000)
$\hat{\delta}_{e1}$	0,000029 (0,0704)	0 (0,9630)	0 (0,9774)	0 (0,9902)	0 (0,0007)	0 (0,9931)
$\hat{\delta}_{e2}$	0 (0,9999)	0 (1,0000)	0 (1,0000)	0 (0,9997)	0 (1,0000)	0 (0,9748)
$\hat{\delta}_{e3}$	0,000008 (0,4159)	0 (0,0059)	0,000023 (0,1245)	0 (0,9987)	0 (0,9863)	0 (0,9828)
$\hat{\delta}_{e4}$	0 (0,9853)	0 (0,4024)	0 (0,9862)	0 (0,9999)	0 (0,9733)	0 (0,9482)

Summary of GARCH model estimations. Event 1 is denoted by $\hat{\delta}_{e1}$, event 2 $\hat{\delta}_{e2}$, event 3 $\hat{\delta}_{e3}$ and event 4 $\hat{\delta}_{e4}$. Significance given by p-values.

Before explaining the meaning of the parameters, we will first explain why the models have different orders. One typically assumes that a GARCH (1,1) is sufficient (Brooks, 2019, p. 521). However, Javad & Mantalos (2013) showed that this assumption could lead to prediction errors. Therefore, we have examined whether the AIC (5.13) becomes better (lower) with different orders, checking for every order from (1,1) to (3,3), as well as for ARMA (1,0) and (1,1) as the mean model. As SBIC tends to prefer the smaller model, we have used the model that minimises AIC. We want to investigate how well the environmental announcements predict the conditional volatility in the event period, which is why we use the order which minimises AIC, and not SBIC. Table 7 reports the first ARCH, GARCH, or leverage terms that are significant.

The first parameter $\hat{\omega}$ can be interpreted as the mean value of the model if all the other parameters are equal to zero. As one can see from table 7, all our intercepts are significant on either a 1% level or, in the case of Spain, at the 5% level. As for the more important parameters $\hat{\alpha}$ and $\hat{\beta}$ the ARCH and GARCH effects, we observe something different. Only two of the estimated ARCH parameters are significant, which can be seen as a serious limitation to the study. The GARCH terms tells us how much time it takes for the ARCH effect to die out, and for all our indices, these parameters are significant at the 1% level. Even though we do not have significant ARCH effects for all indices, we will still analyse our results, and the drawbacks will be discussed in section 7.2.

As explained in the methodology, equation (5.32) is used to model the conditional variance. As this is a GJR-GARCH model, it uses a leverage effect in which negative innovations influence the volatility more than positive ones. In table 7 the leverage effect is represented by $\hat{\gamma}$. If $\hat{\gamma} > 0$ we can say that negative innovation in the last period increases the volatility more than positive ones. Given the values in table 7, we observe that all indices have a positive $\hat{\gamma}$, which is also significant at the 1% level. The analysis therefore supports Brooks (2019, P. 521) by implying that negative shocks affect the volatility more than positive shocks.

By modelling the volatility with a GJR-GARCH model, we test if the financial markets of crude oil exporters are more volatile than importers around environmental announcements. Building on Sengabo & Øverby's (2021) idea, we introduced a dummy variable for each event window. The idea is to check for significant volatility increases around the events. Results from table 7 show that only three of the dummy variables are significant. The German DAX index (10%) and the British FTSE 100 (1%) indices showed significant results for the Paris agreement. At the same time, the Spanish IBEX 35 had a significant volatility increase around the announcement of a clean planet for all. Our results indicate that environmental announcements may affect the European financial markets. However, two out of three indices displaying significant volatility are importers.

The dummy variable only tells us if there is an increase in the volatility inside the event window. However, it could be beneficial to look at a period following and maybe a period before the event window, to identify potential volatile movements. The following subsections will thus examine the fitted conditional variance plots from the GJR-GARCH model and interpret these visually.

6.2.1 Importers

Figure 8: Conditional volatility for Germany (08/01/2014 - 12/31/2019)

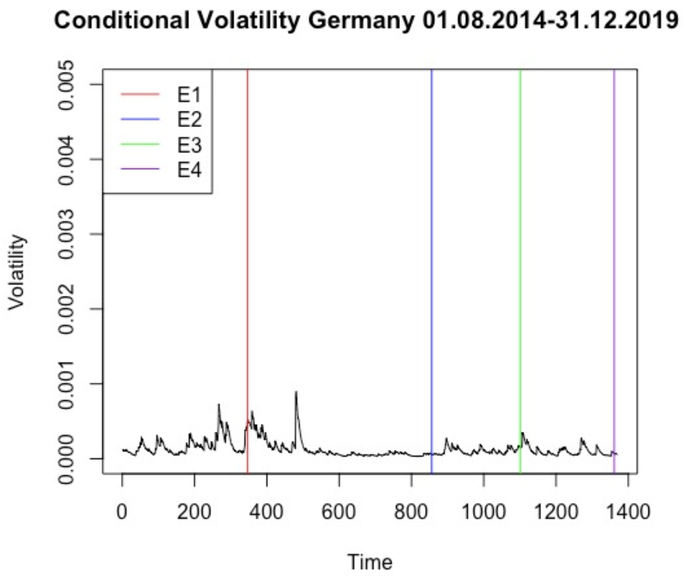


Figure 9: Conditional volatility for Spain (08/01/2014 - 12/31/2019)

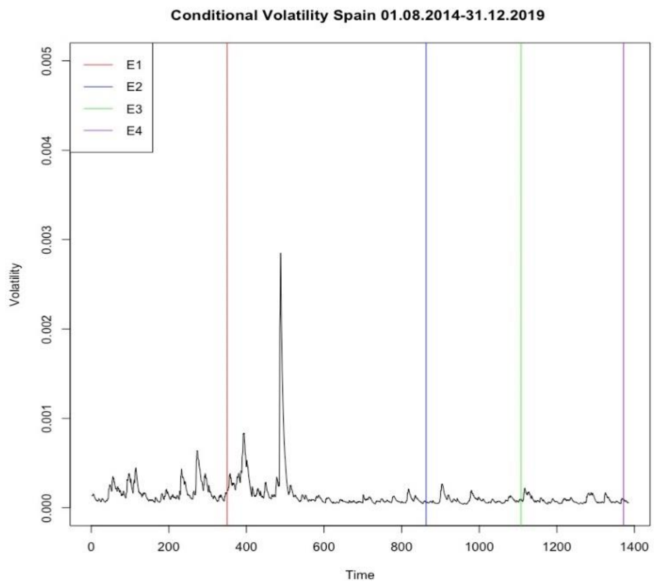
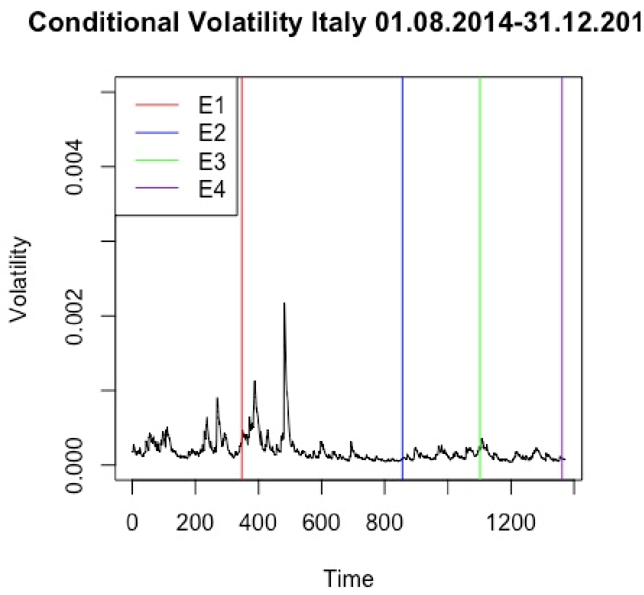


Figure 10: Conditional volatility for Italy (08/01/2014 - 12/31/2019)



The figures for all importers show signs of heteroskedasticity, as there are periods of high volatility and periods of lower volatility. It is also observed that the Italian FTSE MIB and the Spanish IBEX 35 index are more volatile than the German DAX index, with higher spikes and more movements. As mentioned, the German DAX index has a significant volatility increase around the announcement of the Paris Agreement, which can be observed by a steep volatility increase in figure 8. Interestingly, the Italian FTSE MIB and the Spanish IBEX 35 indices have spikes sometime after the Paris Agreement, implying that these indices may have had delayed reactions to the announcement. Another interesting observation to note from the figures is the spike that appears for all importers in the middle of time=400 and time=600. This spike occurred around the date 23rd of June 2016, which according to Sanford (2020), is the date on which the UK voted to leave the European Union, also known as "Brexit." Analysing the time following Brexit, one can observe that the volatility for all importers is more constant and with fewer spikes. However, the Spanish IBEX 35 index had a significant volatility increase around event 3, a clean planet for all, as shown in figure 9. Although not significant, one can also observe a small spike around the same event in the German DAX index and the Italian FTSE MIB, indicating that a clean planet for all announcements might have caused some uncertainty in the market.

6.2.2 Exporters

Figure 11: Conditional volatility for the United Kingdom (08/01/2014 - 12/31/2019)

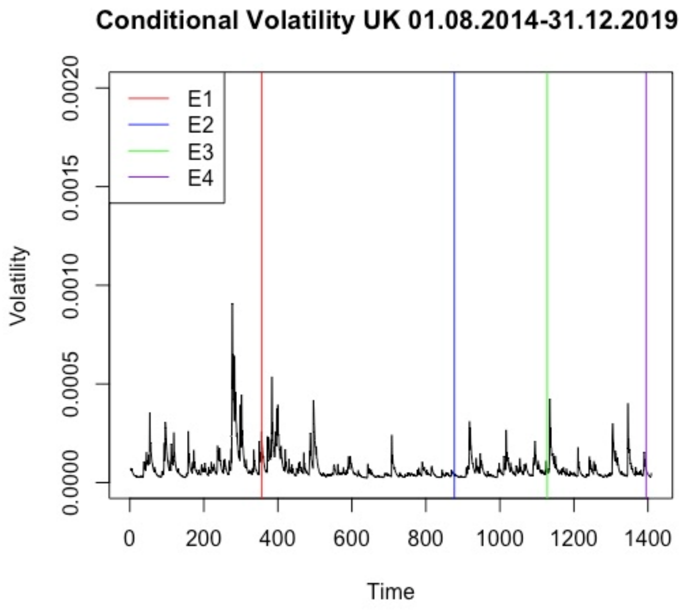


Figure 12: Conditional volatility for Norway (08/01/2014 - 12/31/2019)

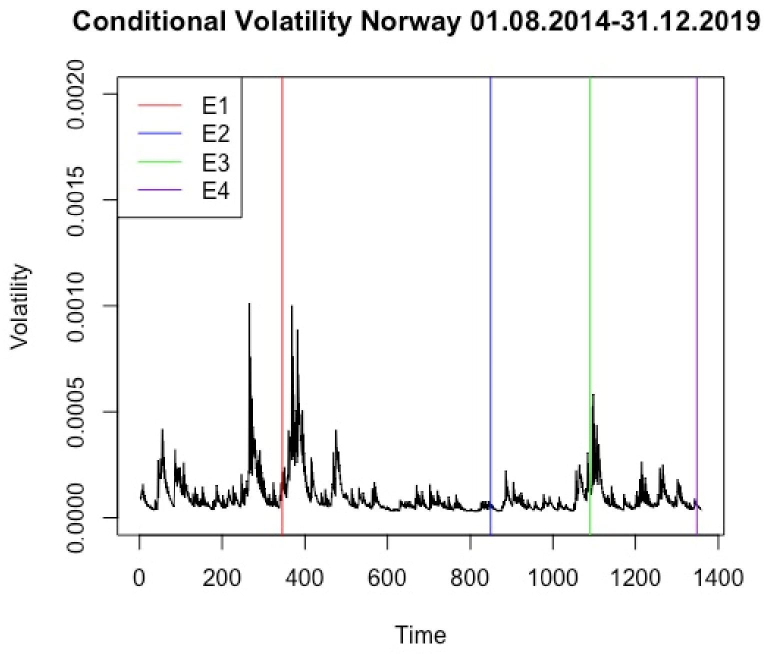
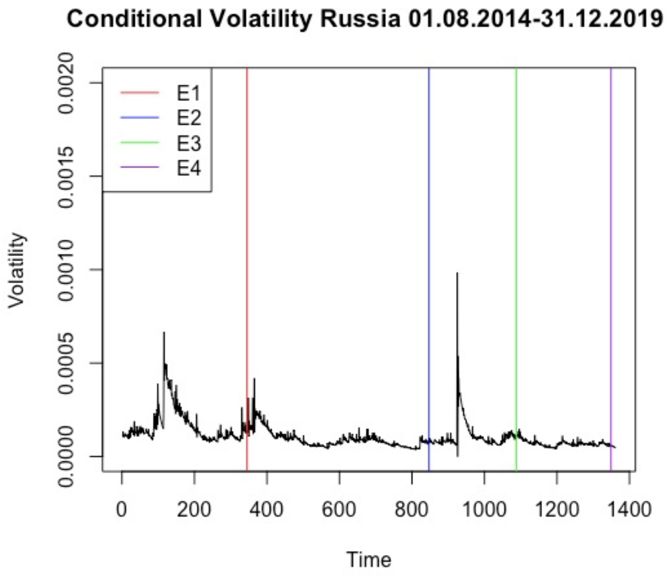


Figure 13: Conditional volatility for Russia (08/01/2014 - 12/31/2019)



Before interpreting the figures, it is important to note that these plots are zoomed-in in relation to the importers to display the volatility better. Looking at the volatility movements, it can be said that all indices have periods of high volatility and periods of low volatility, indicating heteroskedasticity and volatility clustering. At first glance, one can see that the volatility spikes around the announcement of Brexit are smaller for all exporters than for the Italian FTSE MIB and Spanish IBEX 35 indices, which might indicate that the financial markets of crude oil exporters, including the UK themselves were not hit as hard as importers by the UK leaving the EU. The significant increase in volatility for the FTSE 100 index around the announcement of the Paris Agreement can be seen by the rise in volatility around E1. OSEBX and MOEX both show the same pattern as FTSE MIB and IBEX 35 around the Paris Agreement, with a volatility increase after the event period. Looking at figures 11 and 12, we observe volatility spikes around E3, a clean planet for all. However, these spikes fade out rather quickly, which could be why the dummy variables are insignificant.

6.3 Robustness tests

This section will look at the implications of the choice of research design and address potential shortcomings. Underlying OLS assumptions are tested, a vanilla GARCH(1,1) is estimated to control for insignificant ARCH effects in the GJR-GARCH model, and the results of an event study using constant mean return are presented.

6.3.1 OLS Assumption Testing

To estimate the parameters $\hat{\beta}_i$ (5.18) and $\hat{\alpha}_i$ (5.19) used in calculating the market models, we use OLS. This section will investigate two of the underlying Gauss-Markov assumptions of homoscedasticity (A3) and autocorrelation (A4) presented in section 5.1.1.

Homoscedasticity

Testing for homoscedasticity in the market model error term is important to ensure that they display a constant variance. A violation of this OLS assumption means that the model has a problem with heteroscedasticity. If heteroscedasticity is present, the OLS estimates are no longer efficient, and the variance of the parameter estimates will be incorrect. We apply the Breusch-Pagan (1979) test and the White (1980) test to all our market models to test if heteroscedasticity is present in any of our models. Both tests consider the following hypotheses (Breusch & Pagan, 1979).

$$H_0\text{: } \sigma_1^2 = \sigma_2^2 = \cdots = \sigma_k^2$$
$$H_1\text{: } \sigma_1^2 \neq \sigma_2^2 \neq \cdots \neq \sigma_k^2$$

Test statistics and p-values are reported in table 8 and 9.

Table 8: Breusch-Pagan (1979) test results

Country	Event 1	Event 2	Event 3	Event 4	Event 5
Germany	0.0004 (0.9826)	4.0069 (0.04532)	1.4707 (0.2252)	3.9962 (0.0456)	0.0787 (0.779)
Spain	0.2281 (0.6329)	2.7195 (0.09913)	0.3789 (0.5382)	1.2392 (0.2656)	15.552 (0.0000)
Italy	0.7268 (0.3939)	5.5442 (0.0185)	0.0003 (0.986)	0.1189 (0.7302)	2.2371 (0.1347)
UK	0.9627 (0.3265)	3.2763 (0.0702)	0.9118 (0.3396)	0.1127 (0.737)	0.795 (0.3725)
Norway	0.4493 (0.5026)	0.5330 (0.4653)	0.3298 (0.5657)	2.0668 (0.1505)	0.1317 (0.7167)
Russia	1.3476 (0.2457)	0.1036 (0.7475)	0.3268 (0.5675)	0.1847 (0.6673)	0.3793 (0.5379)

Table of BP test statistic and corresponding p-value.

Table 9: White (1980) test results

Country	Event 1	Event 2	Event 3	Event 4	Event 5
Germany	2.15 (0.340)	19.7 (0.0000)	10.6 (0.0049)	7.25 (0.0266)	9.55 (0.0084)
Spain	0.442 (0.802)	2.75 (0.253)	0.934 (0.627)	2.08 (0.353)	85.2 (0.0000)
Italy	1.30 (0.522)	19.2 (0.0000)	0.0744 (0.964)	0.611 (0.737)	3.74 (0.154)
UK	0.963 (0.618)	10.1 (0.0063)	1.04 (0.596)	4.23 (0.120)	9.42 (0.0090)
Norway	2.25 (0.325)	1.55 (0.461)	0.423 (0.809)	2.54 (0.281)	8.77 (0.0124)
Russia	1.39 (0.499)	0.190 (0.909)	0.710 (0.701)	2.33 (0.312)	2.33 (0.313)

Table of white test statistic and corresponding p-value.

Scrutiny of tables 8 and 9 shows that one rejects the null hypothesis of homoscedastic errors for some models. The White (1980) test leads to more rejections than the Breusch-Pagan (1979) test. Especially for events 2 and 5, action plan for the planet and the Glasgow climate pact, we find evidence against homoscedasticity and thus, the estimated variance is not consistent. Looking at Germany's DAX index, the White (1980) test rejects the null hypothesis in four out of five events.

Autocorrelation

The respective market models are also tested for autocorrelation in the error term. If autocorrelation is present in any of our models the minimum variance property of the OLS estimator will not be satisfied. A violation of this assumption results in inefficient OLS estimators. Thus, the estimated regression coefficients will have a biased and inconsistent variance displaying a greater value than what could be found using other methods. In turn, this has consequences for performing significance tests on the CARs. We check our models for the presence of autocorrelation by using the Durbin-Watson (1950) test. The following hypotheses are tested

H_0: First order autocorrelation does not exist

H_1: First order autocorrelation exists

The Durbin-Watson (1950) test always returns a value between 0 and 4 where a value of 2 indicates no sign of autocorrelation. A value lower than 2 indicates positive autocorrelation and conversely a value greater than 2 indicates negative autocorrelation.

Table 10: Durbin-Watson test results lag 1

Country	Event 1	Event 2	Event 3	Event 4	Event 5
Germany	2.0435 (0.718)	2.2777 (0.028)	2.1562 (0.234)	2.1087 (0.382)	2.1701 (0.218)
Spain	2.1838 (0.134)	2.3123 (0.014)	1.9082 (0.51)	2.0326 (0.764)	1.7570 (0.052)
Italy	2.2608 (0.036)	2.3117 (0.01)	1.9581 (0.758)	2.1704 (0.154)	1.8205 (0.116)
UK	1.9676 (0.812)	1.9862 (0.908)	2.0625 (0.578)	1.8508 (0.22)	1.9111 (0.448)
Norway	2.1503 (0.272)	2.4863 (0.0000)	2.1890 (0.142)	2.2434 (0.052)	2.1792 (0.182)
Russia	2.0980 (0.454)	1.7909 (0.114)	2.1531 (0.228)	2.0638 (0.622)	2.1852 (0.144)

Table of DW statistic and corresponding p-value. Significance levels given by 0.1*, 0.05** and 0.01***

Table 10 indicates that some models have autocorrelation in the error terms. Similar to what we saw in the previous subsection, action plan for the planet is especially exposed, with four out of six indices showing significant autocorrelation in the error term. In addition, we see that Spain's IBEX 35 and Italy's FTSE MIB show signs of autocorrelation in the error terms during action plan for the planet and Glasgow climate pact.

There are several known statistical limitations of the event study methodology. These limitations are related to the assumption of no autocorrelation and heteroscedasticity. As we can see, some of our error terms violate these assumptions and thus are no longer considered BLUE (Verbeek, 2018, p. 18). However, MacKinlay (1997) argues that normal return models are robust even if autocorrelation and heteroscedasticity are present. Brown and Warner (1985) support MacKinlay by stating that the characteristics of daily data, such as autocorrelation, impose few problems to the predictability of the parameter estimates. In addition, Verbeek (2004, p. 16) states that one does not need to fulfil all assumptions to use the OLS estimator.

One way to circumvent these limitations is implementing Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors. HAC standard errors are calculated using the estimated variance-covariance matrix for each model. Furthermore, each coefficient is t-tested using the new HAC standard error to check if they are significantly different from zero (Zeileis, 2004). Our test results confirm that all our estimated $\hat{\beta}_i$ (5.18) are significant when tested with the HAC standard errors. Tables with the test results are presented in the Appendix: Table #.

6.3.2 Constant mean return

As we have shown in tables 8, 9 and 10, the assumptions of the OLS estimator are violated. Brown & Warner (1985) claimed that constant mean return model often outperform other normal performance models. Therefore, we conduct a new event study, using constant mean returns instead of the market model to see if it provides other results. The estimated CARs and their p-values are reported in table 11 below.

Table 11: Cumulative abnormal returns using constant mean return model

Country	Event 1	Event 2	Event 3	Event 4	Event 5
Germany	-4.95 (0.4691)	-1,92 (0.5365)	-3,77 (0.3757)	-1,18 (0.7863)	-5,02 (0.2528)
Spain	-6,06 (0.3007)	-1,00 (0.6860)	-2,43 (0.4640)	2,45 (0.4983)	-9,12 (0.0167)
Italy	-6,26 (0.4135)	-2,42 (0.5784)	-0,27 (0.9571)	-1,90 (0.6804)	-6,05 (0.1978)

UK	-0.48 (0.9236)	2,44 (0.3301)	-2,11 (0.5341)	2,72 (0.4545)	-3,47 (0.3849)
Norway	-2,84 (0.5908)	-1,59 (0.6123)	4,44 (0.2341)	1,08 (0.8086)	2,28 (0.6407)
Russia	-4,71 (0.4602)	-2,23 (0.5541)	-1 (0.8381)	1,83 (0.5820)	-9,48 (0.0263)

Table of Cumulative abnormal returns using constant mean return and corresponding p-value.

As shown in table 11, employing the constant mean return to calculate the CARs results in notably higher CARs. Most of which are also negative. However, only one of the insignificant CARs in table 6 is now significant, this is due to the higher variance returned by the constant mean return model. The difference between these estimations of CARs is that instead of calculating how an index usually performs in relation to the market, the constant mean return CARs indicates how it performs against itself. Interestingly, most of the estimates are now negative, indicating that the entire market reacted negatively to some announcements. However, we only have one more significant CAR, which tells us that the overall inference gained from the market model does not change.

6.3.3 Vanilla GARCH

As our GJR-GARCH model has some insignificant ARCH terms, we wanted to check whether this is due to the leverage effect which is present in the GJR-GARCH, by fitting a vanilla GARCH (1,1) model to the sample. The estimates are presented in table 12.

Table 12: Vanilla GARCH (1,1) estimations

Parameter	Germany	Spain	Italy	Norway	UK	Russia
$\hat{\omega}$	0,000003 (0,0008)	0,000004 (0,0000)	0,000004 (0,6441)	0,000003 (0,0000)	0,000006 (0,0000)	0,000001 (0,0429)
$\hat{\alpha}$	0,087503 (0,0000)	0,1067 (0,0000)	0,103789 (0,0000)	0,102176 (0,0000)	0,15263 (0,0000)	0,03466 (0,0000)
$\hat{\beta}$	0,890168 (0,0000)	0,8669 (0,0000)	0,873757 (0,0000)	0,86299 (0,0000)	0,768644 (0,0000)	0,9534 (0,0000
$\hat{\delta}_{e1}$	0 (0,6904)	0 (0,9876)	0,000023 (0,1280)	0 (0,9187)	0 (0,9834)	0 (0,9272)

$\hat{\boldsymbol{\delta}}_{e2}$	0 (1)	0 (1)	0,000001 (0,0000)	0 (0,9999)	0 (1)	0 (0,9958)
$\hat{\boldsymbol{\delta}}_{e3}$	0,000001 (0,0000)	0 (0,9004)	0,000012 (0,8242)	0 (0,7403)	0 (0,1707)	0 (0,9722)
$\hat{\boldsymbol{\delta}}_{e4}$	0 (0,9917)	0 (0,9979)	0 (0,2165)	0 (0,9029)	0 (0,9961)	0 (0,9999)

Table 12 shows that all ARCH and GARCH terms are now significant at the 1 % level, with the same being the case for the intercept, except for Italy's FTSE MIB and Russia's MOEX being significant at the 5% level. Furthermore, the dummy variables show that the values have changed for the German DAX index during event 3, a clean planet for all. The same is evident for the Italian FTSE MIB index around event 2, the action plan for the planet. This tells us that when the leverage effect of negative returns influencing the volatility more than positive returns is removed, our significant events now become insignificant. Implying that our significant results in section 6.2, are due to negative stock market returns, and furthermore supports the use of an asymmetric GARCH model.

7. Discussion

This section will elaborate on our findings presented in the results section. It is organised so that we will discuss each of the results announcement by announcement, both in terms of the CARs and the volatility analysis. Our findings will also be discussed in regard to the current literature which was presented in section 2. Additionally, we will present the limitations of our study in section 7.2.

7.1 Elaboration on findings

7.1.1 Paris Agreement

Section 4.5.1 introduced the main topic of the Paris Agreement and our expectations on how the event will impact our indices. We expected that the Paris Agreement would affect exporters more negatively than importers, especially the Norwegian OSEBX and the Russian MOEX. Additionally, we know that the Spanish IBEX 35 has a large oil and energy sector, so we expected to see negative reactions here as well. Our event study analysis did not show any significant CARs for the Paris Agreement. In figure 3, we can see that the aggregated exporters vs importers plot shows some index movements before and after the event date, but ultimately the CARs are close to zero at the end of the event window. However, table 7 confirms significant increases in volatility around the Paris Agreement for the German DAX index and the British FTSE 100 index. For the DAX index, this is not reflected in the CARs, while the FTSE 100 has close to significant CARs in the event window. Although, the increase in volatility for the German DAX index is in line with the CARs when using a constant mean return, as reported in table 11. The volatility in the event window around the Paris Agreement is consistent with Moosa et al. (2019), who argue that there is an increase in risk around the event for the German stock market. For the FTSE 100 index, our findings are somewhat consistent with Gangemi et al. (2019), who identified significant positive CARs for UK industries around environmental announcements. Dong et al. (2020) found that low-polluting firms perform better than high-polluting firms in the post-event window. We observe no CARs for either OSEBX or MOEX, but figures 12 and 13 show a spike in volatility sometime after the event. This spike could imply delayed reactions after the event window, and it somewhat supports Dong et al. (2020). Our lack of significant CARs during the Paris Agreement announcement supports Birindelli & Chiappini (2020), who argue that information leakage prior to the Paris Agreement explains the lack of abnormal returns. All in all, we find no evidence against the null hypotheses from the announcement of the Paris Agreement.

7.1.2 Action Plan for the Planet

For the action plan for the planet, we expected mild or negative reactions from our indices. Section 4.5.2 further elaborates our expectations for the announcement of action plan for the planet. The event study analysis results somewhat meet our expectations for this event. Although not finding any significant CARs, five out of six indices display negative CARs during the event window. As with the announcement of the Paris Agreement (and all other events), the British FTSE 100 index had positive CARs during the announcement of the action plan for the planet. This supports the findings of Gangemi et al. (2016), who found that the UK stock market generated mostly positive abnormal returns in response to environmental announcements between 2003 and 2012. Another interesting observation in figure 4 is that the importers experience continuously negative CARs starting a couple of days prior to the event until the end of the event window. Despite these movements and a sudden drop for exporters at the start of the event window, our GARCH model identified no significant volatility movements. Moreover, no spikes are found in the conditional volatility figures around the announcement. The latter is somewhat against our expectations, although the event study expectations were mostly met during the announcement of the action plan for the planet. Despite meeting some expectations, this event does not provide evidence to reject either null hypothesis.

7.1.3 A Clean Planet for All

As explained in section 4.5.3, we were unsure about the effects of the announcement of a clean planet for all, as public attention was high, but no strict regulations were announced. The event study analysis found no significant CARs, yet Norway's OSEBX showed more negative CARs than expected, while our two other exporters reacted more in line with our expectations. OSEBX's negative CARs can be seen in association with a volatility spike in figure 12 around E3. Looking at the importers, Italy's FTSE MIB generated surprisingly high positive CARs during the announcement of a clean planet for all, somewhat contradicting the findings of Birindelli & Chiappini (2020). Comparing these results to the volatility estimations, we only found significant volatility increases for the Spanish IBEX 35. The aggregated CAR movements of both importers and exporters in figure 5 show some evidence for rejecting the null hypothesis of a similar reaction to an environmental announcement. However, the numbers in table 6 tell a different story where the overall CARs are relatively similar. On the other hand, significant volatility increases for the Spanish IBEX 35 index during the announcement of a clean planet for all indicate that we fail to reject the null of importers and exporters of crude oil having similar volatility around environmental announcements.

7.1.4 European Green Deal

Our expectation for the announcement of the European Green Deal, as described in section 4.5.4, is that the overall index reactions would be minor. Interestingly, the event study analysis shows that two of the importer's indices return negative but insignificant CARs, while two of the export indices display positive CARs. This can also be seen in figure 6, where the aggregated CARs of importers are lower than exporters. The negative Italian FTSE MIB CARs might be explained by the index's large automobile & parts sector, as the European Green Deal focuses on increasing the number of electric vehicles in the future (European Commission, 2019). These findings are evidence against rejecting the null hypothesis of similar reactions from importers and exporters of crude oil to environmental announcements. Turning to our volatility model, we do not find a significant increase in volatility for any index, gathering evidence against rejecting the null for hypothesis 2. The conditional volatility plots only show a slight increase in risk for the Italian FTSE MIB index, in line with the event study results. It might also be worth mentioning that none of our exporters are a part of the EU, except for Norway having the EEA agreement, which might affect their reaction to EU-specific announcements. Birindelli & Chiappini (2020) found signs of information leakage around the announcement of the Paris Agreement, providing a possible explanation for the drop in CARs before the announcement of the European Green Deal.

7.1.5 Glasgow Climate Pact

This subsection will not discuss volatility, as the GARCH model did not include the Glasgow climate pact announcement. Our expectations for the Glasgow climate pact were that exporters would experience negative CARs while importers would have a mild or positive reaction. The event study analysis results partially met our expectations. Russia's MOEX index generates significant negative CARs during the Glasgow climate pact event window. Figure 2 illustrates MOEX's CARs during the [-10,10] event window, where we see a continuous drop starting several days before the announcement. In line with Birindelli & Chiappini's (2020) findings during the Paris Agreement, this could be the result of information leakage before the event date. The MOEX index's considerable energy (oil & gas) sector could also explain the sharp drop in CARs after the event day. Previous research substantiates this claim, where polluting industries have been found to produce significant negative abnormal returns following an environmental announcement.

Aside from finding negative CARs for MOEX, our expectations for the Glasgow climate pact were not met. All importers show negative CARs around the announcement, indicating that the Glasgow climate pact negatively affected other sectors than oil and energy. Other non-carbon-intensive industries in Europe have been found to generate significant negative CARs after environmental announcements. (Gangemi et al., 2016; Moosa et al., 2019b; Moosa et al., 2020). However, this would require additional research to make an inference. Figure 7 shows that importers and exporters had similar movements leading up to the event date, but a few days prior to the announcement, both importers and exporters experienced negative CARs. Our findings are somewhat in line with the expectation, although we did not anticipate a negative reaction from importers. Exporter and importer reactions are fairly synchronous during the Glasgow climate pact event, providing evidence against the rejection of the event study null hypothesis.

7.2 Limitations

Regarding the event study methodology, we used OLS to estimate the market model parameters $\hat{\beta}_i$ (5.18) and $\hat{\alpha}_i$ (5.19). The coefficients were tested for the presence of homoskedasticity and autocorrelation in the error terms. As can be seen from the robustness test section (6.3), we identified several cases of autocorrelation and evidence against homoskedasticity in the errors. A violation of the OLS assumptions leads to inefficient estimates and a biased variance which could invalidate the results of the t-tests performed on CARs. However, several scholars argue that a breach of these assumptions does not cause big problems for the predictability of the market model. Brown and Warner (1985) and MacKinlay (1997) have found the characteristics of daily data in event studies, such as autocorrelation, to impose few problems to the predictability. One way to circumvent the statistical problems encountered would be to use a generalized method-of-moments approach (MacKinlay, 1997). Despite researchers arguing in favour of the market model even if assumptions are violated, we realise that it could impact our event study results and consider it a limitation to our study.

We have also identified a cofounding event during the event window of the announcement of a clean planet for all. The 2018 United Nations Climate Change Conference (COP24) was held between the 2nd and 15th of December 2018. A clean planet for all was announced on the 28th of November 2018 and thus, the [-10,10] trading days event window interferes with COP24. The effects of another event happening simultaneously as the event in question could bias the event study results and the volatility estimates from the GARCH model. This is considered a breach of one of the underlying event study assumptions (McWilliams & Siegel, 1997).

We modelled the volatility using a GJR-GARCH model and assumed that our sample came from a Gaussian distribution based on the claims by Jakobsen (2018). However, any sample containing daily stock return data is unlikely to follow such a distribution. Liu, Narayan, & Phan (2020) claim that daily data often show signs of skewness and fat tails, which violates the assumption of Gaussian distribution. Brooks (2020, p. 711) supports this by implying that asset returns often follow a fat-tailed distribution. Jarque and Bera (1980) test whether a sample violates these criteria and, consequently, our data stems from another distribution. As shown earlier in table 4, the skewness, kurtosis and the Jarque & Bera (1980) test point toward these assumptions being violated. It may therefore yield better results if one assumes a different probability distribution.

Another limitation is that many of our GARCH estimates contain insignificant ARCH effects. Even though they are insignificant, we still use these estimates. This is because we get clear rejections when using the Lagrange-Multiplier test (Engle, 1982) and the Portmanteau Q test (Mcleod & Li, 1983) to test for ARCH effects, as can be seen in table 14 in the appendix. Therefore, we have assumed that the leverage effect in the GJR-GARCH model is why our model yields insignificant ARCH effects.

As we can see from both the estimates and plots of the CARs, the Glasgow climate pact seems to have the most notable effect on the indices, especially for the Russian MOEX index. Therefore, a substantial limitation of our thesis is that we do not include this event in the volatility analysis. It has been excluded because of the aforementioned structural break between March and April 2020 caused by the COVID-19 pandemic. When including the time leading up to the Glasgow climate pact, the “pandemic market crash” period dominates the volatility, making other events insignificant. Ultimately, including this period hurts the statistical inference of the analysis of the events.

8. Conclusion

The goal of our thesis was to build on the existing literature regarding environmental announcements and financial markets, by examining 6 countries' main stock market indices. We mainly wanted to identify potential cumulative abnormal returns (CAR) and increases in volatility surrounding included events. By dividing the indices into exporters or importers of crude oil, we wanted to research if the export/import status of a country influenced how their main stock market index reacted to environmental announcements.

We built on previous research from Birindelli & Chiappini (2020); Moosa et al. (2015); Fan et al. (2018) by employing the event study and market model to estimate CARs for all indices (Mackinlay, 1997). Furthermore, we also built on earlier work from Moosa et al. (2019b); Moosa et al. (2020); Gehricke et al. (2021), by analysing the risk of indices around chosen events. The model used to examine volatility was inspired by Sengabo & Øverby (2021) and is a GJR-GARCH model including dummy variables for the event windows.

The results of our event study show that the Russian MOEX index generates significant CARs for the announcement of the Glasgow climate pact. Aggregating CARs for exporters and importers and plotting them, reveals interesting movements in the event windows. However, no general trends around environmental announcements can be identified. As for the volatility analysis, the German DAX index & the British FTSE 100 index show a significant volatility increase around the announcement of the Paris Agreement, and the Spanish IBEX 35 has a significant volatility increase around the announcement of a clean planet for all. Various conditional volatility plots indicate that the risk increases slightly around events, especially for exporters of crude oil. However, the lack of significant CARs and event dummy variables implies that the reactions of the European financial markets to environmental announcements are minor.

Based on above results, we fail to reject both our null hypotheses, and we cannot prove that environmental announcements affect exporters of crude oil more than importers, neither for returns nor risk. Therefore, our findings align with Fan et al. (2018), who failed to identify significant abnormal returns for oil & gas firms when environmental policies were announced. There are indications of increasing volatility around the environmental announcements, both visually and numerical. However, this is the case for both exporters and importers of crude oil. This means that our research differs from Moosa et al. (2019, b) and Gehricke et al. (2021), who found increases in risk for polluters around environmental announcements.

Furthermore, our thesis contains methodological limitations. Our OLS estimates used to calculate the normal return, fail to fulfil some of the Gauss-Markov assumptions and thus, entails that our OLS estimates are not BLUE. This issue can be overcome by using either an economic model or, as Mackinlay (1997) proposed, a generalised method of moments estimation. Some of the estimated ARCH effects in our GJR-GARCH model are insignificant, implying that the model could be improved. One of such improvements could be to use another distribution instead of assuming a gaussian distribution. It may be harder to deal with the issue of not including the Glasgow climate pact in the volatility estimations. Still, an option could be to use a new sample that starts after the structural break caused by the Covid-19 pandemic. In general, our findings align with Dong et al. (2020), who also fail to find any clear stock market reactions to environmental announcements but find indications of low-polluting firms performing better in the post-event window. This introduces another potential moderation to our approach, using different event windows. Either shorter event windows or event windows that focus on the post-event period could provide interesting results. Moreover, our lack of significant results may be due to the focus on national indices, which seem to move somewhat similarly according to our conditional volatility plots. Future research could overcome this issue by employing the same research problem, but instead examine specific industries and thus be able to make a better inference.

Appendix

HAC Standard Errors

Table 13 reports the original OLS estimated standard errors and table 14 the HAC standard errors. Calculations are done by using the sandwich package in R.

Table 13: Appendix. Ordinary Least Squares standard errors for the event study

Country	Event 1	Event 2	Event 3	Event 4	Event 5
Germany	0.02688 40.170 (0.0000)	0.04008 26.898 (0.0000)	0.03153 37.459 (0.0000)	0.02672 42.395 (0.0000)	0.02719 40.39 (0.0000)
Spain	0.03226 30.469 (0.0000)	0.06938 16.18 (0.0000)	0.03959 23.839 (0.0000)	0.03431 26.605 (0.0000)	0.05419 22.265 (0.0000)
Italy	0.03811 30.615 (0.0000)	0.07772 16.105 (0.0000)	0.06407 17.751 (0.0000)	0.04123 26.590 (0.0000)	0.03751 30.147 (0.0000)
UK	0.02452 31.946 (0.0000)	0.04613 14.761 (0.0000)	0.031515 24.621 (0.0000)	0.03448 24.454 (0.0000)	0.03799 24.748 (0.0000)
Norway	0.04128 15.379 (0.0000)	0.06586 10.59 (0.0000)	0.05044 15.43 (0.0000)	0.04708 20.322 (0.0000)	0.04737 17.88 (0.0000)
Russia	0.06552 5.603 (0.0000)	0.09334 5.339 (0.0000)	0.08712 6.547 (0.0000)	0.05393 6.556 (0.0000)	0.06384 9.889 (0.0000)

Table of OLS $\hat{\beta}_i$ standard errors and corresponding t statistic and p-value.

Table 14: Appendix. Heteroscedasticity and Autocorrelated Consistent standard errors for the event study

Country	Event 1	Event 2	Event 3	Event 4	Event 5
Germany	0.03087 35.447 (0.0000)	0.05591 19.281 (0.0000)	0.03874 30.490 (0.0000)	0.03202 35.387 (0.0000)	0.03623 30.305 (0.0000)

Spain	0.03670 26.780 (0.0000)	0.06959 16.131 (0.0000)	0.03643 25.925 (0.0000)	0.03200 28.505 (0.0000)	0.11491 10.488 (0.0000)
Italy	0.04148 28.128 (0.0000)	0.10885 11.500 (0.0000)	0.06384 17.814 (0.0000)	0.04446 24.659 (0.0000)	0.04217 26.816 (0.0000)
UK	0.02480 31.584 (0.0000)	0.05532 12.308 (0.0000)	0.03553 24.352 (0.0000)	0.04167 20.235 (0.0000)	0.05357 17.550 (0.0000)
Norway	0.04685 13.549 (0.0000)	0.07079 9.852 (0.0000)	0.05149 15.117 (0.0000)	0.05427 17.628 (0.0000)	0.06159 13.753 (0.0000)
Russia	0.05665 6.481 (0.0000)	0.08682 5.739 (0.0000)	0.06119 9.3208 (0.0000)	0.05741 6.158 (0.0000)	0.07044 8.963 (0.0000)

Table of HAC standard errors for $\hat{\beta}_i$ and corresponding t statistic and p-value.

Test for ARCH effects

Table 15: Appendix. Reported ARCH effects for a ARMA (1,0) model for all indices at order 4.

Country	Germany	Spain	Italy	Norway	UK	Russia
Lagrange-Multiplier Test	857 (0.0000)	4021 (0.0000)	106 (0.0000)	760,4 (0.0000)	592,1 (0.0000)	340 (0,0000)
Portmanteau-Q test	120 (0.0000)	27 (0.0002)	1673 (0.0000)	169 (0.0000)	352 (0.0000)	23,9 (0,0008)

Table of Test statistics and corresponding p-value

R Script

R script for all estimations for Germany is included below. The same procedure was performed on all country indices.

```
library(moments)
library(aTSA)
library(tseries)
library(xtable)
library(tseries)
library(zoo)
library(quadprog)
library(corrplot)
library(pastecs)
library(moments)
library(MTS)
library(lmtest)
library(car)
library(skedastic)
library(sandwich)
library(rugarch)

#Event study Using Market model
#Estimation window and event window length
EST.W <- 252
EV.W <- 21

#Index data

#*******************************Importers*********************************

#Germany - time windows (DAX)
GER.DATA <- read.csv(file.choose(), sep = ",")
GER.DATA <- GER.DATA[,c('Dates','Market','Germany')]

GER.E1 <- GER.DATA[84:336,]
GER.E2 <- GER.DATA[595:847,]
GER.E3 <- GER.DATA[840:1092,]
GER.E4 <- GER.DATA[1101:1353,]
GER.E5 <- GER.DATA[1588:1840,]

EW.GER.E1 <- GER.DATA[336:357,]
EW.GER.E2 <- GER.DATA[847:868,]
EW.GER.E3 <- GER.DATA[1092:1113,]
EW.GER.E4 <- GER.DATA[1353:1374,]
EW.GER.E5 <- GER.DATA[1840:1861,]
```

```
#Descriptive statistics Event study sample
GER.DATA.Desc <- ts(diff(log(GER.DATA[,3])))
GER.MR <- mean(GER.DATA.Desc)*100
GER.SD <- sd(GER.DATA.Desc)*100
GER.MAX <- max(GER.DATA.Desc)*100
GER.MIN <- min(GER.DATA.Desc)*100
GER.KURT <- kurtosis(GER.DATA.Desc)
GER.SKEW <- skewness(GER.DATA.Desc)
GER.JB <- jarque.bera.test(GER.DATA.Desc)
GER.DF <- adf.test(GER.DATA.Desc, k=1)

#Estimation of Market model and abnormal returns

#Germany market model event 1
Ret.GER.E1 = diff(log(GER.E1$Germany))
mu.GER.E1 = mean(Ret.GER.E1)
Ret.M.GER.E1 = diff(log(GER.E1$Market))
mu.M.GER.E1 = mean(Ret.M.GER.E1)

MM.GER.E1 = lm(Ret.GER.E1~ +1 +Ret.M.GER.E1)
beta.GER.E1 <- MM.GER.E1$coefficients['Ret.M.GER.E1']
alpha.GER.E1 = MM.GER.E1$coefficients['(Intercept)']
Mean.sq.GER.E1 <- anova(MM.GER.E1) #Mean squared error for t-test

#Germany market model event 2
Ret.GER.E2 = diff(log(GER.E2$Germany))
mu.GER.E2 = mean(Ret.GER.E2)
Ret.M.GER.E2 = diff(log(GER.E2$Market))
mu.M.GER.E2 = mean(Ret.M.GER.E2)

MM.GER.E2 = lm(Ret.GER.E2~ +1 +Ret.M.GER.E2)
beta.GER.E2 <- MM.GER.E2$coefficients['Ret.M.GER.E2']
alpha.GER.E2 = MM.GER.E2$coefficients['(Intercept)']
Mean.sq.GER.E2 <- anova(MM.GER.E2) #Mean squared error for t-test

#Germany market model event 3
Ret.GER.E3 = diff(log(GER.E3$Germany))
mu.GER.E3 = mean(Ret.GER.E3)
Ret.M.GER.E3 = diff(log(GER.E3$Market))
mu.M.GER.E3 = mean(Ret.M.GER.E3)

MM.GER.E3 = lm(Ret.GER.E3~ +1 +Ret.M.GER.E3)
beta.GER.E3 = MM.GER.E3$coefficients['Ret.M.GER.E3']
alpha.GER.E3 = MM.GER.E3$coefficients['(Intercept)']
Mean.sq.GER.E3 <- anova(MM.GER.E3) #Mean squared error for t-test
```

```
#Germany market model event 4
Ret.GER.E4 = diff(log(GER.E4$Germany))
mu.GER.E4 = mean(Ret.GER.E4)
Ret.M.GER.E4 = diff(log(GER.E4$Market))
mu.M.GER.E4 = mean(Ret.M.GER.E4)

MM.GER.E4 = lm(Ret.GER.E4~ +1 +Ret.M.GER.E4)
beta.GER.E4 = MM.GER.E4$coefficients['Ret.M.GER.E4']
alpha.GER.E4 = MM.GER.E4$coefficients['(Intercept)']
Mean.sq.GER.E4 <- anova(MM.GER.E4) #Mean squared error for t-test

#Germany market model event 5
Ret.GER.E5 = diff(log(GER.E5$Germany))
mu.GER.E5 = mean(Ret.GER.E5)
Ret.M.GER.E5 = diff(log(GER.E5$Market))
mu.M.GER.E5 = mean(Ret.M.GER.E5)

MM.GER.E5 = lm(Ret.GER.E5~ +1 +Ret.M.GER.E5)
beta.GER.E5 = MM.GER.E5$coefficients['Ret.M.GER.E5']
alpha.GER.E5 = MM.GER.E5$coefficients['(Intercept)']
Mean.sq.GER.E5 <- anova(MM.GER.E5) #Mean squared error for t-test

#Germany abnormal returns event 1
AR.GER.E1 = diff(log(EW.GER.E1$Germany)) - alpha.GER.E1 -
beta.GER.E1*diff(log(EW.GER.E1$Market))
CAR.GER.E1 = sum(AR.GER.E1)
#t-test 1
t.test.CAR.GER.E1 <- CAR.GER.E1/(sqrt(0.000028)*sqrt(EV.W))

#Germany abnormal returns event 2
AR.GER.E2 = diff(log(EW.GER.E2$Germany)) - alpha.GER.E2 -
beta.GER.E2*diff(log(EW.GER.E2$Market))
CAR.GER.E2 = sum(AR.GER.E2)
#t-test 2
t.test.CAR.GER.E2 <- CAR.GER.E2/(sqrt(0.0000115)*sqrt(EV.W))

#Germany abnormal returns event 3
AR.GER.E3 = diff(log(EW.GER.E3$Germany)) - alpha.GER.E3 -
beta.GER.E3*diff(log(EW.GER.E3$Market))
CAR.GER.E3 = sum(AR.GER.E3)
#t-test 3
t.test.CAR.GER.E3 <- CAR.GER.E3/(sqrt(0.0000126)*sqrt(EV.W))

#Germany abnormal returns event 4
AR.GER.E4 = diff(log(EW.GER.E4$Germany)) - alpha.GER.E4 -
beta.GER.E4*diff(log(EW.GER.E4$Market))
```

```
CAR.GER.E4 = sum(AR.GER.E4)
#t-test 4
t.test.CAR.GER.E4 <- CAR.GER.E4/(sqrt(0.0000108)*sqrt(EV.W))

#Germany abnormal returns event 5
AR.GER.E5 = diff(log(EW.GER.E5$Germany)) - alpha.GER.E5 -
beta.GER.E5*diff(log(EW.GER.E5$Market))
CAR.GER.E5 = sum(AR.GER.E5)
#t-test 5
t.test.CAR.GER.E5 <- CAR.GER.E5/(sqrt(0.0000116)*sqrt(EV.W))

#Robustness tests

#Homoscedasticity

#Breuch-Pagan and White test
#Germany
BP.GER.E1 <- bptest(MM.GER.E1)
BP.GER.E2 <- bptest(MM.GER.E2)
BP.GER.E3 <- bptest(MM.GER.E3)
BP.GER.E4 <- bptest(MM.GER.E4)
BP.GER.E5 <- bptest(MM.GER.E5)

W.GER.E1 <- white_lm(MM.GER.E1)
W.GER.E2 <- white_lm(MM.GER.E2)
W.GER.E3 <- white_lm(MM.GER.E3)
W.GER.E4 <- white_lm(MM.GER.E4)
W.GER.E5 <- white_lm(MM.GER.E5)

#Autocorrelation

#Germany
DW.GER.E1 <- durbinWatsonTest(MM.GER.E1)
DW.GER.E2 <- durbinWatsonTest(MM.GER.E2)
DW.GER.E3 <- durbinWatsonTest(MM.GER.E3)
DW.GER.E4 <- durbinWatsonTest(MM.GER.E4)
DW.GER.E5 <- durbinWatsonTest(MM.GER.E5)

#HAC standard errors

#Germany
HAC.GER.E1 <- coeftest(MM.GER.E1, vcovHAC(MM.GER.E1), prewhite = F, type =
NeweyWest)
HAC.GER.E2 <- coeftest(MM.GER.E2, vcovHAC(MM.GER.E2), prewhite = F, type =
NeweyWest)
```

```
HAC.GER.E3 <- coeftest(MM.GER.E3, vcovHAC(MM.GER.E3), prewhite = F, type =
NeweyWest)
HAC.GER.E4 <- coeftest(MM.GER.E4, vcovHAC(MM.GER.E4), prewhite = F, type =
NeweyWest)
HAC.GER.E5 <- coeftest(MM.GER.E5, vcovHAC(MM.GER.E5), prewhite = F, type =
NeweyWest)

#Event study Constant mean return

#Germany event 1
Ret.GER.E1 = diff(log(GER.E1$Germany))
mu.GER.E1 = mean(Ret.GER.E1)
Ret.M.GER.E1 = diff(log(GER.E1$Market))
mu.M.GER.E1 = mean(Ret.M.GER.E1)
std.ger.1=sd(Ret.GER.E1)

#Germany event 2
Ret.GER.E2 = diff(log(GER.E2$Germany))
mu.GER.E2 = mean(Ret.GER.E2)
Ret.M.GER.E2 = diff(log(GER.E2$Market))
mu.M.GER.E2 = mean(Ret.M.GER.E2)
std.ger.2=sd(Ret.GER.E2)

#Germany event 3
Ret.GER.E3 = diff(log(GER.E3$Germany))
mu.GER.E3 = mean(Ret.GER.E3)
Ret.M.GER.E3 = diff(log(GER.E3$Market))
mu.M.GER.E3 = mean(Ret.M.GER.E3)
std.ger.3=sd(Ret.GER.E3)

#Germany event 4
Ret.GER.E4 = diff(log(GER.E4$Germany))
mu.GER.E4 = mean(Ret.GER.E4)
Ret.M.GER.E4 = diff(log(GER.E4$Market))
mu.M.GER.E4 = mean(Ret.M.GER.E4)
std.ger.4=sd(Ret.GER.E4)

#Germany event 5
Ret.GER.E5 = diff(log(GER.E5$Germany))
mu.GER.E5 = mean(Ret.GER.E5)
Ret.M.GER.E5 = diff(log(GER.E5$Market))
mu.M.GER.E5 = mean(Ret.M.GER.E5)
std.ger.5=sd(Ret.GER.E5)

#Germany abnormal returns event 1
AR.GER.E1 = diff(log(EW.GER.E1$Germany)) - mu.GER.E1
```

```
CAR.GER.E1 = sum(AR.GER.E1)
#t-test 1
t.test.CAR.GER.E1 <- CAR.GER.E1/(std.ger.1*sqrt(EV.W))

#Germany abnormal returns event 2
AR.GER.E2 = diff(log(EW.GER.E2$Germany)) -mu.GER.E2
CAR.GER.E2 = sum(AR.GER.E2)
#t-test 2
t.test.CAR.GER.E2 <- CAR.GER.E2/(std.ger.2*sqrt(EV.W))

#Germany abnormal returns event 3
AR.GER.E3 = diff(log(EW.GER.E3$Germany)) -mu.GER.E3
CAR.GER.E3 = sum(AR.GER.E3)
#t-test 3
t.test.CAR.GER.E3 <- CAR.GER.E3/(std.ger.3*sqrt(EV.W))

#Germany abnormal returns event 4
AR.GER.E4 = diff(log(EW.GER.E4$Germany)) - mu.GER.E4
CAR.GER.E4 = sum(AR.GER.E4)
#t-test 4
t.test.CAR.GER.E4 <- CAR.GER.E4/(std.ger.4*sqrt(EV.W))

#Germany abnormal returns event 5
AR.GER.E5 = diff(log(EW.GER.E5$Germany)) - mu.GER.E5
CAR.GER.E5 = sum(AR.GER.E5)
#t-test 5
t.test.CAR.GER.E5 <- CAR.GER.E5/(std.ger.5*sqrt(EV.W))

 #GJR-GARCH Modeling

rm(list=ls(all=TRUE))

library(Rsafd)
library(moments)
library(aTSA)
library(tseries)
library(xtable)
library(tseries)
library(zoo)
library(quadprog)
library(corrplot)
library(pastecs)
library(moments)
library(MTS)
library(lmtest)
library(fGarch)
```

```
library(rugarch)

GER.DATA <- read.csv(file.choose(), sep = ",")
GER.DATA=GER.DATA[1:1371, 3]

Dummy.ger.1=read.csv(file.choose(), header=FALSE)
Dummy.ger.1=ts(Dummy.ger.1[1:1370,])

Dummy.ger.2=read.csv(file.choose(), header=FALSE)
Dummy.ger.2=ts(Dummy.ger.2[1:1370,])

Dummy.ger.3=read.csv(file.choose(), header=FALSE)
Dummy.ger.3=ts(Dummy.ger.3[1:1370,])

Dummy.ger.4=read.csv(file.choose(), header=FALSE)
Dummy.ger.4=ts(Dummy.ger.4[1:1370,])

 Dummies=cbind(Dummy.ger.1,Dummy.ger.2, Dummy.ger.3, Dummy.ger.4)
# Germany

GER.ret=diff(log(GER.DATA))
GER.ret=ts(GER.ret)

# Descriptive statistics GARCH sample

mu.ger<-mean(GER.ret)*100
Std.ger<-sd(GER.ret)*100
max.ger<-max(GER.ret)*100
min.ger<-min(GER.ret)*100
Skew.ger<-skewness(GER.ret)
Kurt.ger<-kurtosis(GER.ret)
JB.ger<-jarque.bera.test(GER.ret)
GER.ar=arima(GER.ret,order =c(1,0,0));GER.ar
ger.stat<-adf.test(GER.ret)
ger.arch<-arch.test(GER.ar)

Ger.GJR.garch.par=ugarchspec(variance.model = list(model="gjrGARCH",
                       external.regressors=Dummies, garchOrder=c(1,1)),
                      mean.model = list(armaOrder=c(1,0)))
GER.GJR.garch.fit.=ugarchfit(Ger.GJR.garch.par,data=GER.ret);GER.GJR.garch.fit.

#Plot
vole.Ger=ts(GER.GJR.garch.fit.@fit[["sigma"]]^2)
plot(vole.Ger,ylab="Volatility", main="Conditional Volatility Germany 01.08.2014-
31.12.2019 ", ylim=c(0,0.005))
lines(abline(v=346, col="red"))
```

```
lines(abline(v=479, col="red"))
lines(abline(v=856, col="blue"))
lines(abline(v=1101, col="green"))
lines(abline(v=1361, col="purple"))
legend("topleft", legend=c("E1", "E2", "E3", "E4"),
      col=c("red", "blue", "green", "purple"), lty = 1)

#Vanilla GARCH

#Germany

Ger.van.garch=ugarchspec(variance.model = list(model="sGARCH",
                                          external.regressors=Dummies, garchOrder=c(1,1)),
                         mean.model = list(armaOrder=c(1,0)))
GER.van.garch.fit.=ugarchfit(Ger.van.garch,data=GER.ret);GER.van.garch.fit.
```

Discussion papers

Markus Bjørntvedt

As is required by the school of business and law at the University of Agder, I have written a discussion paper that will discuss how our thesis topic relates to the concept of "responsible." I will start by explaining how our thesis relates to the concept of "responsible" by linking it to the term known as responsible investing and corporate social responsibility. I will then explain our process from the idea creation until a finished thesis. The process of writing a master thesis has been challenging but educational. Writing the thesis together with a partner has also been both demanding and enjoyable. It has taught me that although two people may have differing views on something, two eyes and brains are better than one.

At first, I did not find our thesis to be related to responsibility, but the more I thought about it, I realised that our topic relates to responsible investing. In 2006 the UN launched "The Principles of Responsible Investment" (Bose, 2019, p. 11), which aims to ensure a sustainable global financial system, and redirect capital towards more sustainable processes. The topic of our thesis is whether or not exporters of crude oil are more affected by environmental announcements than importers. Our topic relates to the principles of responsible investment because if our null hypotheses are rejected, then we have evidence for the principles somewhat working, as it would show that investors redirect capital from fossil-fuels-based economies towards more sustainable ones. It is also possible to relate our thesis topic to the concept of CSR. CSR stands for Corporate Social Responsibility and can be described as a way in which companies can integrate both social and environmental concerns into their strategy, and a way to positively address all stakeholders (Becker, 2019, p. 102). Although not the exact same as CSR, Edmans (2020, p. 27) pieconomics builds on the idea that a company that does something good for society is rewarded in the end. Edmans (2020, p. 27) explains that a company that focuses on all stakeholders and shows responsibility for example for the environment generates higher shareholder value(higher stock market returns). As explained, if we reject both our null hypotheses, we provide evidence for these theories being true.

The idea of writing a thesis that focused on the effects of environmental announcements on capital markets came from the subject TFL400-1: Sustainable Capitalism. After learning about the severity and state of the planetary boundaries, we wanted to see if it was possible to relate this issue to capital markets. From our literature review, we found that numerous different researchers like Birindelli & Chiappini (2020); Gehricke, Rainet, Roberts & Zhang (2021) and more have investigated how announcement of environmental regulations, policies and elections affect different financial markets. A number of papers have found evidence that polluting industries generate negative abnormal returns around environmental announcements (Moosa, Pichelli & Ramiah, 2015; Moosa, Nguyen, Pham, Ramiah & Saleem, 2019; Moosa, Nguyen, Pham & Ramiah, 2020). Some of these also find increasing risks around environmental announcements (Moosa et al. (2020). Given these research papers, we figured that we wanted to examine whether big indices where affected by announcements, and not just particular industries. We therefore decided to investigate whether there are any differences in abnormal returns and risk for exporters and importers of crude oil, to see whether the financial markets of fossil-fuel-based economies were affected more negatively than others. We consider the main stock market index of crude oil exporters as proxies for polluters, and the main stock market indices for importers as proxies for environmentally friendly companies.

By employing the event study methodology by Mackinlay (1997) we estimated cumulative abnormal returns around five different environmental announcements. These announcements were either announced by the European Commission, or by the United Nations. The events we chose to examine were the announcements of: the Paris Agreement (United Nations, 2015), action plan for the planet (European Commission, 2018), Clean planet for all (European Commission, 2018b), the European green deal (European Commission, 2019) and the Glasgow climate pact (United Nations, 2021). The things that these announcements have in common is that they contain either regulation, policies, or long-term plans for how Europe or the world is supposed to reduce their greenhouse gas emissions. As explained by Mackinlay (1997) we use the market model which uses a market portfolio to calculate the normal performance of an asset, then calculate whether the asset performs abnormally inside a defined event period. In order to estimate the expected normal performance of the asset, the market model typically uses Ordinary Least Square Estimation (OLS). As I have explained earlier, some research papers examine whether assets have increases in risk around events. The OLS estimator is a homoscedastic model, meaning it has a constant variance, as Brooks (2019, P. 732); Mackinlay (1997); Brown & Warner (1985) suggest, the volatility often increases inside an event period, leading to a homoscedastic variance not being particularly representative. Therefore, we introduced a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model which has a variance that evolves over time (Brooks, 2019, p. 512). In order to better check if exporters have higher volatility than importers, we used a GJR-GARCH (Brooks, 2019, 521) with dummy variables for the event period, building on the approach from Sengabo & Øverby (2021). Our hypotheses are as follows:

> **H0:** The main indices of European exporters and importers of crude oil will have a similar reaction to environmental announcements.
>
> **H1:** The main indices of European exporters will react more negatively than importers of crude oil to environmental announcements.
>
> **H0:** The main indices of European exporters and importers of crude oil have the same volatility around environmental announcements.
>
> **H1:** The main indices of European exporters crude oil have more volatile markets than importers around environmental announcements.

If we were to reject both of our null hypotheses, we would find evidence that investors invest responsibly around the environmental announcements. This is because we examine potential negative stock market movements for the indices. Furthermore, the GJR-GARCH model will show more volatile around events for negative returns due to a leverage effect, again implying that exporters' financial markets would be riskier in the event period. Rejecting the null hypotheses would also prove Edmans (2020, p. 27) pieconomics theory.

I will now present some of the underlying assumptions that are related to the methodology. First of all, as we have presented in the thesis, there are four Gauss-Markov assumptions for OLS estimations (Verbeek, 2004, p. 16). We tested two of these assumptions, because if the assumptions are not fulfilled, it could affect the reliability of the estimations (Zdaniuk, 2014). We tested the assumption of no autocorrelation in the error terms, and the assumptions of homoscedasticity (constant variance). We used both the Breusch-Pagan (1979) test, and the White test (1980) to check the models for homoscedasticity, and the Durbin-Watson (1950) test for autocorrelation. We find that for some of the estimation periods, we have problems with both homoscedasticity and autocorrelation, meaning that for some of our events, the OLS estimation might not be optimal. As for our GJR-GARCH model, we test the sample periods of Gaussianity through the Jarque-Bera test (1980), test for stationarity using the Dickey-Fuller test (1979), and a Lagrange-Multiplier test (Engle,1982) and a Portmanteau-Q test (Mcleod & Li, 1983) to check for ARCH effects. We find that all of our log-transformed returns are stationary, and both the Lagrange Multiplier test and Portmanteau-Q test show clear signs of ARCH effects. Implying that our estimations are reliable. However, for the case of simplicity, we assumed that our sample came from a Gaussian distribution in line with Jakobsen (2018), but we get clear rejections of this from the Jarque-Bera test. The assumption testing is in line with what we have been taught in both subjects SE-419: Financial Econometrics, and BE-510 Empirical Finance.

I will now present the findings of our thesis, and provide some discussion on the results, event by event, and imply how the results relate to responsibility, pieconomics and former literature. The Paris Agreement was signed by 195 parties at COP21 and is a legally binding treaty to limit the emission of greenhouse gases (United Nations, 2015). We expected this environmental announcement to affect exporters by negative abnormal returns, as found by Moosa et al. (2019); De Angelis & Monatrolo (2020); Gehricke et al. (2021). We also expected an increase in risk for exporters in the event period. Our findings show evidence of more volatile movements in the event period for the German DAX index and the British FTSE 100 index, while we do not have any CARs for any of the indices around the announcement of the Paris Agreement. These results do not provide any evidence for rejecting either null hypothesis, implying that the crude oil export/import status do not affect the main stock market index.

Inspired by the research from Birindelli & Chiappini (2020) we also wanted to focus on European specific environmental announcements. We expected the three European announcements to have a smaller impact on the stock markets of both importers and exporters, as they were mostly long-term plans and strategies, and not regulations and laws. Examining the results, we found that our expectations of these events were somewhat met. We find some abnormal returns, both positive and negative around these announcements, however, none are significant. There is also no clear indication of any differences in CARs for exporters of crude oil and importers. Turning our attention to the GJR-GARCH model, we only find significant volatility increases for one index at one event. The Spanish IBEX 35 have significant volatility increase around the clean planet for all announcements. We also visually examine the volatility around the events and find indications that the volatility of some exporters increases around the same announcement, but not enough that it is significant.

The last event we examined was the announcement of the Glasgow Climate Pact. We find significant negative CARs for the Russian MOEX index. In general, this is the event that produces the most abnormal returns, and movements for the CARs plots. However, only one of the indices produce significant CARs, leading to the overall indication being that there is no difference between importers and exporters. A serious limitation of the study, however, is that we do not estimate the volatility for this event. Sengabo & Øverby (2021) found that the Covid-19 pandemic "market crash" caused a significant increase in volatility. We found the same when we tried to estimate the volatility for the Glasgow climate pact period. The market crash volatility dominated the analysis and caused all our other events to be highly insignificant, which led to the period being excluded.

Overall, we fail to reject any of our null hypotheses, meaning that we do find evidence of ither increased risk or negative abnormal returns for exporters of crude oil compared to importers. As we used Crude oil as our metric for "polluters", we can see that our findngs are somewhat in line with Fan, Fag, Hua, Zhao (2018) who found that oil & gas firms do not experience negative abnormal returns when environmental regulations and policies are announced. Relating this to the concept of responsible, we find that it does not seem like the environmental announcements lead to more responsible investing, somewhat disagreeing with pieconomics from Edmans (2020, p. 27), at least not when it comes to oil.

Lastly, I would like to thank all the professors that I've had at the University of Agder for their guidance and encouragement. A special thanks to the professors in subject TFL400-1: Sustainable Capitalism for helping me realise the severity of the planetary boundaries, and how one can link climate change to economic activities. Also, I am very thankful that Jochen Jungeilges who was my professor in both BE-510 Empirical finance and SE-419: Financial Econometrics wanted to be our supervisor on this project, as he has guided us and motivated us through the process. Finally, I also want to thank my partner and great friend Simon Tobiassen Stikholmen, it has been an honour to work with you. In general, I will remember my 2 years at the University of Agder with pride and joy.

Simon Tobiassen Stikholmen

This discussion paper is written as a requirement by the University of Agder in relation to my master thesis. The point of discussion is how the term “international” relates to the topic and content of my thesis. It has been a challenging task to write such an extensive paper, but I also learned a lot of valuable lessons that I will benefit from in my professional career. Writing the thesis with a fellow student over the last few months have been very helpful and comforting. Before jumping into the thesis discussion, I also want to commend the University of Agder and their focus on being an international university. I have taken advantage of this myself by having a semester abroad in Liverpool during my master’s course. Going abroad was a great experience and I am very thankful for the opportunity.

Brief thesis introduction

I will start off with a brief introduction of our thesis. The title of our thesis: “Impact of environmental announcements on the financial markets of European crude oil exporters and importers” assumes an international scope. We aim to explore whether large European exporters of crude oil is more affected than importers of crude oil to the announcement of new environmental strategies, policies or regulations. Therefore, our research question is: “Are the financial markets of crude oil exporters more impacted than importers by environmental announcements.” To evaluate the effect of environmental announcements on the European financial markets we consider the main stock market indices of large European exporters and importers of crude oil. Included countries are Russia (MOEX), Norway (OSEBX) and the United Kingdom (FTSE 100) as exporters and Germany (DAX), Spain (IBEX 35) and Italy (FTSE MIB) as importers.

Examined announcements are publicised and drafted by intergovernmental organisations (IGO), namely the United Nations (UN) and the European Commission. Starting with the announcement of the Paris Agreement in 2015, we also analyse the announcement of the action plan for the planet (2017), a clean planet for all (2018), the European Green Deal (2019) and the Glasgow climate pact (2021). To measure the effect of these announcements for each index, we employ the event study methodology and a Generalised Autoregressive Conditional

Heteroskedasticity (GARCH) model. Applied methods are well known and used in similar research papers analysing financial markets all over the world. To further elaborate on the research question, we have formulated two separate hypotheses, one for the event study analysis and one for the GARCH volatility analysis.

The analysis results indicate that we fail to find a significantly different reaction to environmental announcements from large crude oil importers and exporters in Europe. However, some events highlight interesting index features which will be elaborated later in the next section of the discussion paper.

Analysed events

The first topic of discussion is regarding the selected events, introducing their main content and purpose. As mentioned, we consider five separate events that originate from the UN or European Commission that targets a broad area of the economy in Europe, and also globally. The increasing threat of climate change makes it more important than ever to take collective action on reducing greenhouse gas emissions. This is highlighted by an increasing number of environmental regulations, policies and strategy plans being drafted and put into force in later years. Furthermore, to ensure large scale collective action to fulfil the purpose of these policies, international cooperation is crucial.

The Paris Agreement represents a historic agreement between 195 parties. Announced and signed at the Conference of the Parties (COP21) 12th of December 2015, it is a legally binding international treaty where all nations pledged to reduce emissions and take joint action on climate change. The main goal of the Paris Agreement is to limit global warming to 2 degrees Celsius, ideally below 1.5 degrees, compared to pre-industrial levels. Achieving this goal requires the world to reach peak greenhouse gas emissions as soon as possible and ultimately decreasing emissions towards 2050. These goals can only come to fruition though a gradual shift in social and economic structures, enabling a more sustainable way of living for people and companies (United Nations, 2015, 2022).

The other environmental announcements considered in the thesis aims to ensure that the targets of the 2015 Paris Agreement is met. Through the commitment of the European Commission, the European Union (EU) have led the way in battling climate change by introducing numerous policies and strategy plans in recent years. One of these polices, the action plan for the planet announced on the 12th of December 2017, introduced ten transformative initiatives to help guide and accelerate the way towards the Paris Agreement targets. The European Commission also have their own goal of reducing the carbon-dioxide emissions by 40% in all sectors in Europe by 2030. Ensuring the shift towards a future built on innovative technologies and renewable energy sources is the target of the ten initiatives and how EU will reach its 2030 goal (European Commission, 2018a).

Another goal of the European Commission is to have the European economy being climate neutral by 2050. A clean planet for all was announced on the 28th of November 2018 and is the strategy plan that will lead the way towards the long-term goal in 2050 (European Commission, 2018b). With the same goal in mind, the European Green Deal was announced on the 11th of December 2019. The new deal represents a growth strategy aiming to transform the EU into a modern and resource efficient economy. Unlike a clean planet for all, the European Green Deal introduces many new policies and regulations that will impact all sectors of the economy (European Commission, 2019).

The last event we examined is the Glasgow climate pact. 200 countries was present at COP 26 and came to a critical agreement ensuring that there are still hopes of reaching the 1.5-degree Celsius goal from the 2015 Paris Agreement. The new climate pact builds on four main action points: mitigation, adaption, finance and collaboration (United Nations, 2021).

The concept of international is very important when looking at these environmental announcements. International collaboration between countries and regions is the only way climate change can be halted (United Nations, 2021). Our reason for choosing to analyse environmental announcements, such as those introduced above, is mainly due to the sustainable capitalism subject we had during our masters course. In sustainable capitalism we learned a lot about how society and the economy have to change in order to enable a sustainable way of living and doing business (Harris & Roach 2018; Becker, 2019; Bose, 2019; Edmans, 2020) We were also introduced to environmental announcements such as the European Green Deal and the role of financial markets in achieving sustainability. Thus, this largely inspired and motivated our theme for the thesis. It was also very interesting to dive deeper into some of the environmental policies and learn more about their content and scope.

Methodology

To determine whether any of the environmental announcements have an impact on the main stock market indices of large European exporters and importers of crude oil, we applied some statistical methodologies. Through subjects like econometrics and empirical finance we were introduced to numerous statistical models and concepts. These subjects inspired us to undertake an empirical research project where we could build on previous experience and methods. We also employ new statistical tools that we were exposed to when reading existing literature on the topic at hand (Birindelli & Chiappini, 2020; Moosa, Pichelli & Ramiah, 2015; Fan, Fang, Hua & Xhao, 2018) How this relates to the concept of international, is that similar research projects all over the world mostly use the same methodology, with some modifications. We adopt this global methodology trend in our thesis, and consider the following hypotheses, where the first hypothesis covers the event study and the second covers the GARCH model.

> **H0:** The main indices of European exporters and importers of crude oil will have a similar reaction to environmental announcements.
>
> **H1:** The main indices of European exporters will react more negatively than importers of crude oil to environmental announcements.
>
> **H0:** The main indices of European exporters and importers have the same volatility around environmental announcements.
>
> **H1:** The main indices of European exporters have more volatile markets than importers around environmental announcements.

These hypotheses were formulated with the efficient market hypothesis in mind. The efficient market hypothesis states that an efficient market is one where all available information is reflected in security prices at all times (Fama, 1970). Thus, the announcement of new environmental policies, regulations and strategies brings new information to the market.

Analysing the investor reaction these events, we can get an indication if countries with a high production of crude oil is less favoured.

Looking at research papers similar to the topic we wanted to study, we were introduced to the event study methodology. Even though we had never learned about this methodology in our courses, our supervisor Jochen Jungeilges encouraged us to explore it further. He was also available for any questions that we might have concerning this methodology. The event study methodology works by calculating abnormal returns in an event window surrounding an environmental announcement. Abnormal returns is found by estimating a market model conditioned to normal market returns in the period leading up to the event window. There are numerous ways of calculating the abnormal returns, but the market model presented by MacKinlay (1997) is straightforward and widely used in the literature. The abnormal returns can be summarised, giving cumulative abnormal returns (CAR) over the event window. Furthermore, CARs is tested for significance using a t-test, and if found significant, there is a clear reaction to the environmental announcement by a specific index. Another popular model in the literature, is the GARCH model which we use to measure volatility surrounding the environmental announcements (Moosa, Nguyen, Pham, Ramiah, 2020). The GARCH model also have a range of different iterations. We ended up employing a GJR-GARCH with dummy variables for each event inspired by the work of Sengabo & Øverby (2021).

Results

From our results we can not prove that exporters of crude oil are more affected than importers by environmental announcements. We only find a few significant movements across both our methodologies. However, we have a pretty clear image of why this is the case, and some alterations of the research could generate more insightful findings. We also have a better understanding of the importance of financial markets in achieving a sustainability, which is highlighted by the policy content in the examined environmental announcements. Providing research on how these announcements affect financial markets is useful in knowing how to design future policies and regulations to be even more effective.

All in all, out thesis relates to the concept “international” on several levels. From the analysed events that impact financial markets all over the world, to the broadly used methodology.

Lastly, I want to thank my professors at the University of Agder for sharing their broad insight and knowledge throughout my master's course. A special thanks to Jochen Jungeilges for his supervision and continuous support and encouragement these last few months. It was also a great pleasure to work and collaborate closely with my good friend Markus Bjørntvedt.

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