BI

WISEflow
Europe/Oslo(CEST)
02 Jul 2023

Handelshøyskolen BI

GRA 19703 Master Thesis

Thesis Master of Science 100% - W

Predefinert informasjon

Startdato:	09-01-2023 09:00 CET	**Termin:**	202310
Sluttdato:	03-07-2023 12:00 CEST	**Vurderingsform:**	Norsk 6-trinns skala (A-F)
Eksamensform:	T		
Flowkode:	202310||11184||IN00||W||T		
Intern sensor:	(Anonymisert)		

Deltaker

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Informasjon fra deltaker

Tittel *:	A Lag Augmented Vector Autoregressive Analysis Of Clean Energy Stocks Before And After The Paris Agreement
Navn på veileder *:	Negar Ghanbari

Inneholder besvarelsen konfidensielt materiale?:	Nei	**Kan besvarelsen offentliggjøres?:**	Ja

Gruppe

Gruppenavn:	(Anonymisert)
Gruppenummer:	99
Andre medlemmer i gruppen:	

BI Norwegian Business School
Oslo, Spring 2023

A Lag Augmented Vector Autoregressive Analysis Of Clean Energy Stocks Before And After The Paris Agreement

Supervisor: Negar Ghanbari

Master thesis, Sustainable Finance

BI Norwegian Business School

Acknowledgments

Thank you, Negar, for challenging us and providing us with valuable feedback and academic insight. We like to express our gratitude to Frida and Anette for their support throughout this journey. Additionally, we want to thank Hennie and Åse for their invaluable contributions.

Thank you.

BI Norwegian Business School

Oslo, June 2023

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Abstract

The main goal of this paper is to investigate if determining factors of clean energy stock performance in Europe have been influenced by the Paris Agreement. The analysis consist of three models in the time period before the Paris Agreement, and three models in the time period after the Paris Agreement. The models consist of variables related to the stock- and energy market and climate factors as well as a European clean energy index. To conduct our analysis we utilize a LA-VAR and a VAR framework. Using the results from this we examine the Granger causality, impulse responses and variance decomposition.

The main findings of this paper are the shift in Granger causality before and after the Paris Agreement. We find that the stock market factors Granger-causes the clean energy index prior to the Paris Agreement, but not following the Agreement. On the other hand, we find that the climate- and energy factors do not Granger-cause the clean energy index prior to the Paris Agreement, but Granger-causes in the period following the Paris Agreement. This indicates that the Paris Agreement have influenced determining factors of clean energy stock performance in Europe.

Keywords – Clean energy, climate change, Paris Agreement

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1 Introduction & Motivation

In today's world, there is an urgent need to address the challenges of climate change. The consequences of this global issue pose significant threats to our planet and future generations. Efficient political regulations and policies are crucial, in order to combat climate change and mitigate its impact. The urgency of the climate crisis demands immediate and coordinated action from governments worldwide, to drive innovation, and create a sustainable pathway forward.

The Paris Agreement (PA), announced on December 12, 2015, is widely recognized as the most significant milestone in global climate mitigation and adaptation efforts. Its emergence took many by surprise as, for the first time, a majority of UN countries agreed on the urgent need to limit global temperature increase "well below 2°C" above pre-industrial levels. The Agreement also emphasized strengthening countries' abilities to address the impacts of climate change and committing to align financial flows with low greenhouse gas emissions and climate-resilient development (UNCC, 2018). There is also an ongoing debate surrounding the question of whether implementing climate policies to meet the 2-degree Celsius target generates systemic risks, or presents opportunities for low-carbon investments and economic growth (Battiston et al., 2017).

There exist several studies that looks at the determining factors of clean energy assets. Studies have also been done to examine the impact of the Paris Agreement. Building on these studies we aim to further contribute to the literature by examining the relationship between a set of selected variables and a European clean energy index. Specifically we aim to analyse the causal relationship between the European clean energy index and climate-, energy-, and stock market based factors. Understanding the dynamics between such variables is critical for policy makers, regulators, and investors in energy- and financial markets. The learning process around these dynamics is vital for anticipating market shifts, structuring effective energy policies, and identifying promising investment opportunities in the clean energy sector.

Specifically our main research question is:

- *Did the Paris Agreement influence determining factors of clean energy stock performance in Europe?*

1.1 Variables and Methodology

In our thesis, we carefully chose a specific set of variables that we believe are important in understanding how European clean energy assets perform. Our goal was to analyze the underlying factors that influence the performance of these assets. Due to data availability and the impact of the Covid-19 pandemic, we focused on the time period from January 1, 2011, to January 31, 2020. In order to examine any potential changes we divided the time period into two parts, one before and one after the Paris Agreement.

To capture European clean energy assets, we have used the NASDAQ OMX Clean Energy Focused Index. The other variables we considered were grouped into two categories. The first category included stock market factors: MSCI Europe Growth Index, STOXX Europe 600, and Euribor 3-month interest rate. The second category consisted of climate- and energy-related factors: Brent Crude oil price, Climate Policy Uncertainty Index, and Carbon Emissions futures price.

Inspired by the methodology by Toda and Yamamoto (1995) we implement a Lag-Augmented Vector Autoregressive model to examine the causal relationship between our variables. In addition, we implement a standard VAR model and perform impulse response functions and variance decomposition analysis. Finally we complete our analysis with robustness checks using US and Asian clean energy indexes.

1.2 Outline

This thesis is structured into seven chapters, with the current chapter serving as the introduction. Chapter 2 offers a comprehensive overview of the existing literature, encompassing various aspects and perspectives related to the research question. In chapter 3, we outline our hypotheses, which are formulated based on our own theories and insights gained from the existing literature. Chapter 4 presents the theoretical methodology employed to analyze these hypotheses. Chapter 5 presents the data collected and provides detailed information on each individual variable utilized. The sixth chapter presents our six distinct models, along with our findings, discussions, and robustness tests. Finally, chapter 7 concludes the thesis by summarizing the key findings, acknowledging shortcomings and limitations, and suggesting questions for future research.

2 Litterature Review

In the literature, the subjects of oil price fluctuations, clean energy stock performance, climate change, and carbon risk have been extensively debated and studied. In the last decade, an increased emphasis has been placed on addressing the pressing challenge of climate change. Consequently, substantial efforts have been made in this direction, reflecting a growing recognition of the importance of sustainability and clean energy. In the process of selecting relevant literature for our thesis, we have put great effort into including high-quality papers from well-cited journals with a high impact factor. By doing so, we aim to ensure that our thesis is supported by reliable, reputable and relevant sources.

Henriques and Sadorsky (2008), utilize a four-variable vector autoregressive model to explore the connection between oil prices, technology stock prices, interest rates, and the financial performance of alternative energy companies. The results highlight that both technology stock prices and oil prices independently Granger-cause the stock prices of alternative energy companies. Through simulations, they find that a shock to technology stock prices exerts a more substantial impact on alternative energy stock prices compared to a similar shock to oil prices. They argue that these findings hold significant implications for a range of stakeholders, including investors, managers, and policymakers, given the increasing prominence of energy security and climate awareness (Henriques and Sadorsky, 2008).

Inspired by the findings of Henriques and Sadorsky (2008), Kumar et al. (2012) apply a vector autoregressive analysis to investigate the interrelationship among clean energy firms' stock prices, oil prices, carbon markets, and technology firms' stock prices. Their empirical evidence provides support to the theory that increasing oil prices catalyze the transition towards alternative energy sources. Furthermore, they suggest that investors perceive clean energy firms similar to high technology stocks. Intriguingly, the study finds no substantial correlation between clean energy stock performance and carbon pricing, attributing this to low carbon prices during the observed period, and geographic differences. Nonetheless, given the recent increase in carbon prices, this aspect may bear more significance in more recent times.

In similar fashion Reboredo and Ugolini (2018) assesses the impact of quantile price movements in oil, gas, coal and electricity on the quantiles of clean energy stock returns. They use a multivariate vine-copula dependence setup in the time period from 2009 – 2016. Their findings suggest that the price of electricity and oil has a major contribution to the dynamics of clean energy stock returns in the US and the EU (Reboredo and Ugolini, 2018). Coal and gas prices played a minor role. In addition, they find that the impact is symmetric with both negative and positive price movements in energy prices. The findings of this article can be useful both in a risk management perspective for private investors and for policymakers looking to support the development of clean energy (Reboredo and Ugolini, 2018).

Zhou et al. (2023) is analyzing the time varying and dynamic relationship between climate policy uncertainty, oil price and renewable energy consumption over the period from 2005 to 2021. They develop a time-varying parameter VAR and find similar results to the above mentioned articles. Increased climate policy uncertainty positively affects the oil price and the consumption of renewable energy (Zhou et al., 2023). Their findings have several interesting policy implications. Firstly, the positive relationship between climate policy uncertainty and the oil price suggest that this relationship should be considered when formulating climate policy to avoid macroeconomic consequences related to an increasing oil price. Secondly, there should be an increased policy support towards renewable energy and increased investments which again will increase the consumption of renewable energy and reduce emissions (Zhou et al., 2023).

An article by Fahmy (2022) hypothesize that the increased focus on green investment and climate risk awareness should have had an impact on the relationship between clean energy prices, oil price and technology stocks before and after the Paris Agreement. After controlling for carbon price, market volatility and policy uncertainty, the author finds that, before the Paris Agreement oil price is the best regime driver for clean energy. In the post Paris Agreement period however, technology stocks are the best driver, and the effect of the oil price is completely absent. This indicates a significant shift in investor awareness and the perspective on clean energy assets. Further, these findings indicate that large climate policy agreements and other important climate related events do have a significant impact on decoupling clean energy assets from the traditional energy markets

(Fahmy, 2022).

In an analysis of the stock market reaction of the Paris Agreement Monasterolo and de Angelis (2020) aim to understand how and if markets react to climate related announcements, and if assets are rewarded or penalized according to their carbon intensity. They structure tests to see how the market price the Paris Agreement and how the systematic risk is affected. They find that after the Paris Agreement the correlation between high and low carbon indices drops, indicating that the Paris Agreement has led to a further differentiating of high and low carbon assets. This implies that investors have changed their perception of low carbon investments. However, high carbon assets have faced mild reaction to the Paris Agreement (Monasterolo and de Angelis, 2020).

The article by Bolton and Kacperczyk (2021) explores the area of carbon risk. Similar to the study done by Monasterolo and de Angelis (2020), they study if carbon emissions affects US stock returns. After controlling for various return predictors, they find that firms with high carbon emissions earn higher returns. These results are consistent with the notion that investors demand compensation for exposure towards carbon risk (Bolton and Kacperczyk, 2021). This is highly relevant for investors and policy makers that are trying to price and understand the market dynamics and the implications of carbon risk.

The study by Battiston et al. (2017) employs a network-based climate stress-test methodology, redefining current economic activities into climate-policy-relevant sectors. The research reveals substantial direct and indirect exposure to these sectors across financial actors' portfolios, thereby highlighting the systemic risk tied to sudden climate policy changes. The authors underscore the critical role of early and stable implementation of climate mitigation policies, allowing investors to anticipate effects and avoid systemic risk. They further suggest that these policies may lead to increased portfolio volatility and could result in both winners and losers among financial actors depending on their portfolio composition. The study emphasizes the need of a stable policy framework and robust climate-related financial disclosure (Battiston et al., 2017).

3 Testable Hypothesis

Hypothesis 1: The Paris Agreement has influenced determining factors of clean energy stock performance in Europe.

Our primary objective is to investigate whether factors driving the performance of clean energy stocks have been in influenced by the Paris Agreement. Building on the research conducted by Fahmy (2022) and Monasterolo and de Angelis (2020), who found an increase in investor awareness following the Paris Agreement, we propose that the Agreement also prompted a shift in determining factors of clean energy stock performance. By examining the post-Paris Agreement period, we aim to contribute to the existing literature and shed light on any changes in some of these determining factors.

Hypothesis 2: Climate- and energy factors have seen an increase in significance after the Paris Agreement.

In line with the growing importance of climate change and sustainable development, we hypothesize that climate- and energy-related factors have gained greater significance in influencing the performance of clean energy stocks following the Paris Agreement. This hypothesis builds upon the premise that the Agreement's focus on addressing climate challenges has amplified the relevance of climate- and energy-related factors in the market, potentially impacting the performance of clean energy stocks.

Hypothesis 3: An increase in the price of carbon (MO1) will have a positive effect on clean energy stock prices.

Drawing on the findings of Kumar et al. (2012), we propose that an increase in the price of carbon emission allowances (MO1) is likely to attract investors towards clean energy companies. As the cost of carbon emissions rises, we propose that clean energy companies will become relatively more attractive due to their cleaner and more sustainable energy sources, that are not affected by an increase in the cost of emitting. Consequently, this increased demand for clean energy stocks is expected to have a positive effect on their stock prices.

Hypothesis 4: There exists a significant relationship between the MSCI Growth Index (GRW) and clean energy stocks.

Differing from existing literature that primarily associates technology stocks with clean energy stocks, we suggest that clean energy companies are closely aligned with growth stocks. This hypothesis aims to challenge the prevailing assumption and explore the specific relationship between growth stocks and clean energy stocks.

Hypothesis 5: The Paris Agreement has contributed to improve the risk adjusted returns for the clean energy index.

We believe that the Paris Agreement has contributed to an increased focus on climate risk, sustainable innovations, and more attractive investment cases within clean energy assets. In addition, the Agreement has incentivized governments to implement more favourable climate policies. As a result of this, we believe that the risk return relationship for clean energy assets has improved.

By formulating these hypotheses, we aim to contribute to the academic and theoretical understanding of the factors influencing the performance of clean energy stocks. Through empirical analysis and examining the selected variables, we expect to discovering valuable insights that may challenge or complement the existing literature on this subject matter.

4 Methodology

4.1 VAR

We employ a standard vector autoregressive model (VAR) and a lag augmented vector autoregressive model (LA-VAR) to investigate the relationships between the GRNEUR index and our selected variables. We view this approach as the most suitable for our research objectives. VAR models are among the most popular estimation techniques used in econometrics. The utilization of a VAR model offers various advantages. Specifically, it obviates the necessity to explicitly determine the exogenous and endogenous variables, as all variables are treated as endogenous. Consequently, each variable can rely on past values of both the dependent variables and all other variables within the model (Brooks, 2019). This characteristic offers greater flexibility in examining relationships and facilitates the adoption of a more comprehensive framework. Moreover, VAR models have demonstrated superior forecasting performance in comparison to conventional structured models (Brooks, 2019).

A VAR model can be estimated using OLS. Shown below is an example of a VAR(3) model with two variables:

$$y_{1t} = \alpha_{10} + \beta_{11}y_{1t-1} + \beta_{12}y_{2t-1} + \gamma_{11}y_{1t-2} + \gamma_{12}y_{2t-2} + \delta_{11}y_{1t-3} + \delta_{12}y_{2t-3} + u_{1t}$$
$$y_{2t} = \alpha_{20} + \beta_{21}y_{1t-1} + \beta_{22}y_{2t-1} + \gamma_{21}y_{1t-2} + \gamma_{22}y_{2t-2} + \delta_{21}y_{1t-3} + \delta_{22}y_{2t-3} + u_{2t}$$

The utilization of a VAR model is based on several assumptions. To ensure the suitability of the VAR model, we assume that the data exhibits stationarity, follows a normal distribution, demonstrates stability, and possesses no autocorrelation in the residuals. Furthermore, it is essential for the variables to be non-cointegrated, meaning they lack a shared long-term trend or relationship. In cases where variables are cointegrated, a VECM (vector error correction model) becomes a more appropriate choice (Brooks, 2019). We will discuss this further later in this chapter.

As all econometric models, VAR models are subject to limitations. VAR models have limitations as they are not heavily guided by established theories, making it challenging to derive clear policy implications. Hence, researchers run a higher risk of discovering misleading relationships when analyzing the data. Interpreting coefficient estimates in VAR models can be complex, and determining the appropriate number of time lags remains a subject of ongoing debate. Additionally, estimating VAR models with numerous parameters can yield imprecise results and wide confidence intervals around the estimated coefficients. Ensuring stationarity in all variables is crucial for hypothesis testing in VAR models, but deciding whether to use differencing or not presents a complex choice (Brooks, 2019).

4.2 Lag Augmented VAR

Toda and Yamamoto (1995) introduced a lag-augmented vector autoregression (LA-VAR) testing procedure, distinguished by its robustness to both integration and co-integration properties of data and its distinctive capability to circumvent the potential pre-test bias. Provided that the data integration's order doesn't surpass the model's true lag length, a common lag length selection criterion can be employed to determine the suitable lag length. We estimate a VAR with $k + d_{\text{MAX}}$ lags, with k representing the optimal lag length according to the information criteria, and d_{MAX} representing the predicted maximum order of integration. We have adopted this approach to overcome some of the limitations associated with the standard VAR model and to establish a more robust framework for our analysis.

Below is an example of a two variable LA-VAR model with $k + d_{\text{MAX}}$ lags:

$$
\begin{aligned}
Y_{1,t} = \beta_{1,0} + &\beta_{1,1}Y_{1,t-1} + \cdots + \beta_{1,p}Y_{1,t-p} + \beta_{1,p+d}Y_{1,t-p-d} \\
&+ \alpha_{1,1}Y_{2,t-1} + \cdots + \alpha_{1,p}Y_{2,t-p} + \alpha_{1,p+d}Y_{2,t-p-d} + u_{1,t}
\end{aligned}
$$

$$
\begin{aligned}
Y_{2,t} = \beta_{2,0} + &\beta_{2,1}Y_{2,t-1} + \cdots + \beta_{2,p}Y_{2,t-p} + \beta_{2,p+d}Y_{2,t-p-d} \\
&+ \alpha_{2,1}Y_{1,t-1} + \cdots + \alpha_{2,p}Y_{1,t-p} + \alpha_{2,p+d}Y_{1,t-p-d} + u_{2,t}
\end{aligned}
$$

As Yamada and Toda (1998) discuss, the choice between a VECM and a LA-VAR involves a trade-off between size and power. The LA-VAR model exhibits better performance regarding the probability of falsely rejecting the true null hypothesis (Type I error), while the VECM exhibits better performance regarding the possibility of not rejecting a false null hypothesis (Type II error). These finding were validated by Clarke and Mirza (2006).

To conduct the Granger causality tests, we employ a modified Wald test on the initial (k) lags, determined by the optimal lag length. For instance, if the optimal lag length is determined to be $k = 3$, and there is a level of integration of 1, the total lag length of the model would be 4. However, due to the nature of the modified Wald test, we consider only the first 3 lags (Toda and Yamamoto, 1995).

4.3 Lag Length

In order to establish the VAR model appropriately, it is essential to determine the suitable lag length. Various methods exist for this purpose, and one commonly employed approach is the utilization of information criteria. This method effectively captures the trade-off between the reduction in residual sum of squares (RSS) achieved by incorporating additional lags and the simultaneous increase in the penalty term value. By specifying a predetermined maximum number of lags, the optimal lag length is determined by identifying the number of lags that minimizes the selected information criteria (Brooks, 2019).

4.4 Stationarity / Unit Root

For the VAR model to yield reliable outcomes, it is essential that the variables exhibit stationarity and integration of the same order. Stationarity, as defined by Brooks (2019), refers to a series having a constant mean, constant variance, and constant autocovariance for each given lag. Financial data commonly includes both a trend component and shocks to the time series, which often results in non-stationarity. To ascertain what the order of integration is, and whether the data is stationary, or contains a unit root, various tests need to be employed (Brooks, 2019).

The Augmented Dickey-Fuller (ADF) test is employed to investigate the presence of a unit root in a time series. Additionally, the KPSS (Kwiatkowski-Phillips-Schmidt-Shin) and Phillips-Perron tests are employed. The Phillips-Perron test is similar to the ADF test but incorporates a correction to account for autocorrelated residuals. In most cases, the Phillips-Perron test yields similar outcomes to the ADF test. Finally, the KPSS test can be employed to ensure conclusive results across all three tests (Brooks, 2019).

There are four possible outcomes of the unit root/stationarity tests. In order to reach confirmatory results of no unit root, we want to reject the null hypothesis for ADF and PP. Additionally, we do not want to reject the null hypothesis for KPSS.

ADF / PP	KPSS
$\text{H}_0 : y_t \sim I(1)$	$\text{H}_0 : y_t \sim I(0)$
$\text{H}_1 : y_t \sim I(0)$	$\text{H}_1 : y_t \sim I(1)$

(1)	Reject H0	&	Do not reject H0
(2)	Do not reject H0	&	Reject H0
(3)	Reject H0	&	Reject H0
(4)	Do not reject H0	&	Do not reject H0

Table 4.1: Unit root / stationarity conclusions (Brooks, 2019)

To ensure reliability of our conclusions, it is crucial that our results align with either outcome (1) or (2). This alignment will be achieved when both of our tests unanimously conclude that the data series is either stationary or non-stationary. If we encounter outcomes (3) or (4), it indicates a discrepancy in the results (Brooks, 2019).

If it is determined that the data contains a unit root and is non-stationary, the subsequent step involves differencing the data and repeating the testing procedure to examine whether the data has become stationary. If the data achieves stationarity following first differencing, it can be concluded that the data is integrated of order 1. When implementing the LA-VAR it is crucial to ensure that the data is integrated of the same order, hence we verify that the data becomes stationary when conducting the stationarity tests on first differences (Brooks, 2019).

4.5 Cointegration & VECM

In addition to establishing the order of integration for the data, the data needs to be tested for cointegration. In the presence of cointegration, the use of a vector error correction model (VECM) is the appropriate choice. It is not uncommon for financial time series to be non-stationary, but move together over time. This long-term relationship or equilibrium between the time series can be seen as the cointegrated relationship. The cointegrated relationship can be viewed as the long-run equilibrium between the variables, with short-term deviations (Brooks, 2019). Even with non-stationary data, a linear combination of the variables may be stationary over time. To test for cointegration we employ the Johansen test for cointegration Johansen (1988). The Johansen testing procedure for cointegration is a method used to determine if variables are related in the long run. It involves analyzing a non-stationary vector autoregressive process with a specific order of integration and Gaussian errors. This method calculates the maximum likelihood estimator for the cointegration vectors and uses a likelihood ratio test to assess the dimensionality of the dataset. It also examines linear hypotheses about the cointegration vectors. The test statistics used in this procedure have certain distributions, including a multivariate variant of the standard test for a unit root and a chi-square test (Johansen, 1988).

4.6 Granger causality

When we have multiple variables and lags in a vector autoregressive model, it can be challenging to determine which variables have a significant impact on the dependent variable. To address this challenge, we can use Granger causality tests. These tests help us assess the influence of one variable on another by setting the lags of the selected variable to zero and using the F-test framework for analysis. This allows us to test all the lags of a variable together, rather than individually examining each variable. The main goal of this test is to determine if changes in one variable, let's say y, cause changes in another variable, x. If the lags of y are significant in explaining the changes in x while the reverse is not true, we can conclude a unidirectional causality from y to x. Conversely, if the variables influence each other in both directions, it indicates a bi-directional causal relationship (Brooks, 2019).

Theoretical explanation of the Granger causality test in relation to the LA-VAR models are explained in the LA-VAR section.

	Hypothesis	Implied restriction
1	Lags of y_{1t} do not explain current y_{2t}	$\beta_{21} = 0$ and $\gamma_{21} = 0$ and $\delta_{21} = 0$
2	Lags of y_{1t} do not explain current y_{1t}	$\beta_{11} = 0$ and $\gamma_{11} = 0$ and $\delta_{11} = 0$
3	Lags of y_{2t} do not explain current y_{1t}	$\beta_{12} = 0$ and $\gamma_{12} = 0$ and $\delta_{12} = 0$
4	Lags of y_{2t} do not explain current y_{2t}	$\beta_{22} = 0$ and $\gamma_{22} = 0$ and $\delta_{22} = 0$

Table 4.2: Granger causality framework (Brooks, 2019)

4.7 Impulse Response & Variance Decomposition

Employing the F-test framework in the Granger causality test affords valuable insights regarding which variables exert a statistically significant influence over others. However, it does not provide information about the direction of this impact (positive or negative) or the requisite time for the effect to manifest. In order to explore the more nuanced information about the relationships, we examine the impulse response function (IRF) and the variance decomposition (VDC) of the VAR model. The IRF exposes the responsiveness of the dependent variable to shocks in each variable, essentially serving as the partial derivatives of the variables with respect to the error term. Typically, a one standard deviation shock is employed to find this responsiveness (Brooks, 2019).

Contrary to the impulse response function (IRF), the variance decomposition (VDC) serves a marginally different purpose. The VDC quantifies the proportion of fluctuations in the dependent variable that can be attributed to its own shocks, as well as shocks to other variables. Naturally, a shock to a specific variable will directly influence that variable, but owing to the dynamics of the VAR model, other variables will also be affected. The variance decomposition shows the proportion of the s-step ahead forecast error variance for a given variable that is accounted for by changes to each explanatory variable at each s-step (Brooks, 2019).

An important similarity between the VDC and IRF is the necessity to correctly ordering the variables. In order to achieve an accurate ordering, one might use financial theory to arrange the data in accordance with which variables are likely to trigger movement and which are anticipated to react. Failure to maintain this order could compromise the interpretation and results of the analysis (Brooks, 2019).

5 Data

We have obtained monthly closing prices from 31st of January 2011 to 31st of January 2020, generating a total of 108 end of month observations. We have chosen monthly data in order to reduce noise and avoid non-trading days. Our decision on the time period takes into account the data accessibility as well as the impact of the COVID-19 crisis. The variables used are NASDAQ OMX Clean Energy Focused Index, Brent Crude oil price, Climate Policy Uncertainty Index, MSCI Europe Growth Index, STOXX Europe 600, Euribor 3-month interest rate, Carbon Emissions Futures Price, NASDAQ OMX Clean Energy Focused Asia Index and NASDAQ OMX Clean Energy US Index. All data is gathered from Bloomberg, Refinitive/Eikon and www.policyuncertainty.net.

Variable name	Ticker
Nasdaq OMX Clean Energy Focused Europe Index	GRNEUR
Brent Crude oil	CO1
Climate Policy Uncertainty Index	CPU
MSCI Europe Growth Index	GRW
Euribor 3-month interest rate	ECB
CO2 Futures	MO1
Stoxx Europe 600	STX

Table 5.1: Variables of study

5.1 Nasdaq OMX Clean Energy Focused Europe Index

The NASDAQ OMX Clean Energy Focused Europe Index (GRNEUR) is specifically created to monitor and reflect the progress of sectors within the green economy that promote the development of energy generation from non-fossil fuel sources. The indexes encompass the following sectors: Renewable Energy, Energy Efficiency, Advanced Materials, and Bio/Clean Fuels. To analyze the robustness of our results we have included the same index for the US and Asia; NASDAQ OMX Clean Energy Focused Asia Index and NASDAQ OMX Clean Energy Focused US Index (Nasdaqomx.com).

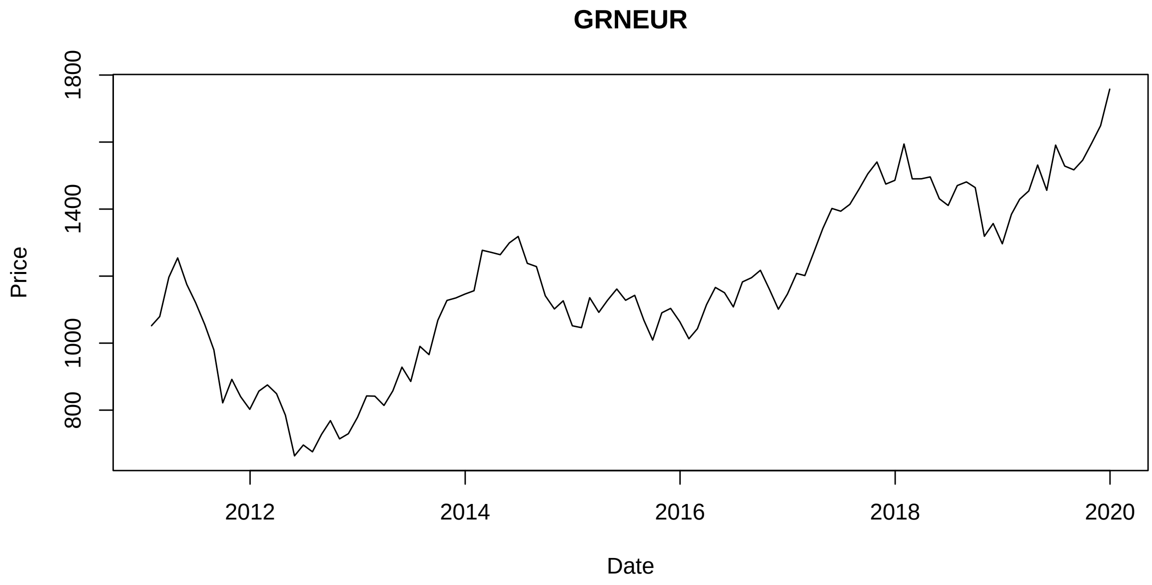

Figure 5.1: GRNEUR price plot

5.2 Brent Crude oil

The Brent Crude price (CO1) is considered a benchmark for international oil prices and is used as a reference for crude oil in Europe (Wittner, 2020). Incorporating the price of oil in our analysis of clean energy stock variations is crucial due to the intricate relationship between oil prices and the clean energy sector. Oil, as the world's most traded physical commodity, exerts a profound influence on the global economy and energy landscape. When oil prices rise, production costs for goods and services often increase, consequently impacting cash flows and stock prices negatively. This can, in turn, stimulate the search for alternative energy sources, incentivizing investments in clean energy firms. Additionally, oil price fluctuations, particularly upward trends, often signal inflationary pressures, which may prompt central banks to raise interest rates, thereby affecting the discount rates used in equity valuation (Basher and Sadorsky, 2006). As clean energy represents an alternative to oil, its attractiveness and, consequently, its stock prices could be inversely associated with oil prices. Therefore, the inclusion of Brent Crude price in our analysis provides a more comprehensive understanding of the factors influencing clean energy stock fluctuations. A lot of literature covers the significant relationship between oil price movements and equity prices, and in more recent years, research has been done on the relationship between oil price and alternative energy companies (Basher and Sadorsky, 2006; Boyer and Filion, 2007; Henriques and Sadorsky, 2008; Kumar et al., 2012; Reboredo and Ugolini, 2018)).

There is conclusive research on the connection between oil price and clean energy stock performance. Reboredo and Ugolini (2018) find that fluctuations in oil prices and electricity prices are significant determinants in driving the movements of clean energy stock returns within the US and Europe. Henriques and Sadorsky (2008) find that both technology stock prices and oil prices individually Granger-causes the stock prices of alternative energy companies. This suggests that past values of these variables can help in predicting the future direction of clean energy stock prices.

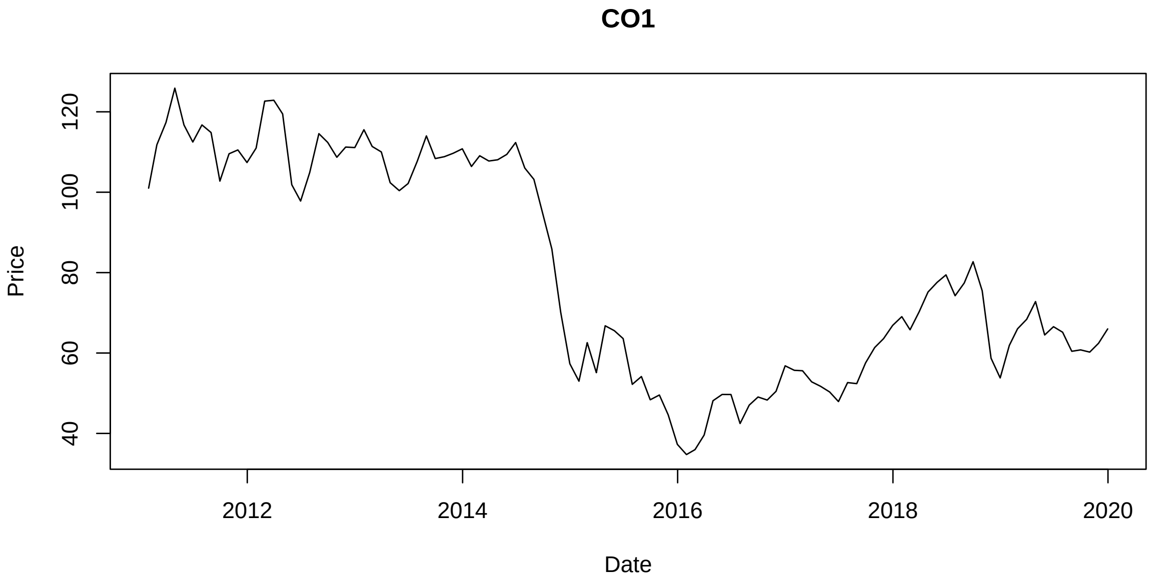

Figure 5.2: CO1 price plot

5.3 Climate Policy Uncertainty Index

The Climate Policy Uncertainty (CPU) Index tracks articles from eight prominent US newspapers that mention terms related to climate and policy (Gavriilidis, 2021). The index experiences spikes during significant events concerning climate policy, such as the introduction of new emissions legislation, global strikes focusing on climate change, and statements made by the President regarding climate policy. The CPU Index is our only variable that is non-tradable, hence, it has some specific properties that we explain in more detail in the Descriptive Analysis part.

In general, uncertainty often lead companies to postpone investments. This delay can result in reduced investments in new equipment and research and development (Bloom, 2009). However, when it comes to uncertainty specifically associated with climate policy, the effect may be different. Bouri et al. (2022) provide empirical evidence that the performance of green energy stocks as compared to brown energy stocks is significantly influenced by climate policy uncertainty. During periods of crisis, this uncertainty has a positive impact, causing green energy stocks to perform better.

While our study primarily concentrates on Europe, we posit that the CPU Index, which is based on US news articles, can act as an effective representative measure for uncertainty within the European context too. The economic alliance between the EU and the US stands as a critical pillar of worldwide economic growth, commerce, and wealth. Combined, the EU and the US make up 42 percent of the global GDP. As each other's primary trading partners, they form the world's most substantial bilateral trade relationship (EU, 2021).

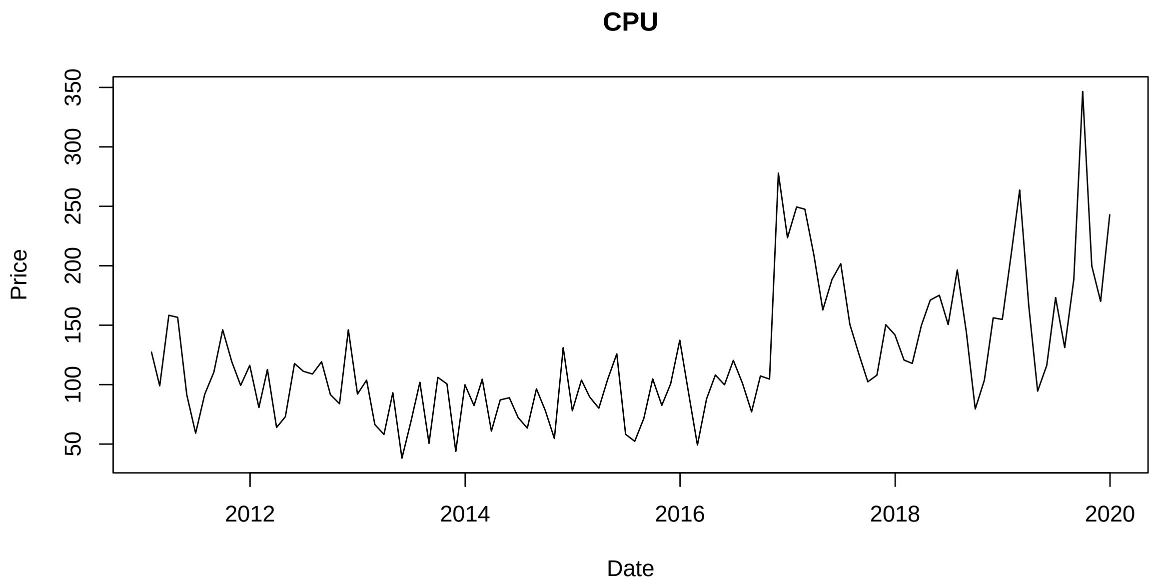

Figure 5.3: CPU price plot

5.4 MSCI Europe Growth Index

The MSCI Europe Growth Index (GRW) represents large and mid-cap securities across 15 developed European countries, which display general characteristics of a growthoriented investment style. In light of the significant growth observed by numerous clean energy equities over the previous decade, it can be hypothesized that investors perceive these firms as growth companies. Consequently, this index has been incorporated to encapsulate this particular market sentiment. The criteria for index inclusion are dictated by five parameters: long-term forward EPS growth rate, short-term forward EPS growth rate, current internal growth rate, long-term historical EPS growth trend and long-term historical sales per share growth trend (Msci, 2023). GRNEUR is largely weighted in industrials (37.64%), with only a small fraction in telecommunications (5.57%). MSCI Europe Growth Index is also largely weighted in industrials (20.14%) and more moderately weighted in information technology (11.78%). Hence, one of the reasons for why we have chosen to include the MSCI Europe Growth Index rather than a pure technology index, is the similar weighting of industrials in GRNEUR.

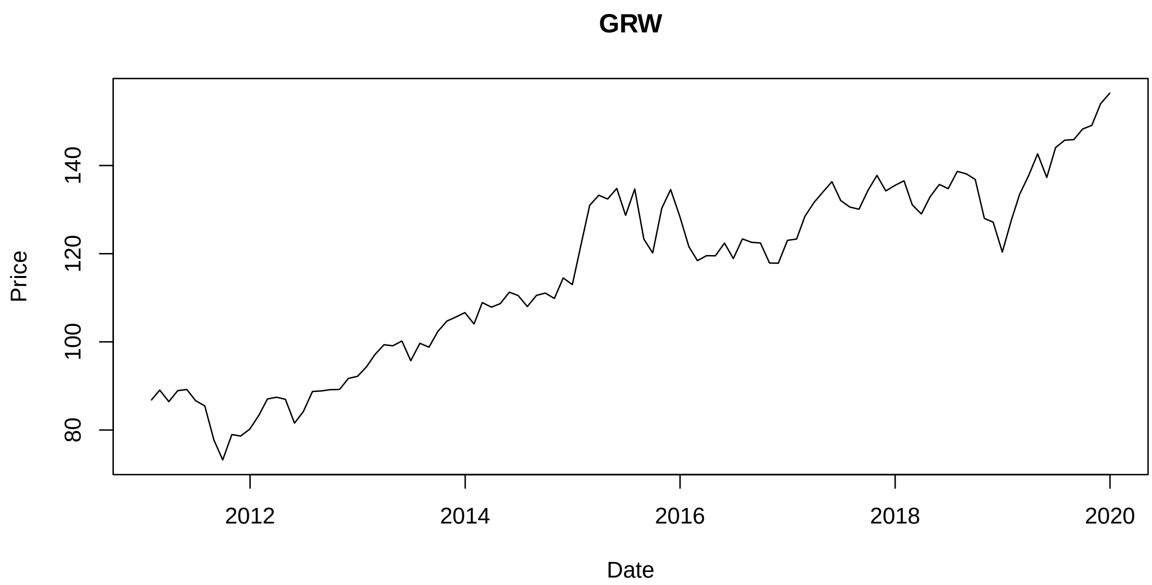

Figure 5.4: GRW price plot

5.5 Euribor 3-month

The Euribor 3-month interest rate (ECB) is included to capture the relationship between cost of capital and asset valuation. The rationale for choosing a short-term maturity for this interest rate is primarily attributed to its trade liquidity and minimal, if not non-existent, exposure to interest rate fluctuations. Fundamental financial theory suggests that if the long-term real interest rate is low, the corresponding discount rate employed for calculating present values will be low, thereby resulting in high present values. Despite the observed rise in long-term rates over the recent years, these rates in the context of the 21st century remain relatively low (until recently), both nominally and in real terms, especially when compared to historical averages. As a consequence, asset valuations such as stock prices, house prices and commercial real estate prices, and even prices of oil and other commodities are reported to be exceptionally high. A reduction in interest rates reduces the cost of borrowing, leading to an increase in investments. Consequently, this results in an increase in the value of the respective assets (Ubl, 2014). More recent research done by Monnin (2015) find that interest rate changes have a greater impact on the costs of clean energy technologies, relative to brown energy technologies. He further suggests that to enhance the proportion of green energy investments relative to brown energy investments, there could be potential merit in contemplating either a reduction in interest rates for the former or a premium on interest rates for the latter (Monnin, 2015).

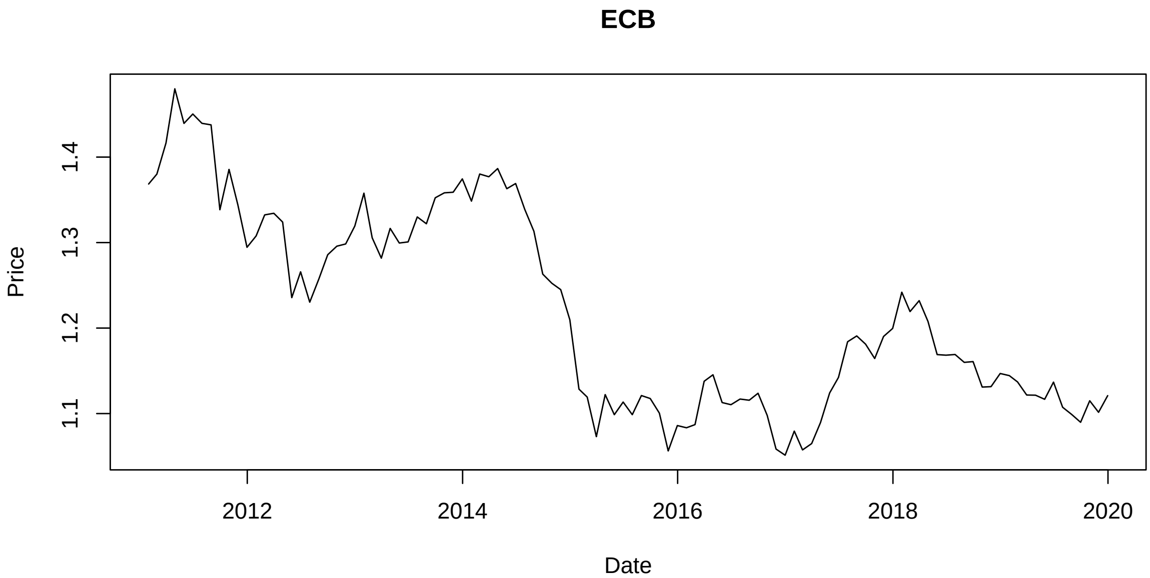

Figure 5.5: ECB price plot

5.6 CO2 Futures

The Carbon Emission futures price, or CO2 futures (MO1), is denoted in Euros per emission ton allowance. It is often referred to as European Union Allowances (EUA), as traded on the Intercontinental Exchange Group's (ICE) European platform. The EUA represents a form of climate credit, or carbon credit, utilized within the framework of the European Union (EU) Emissions Trading System (ETS). Traded on the ICE, EUA futures contracts obligate participating traders to either deliver or receive a total of 1,000 emission allowances. Each of these allowances permits the emission of one ton of carbon dioxide-equivalent gas.

In Hammoudeh et al. (2020), they identified a significant causal relationship, which fluctuated over time, emanating from the price of CO2 emission allowances and influencing green bonds. However, Hung (2021) find that green bonds have a unidirectional connection with the CO2 price, indicating that green bonds affect the price of CO2 but not vice versa. Furthermore, Kumar et al. (2012) did not find any significant evidence of Granger causality or impulse responses between carbon price and clean energy indexes. Given the varied and inconclusive findings in the existing literature, much of which is centered around the US stock market, we find it intriguing to incorporate this aspect into our analysis of the European market.

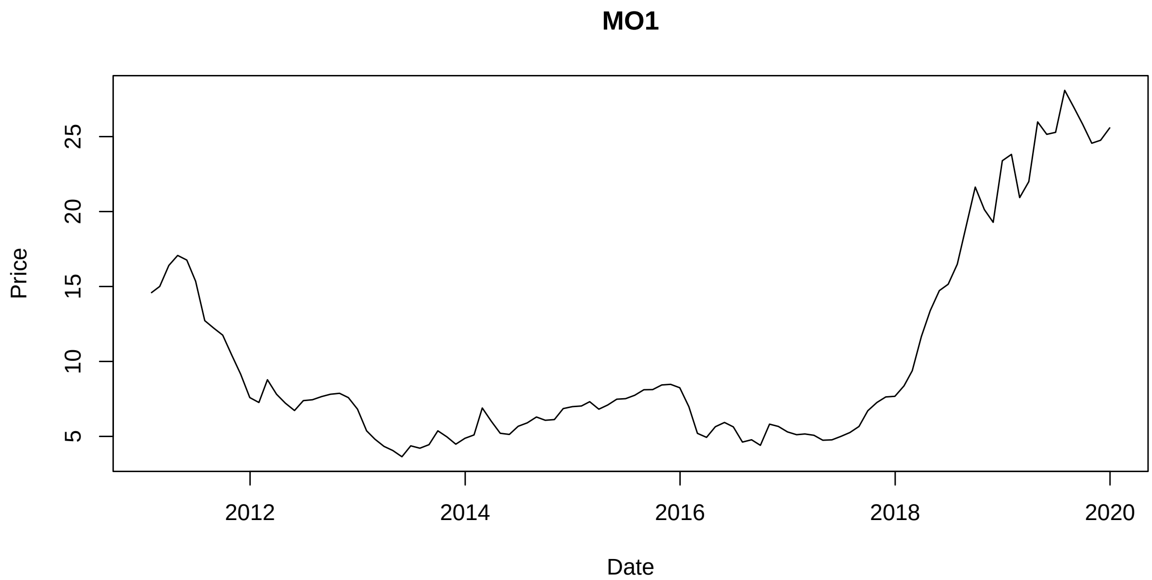

Figure 5.6: MO1 price plot

5.7 Stoxx Europe 600

The STOXX Europe 600, commonly known as STOXX 600 (STX), is a stock index created by STOXX Ltd. It comprises a fixed number of 600 components that represent companies of varying sectors and market capitalization from 17 European countries. This comprehensive index covers approximately 90% of the free-float market capitalization of the European stock market. The stock market serves as a broad indicator of overall market sentiment and economic conditions. By considering the market exposure, one can assess the impact of general market movements on the returns of individual stocks within the clean energy sector. This variable helps to capture the systematic risk associated with the broader market, which can influence investor behavior and the pricing of clean energy equities.

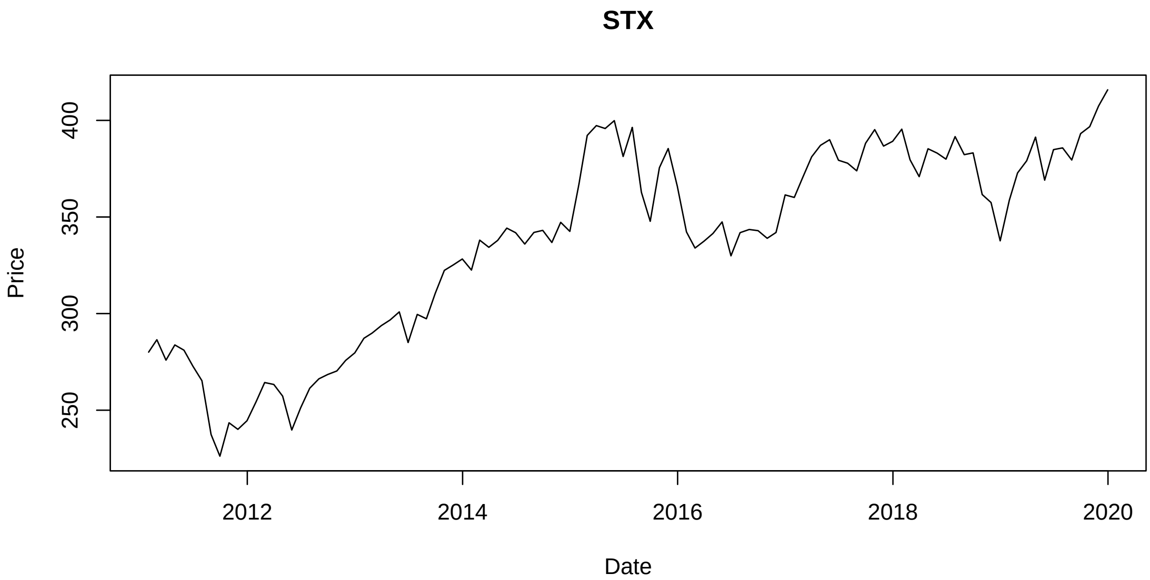

Figure 5.7: STX price plot

5.8 Descriptive Analysis

To facilitate better understanding and comparison of the variables, we provide summary statistics for the log returns of each variable. The descriptive statistics for the monthly log returns are presented in Table 5.2 for the period prior to the Paris Agreement (pre-PA) and Table 6.13 for the period after the Paris Agreement (post-PA).

Prior to the PA, GRNEUR had an average monthly return of 0.02% and a standard deviation of 6.33%. Compared to STX and GRW, which we see as the most similar assets, GRNEUR had a much lower average monthly return-to-standard deviation-ratio in the pre-PA period. CO1 has the largest (in absolute terms) monthly average return of -1.69% pre-PA, which comes as a result of the oil crisis in 2014, where the Brent Crude oil price plunged from a price of USD 110.80 at the beginning of 2014, to a price of USD 37.28 at the end of 2015. CO1 has the second highest standard deviation (after MO1) among the traded variables, which is in line with oil being, historically, a volatile commodity. At the same time as the oil price plunged, the European Central Bank ran an expansive monetary policy. As a result, the monthly average return for ECB was -0.39% in the pre-PA period. GRW and STX has stable positive average monthly returns and standard deviation in both the pre- and post-PA period. MO1 had a monthly average return of -0.97% and a standard deviation of 9.96% in the period before the Paris agreement. Common to a lot of financial data, most of our variables are negatively skewed, meaning they exhibit fat tails on on the left side of the distribution. The negative skewness observed in financial data implies that investors can anticipate relatively frequent occurrences of small gains, alongside few large losses. Kurtosis provides insights into the presence of outliers within the data distribution. Negative excess kurtosis indicates a lower likelihood of extreme outliers, suggesting that the data tends to have fewer observations that deviate significantly from the mean. Conversely, positive excess kurtosis suggests a higher probability of observing extreme outliers, indicating a distribution with a greater tendency to exhibit values that deviate significantly from the mean. Interestingly, GRW and STX has a leptokurtic distribution, while GRNEUR has a platykurtic distribution.

	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
GRNEUR	0.019	11.186	-17.600	6.334	-0.370	-0.043
CO1	-1.689	19.207	-20.208	8.191	-0.231	0.317
CPU	0.128	87.399	-89.411	41.467	-0.090	-0.636
GRW	0.664	8.109	-9.453	3.710	-0.443	0.345
STX	0.453	7.664	-11.080	3.824	-0.600	0.462
ECB	-0.392	4.483	-7.157	2.667	-0.552	-0.029
MO1	-0.967	30.195	-23.866	9.964	0.390	0.626

Table 5.2: Summary statistics for monthly log returns pre-PA

I the post-PA period, all variables have positive average monthly returns. The GRNEUR increases to a monthly average return of 1.04% and the standard deviation is reduced by 2.07 percentage points. This results in higher return-to-standard-deviation-ratio than STX and GRW in the post-PA period. After the oil crisis the European Central Bank ran a more restrictive monetary policy, with higher interest rates, resulting in a monthly average return of 0.04% for ECB. MO1's average monthly returns has increased significantly post-PA, yielding a monthly average of 2.23%. At the same time the standard deviation has increased by just under 100 basis-points (to 10.74%), meaning the return-to-standard-deviation-ratio has increased for MO1 even thought the standard deviation is still relatively high. In the post-PA period, the excess kurtosis of GRNEUR, GRW, and STX is notably more alike than it was before the Agreement.

	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
GRNEUR	1.042	8.872	-10.450	4.266	-0.470	-0.456
CO1	0.908	19.508	-25.113	8.046	-0.665	1.028
CPU	0.860	97.703	-62.091	33.580	0.277	-0.008
GRW	0.414	5.904	-6.678	2.906	-0.454	-0.426
STX	0.236	6.039	-6.651	3.043	-0.438	-0.403
ECB	0.043	4.558	-3.655	1.857	0.242	-0.387
MO1	2.229	27.836	-29.391	10.735	-0.241	0.549

Table 5.3: Summary statistics for monthly log returns post-PA

Due to CPU being a news article index, it will remain low in times when little is being written about climate policy and spike around major events, such as the Paris Agreement. As a result, it is difficult to interpret the monthly average return. The index is relatively volatile, but the standard deviation has decreased significantly in the period after the Paris Agreement, with a standard deviation of 41.47% pre-PA and 33.58% post-PA.

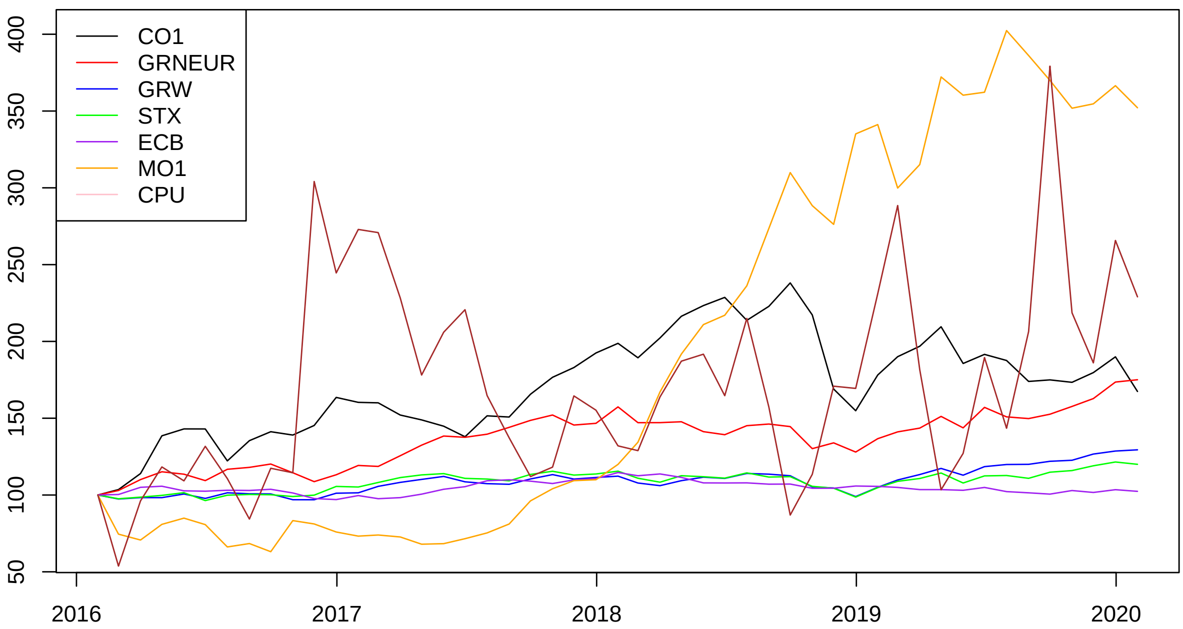

Figure 5.8: All variables indexed

We have constructed two correlation matrixes, Table 5.4 and 5.5 to reveiew the correlation between the variables in each period. During the pre-PA period, we have made several interesting findings. Firstly, we observe a negative correlation (-0.23) between GRNEUR and CO1. This finding is somewhat surprising, as we would typically expect an increase in oil prices to correspond with an increase in GRNEUR. However, the correlation indicate that this may not be the case, possibly due to the rapid decline in oil prices during this period.

Secondly, we find positive correlations between GRW and STX, with coefficients of 0.56 and 0.66, respectively. These findings align with our expectations, although they may fall slightly below what we anticipated. One particularly interesting finding is the very low correlation (coefficient of 0.05) between the ECB rate and GRNEUR. This suggests a weak relationship between the two variables, and is very surprising as this rate directly influences the cost of capital which again directly influences the value of the assets included in GRNEUR. This is in contrast to STX and GRW which have a correlation coefficient of -0.75 and -0.66 with the ECB. This relationship is as expected, STX and GRW are increasing when interest rates are decreasing. We see no obvious reason for the GRNEUR to have such a low correlation with ECB. A possible explanation could be that the stocks in the GRNEUR index is less sensitive to interest rate due to lower levels of leverage or because of cash flows that are resilient towards changes in the interest rate.

The MO1 has a correlation of 0.11 with the GRNEUR which indicates a weak relationship and that the two variables move independent of each other. Similar patterns are observed for the CPU and GRNEUR which has a correlation coefficient of -0.12.

	GRNEUR	CO1	CPU	GRW	STX	ECB	MO1
GRNEUR	1						
CO1	-0.23	1					
CPU	-0.12	0.03	1				
GRW	0.56	-0.82	-0.24	1			
STX	0.66	-0.76	-0.24	0.99	1		
ECB	0.05	0.90	0.08	-0.75	-0.66	1	
MO1	0.11	0.13	0.46	-0.34	-0.30	0.30	1

Table 5.4: Correlation matrix pre-PA

During the post-PA period, we observe notable changes in the correlations between the variables. The correlation coefficient between CO1 and GRNEUR is 0.66, which aligns with our expectation that higher oil prices would lead to an increase in GRNEUR. However, it is important to consider that CO1 started from very low levels at the beginning of the period due to the oil crisis, and GRNEUR performed well throughout the period. This could result in a significant positive correlation between the two variables, regardless of their underlying relationship.

The correlations between GRW, STX, and GRNEUR are even stronger in the post-PA period compared to the pre-PA period. This suggests that the movements in GRNEUR are largely influenced by the same factors that drive GRW and STX. Surprisingly, the correlation between GRNEUR and the ECB rate is positive at 0.44 during this period. This contradicts much of the financial theory and the concept of capital cost, but gives support to the notion that GRNEUR´s cash flow and performance is less interest rate sensitive and are resilient towards increases in interest rates.

In the post-PA period, we observe a more significant relationship between MO1 and GRNEUR, with a correlation coefficient of 0.65. This may indicate that the higher carbon price has increased the attractiveness of the GRNEUR index, highlighting the growing importance of the EU ETS in this market. Both the carbon price and GRNEUR have experienced significant increases over the period. However, the correlation between CPU and GRNEUR remains relatively low at 0.26.

	GRNEUR	CO1	CPU	GRW	STX	ECB	MO1
GRNEUR	1						
CO1	0.66	1					
CPU	0.26	0.16	1				
GRW	0.91	0.53	0.34	1			
STX	0.91	0.61	0.35	0.91	1		
ECB	0.44	0.47	-0.31	0.10	0.28	1	
MO1	0.65	0.58	0.26	0.70	0.46	-0.01	1

Table 5.5: Correlation matrix post-PA

6 Result & Analysis

To investigate the relationship in our analysis we employ a multifactor lag-augmented vector autoregressive model, as well as a simple VAR model with first difference data. We examine the Granger causality, impulse response function and variance decomposition. For the majority of our analysis the dependent variable is set to the NASDAQ OMX Clean Energy Focused Europe Index (GRNEUR).

6.1 The models

We split our sample period into two distinct sub-samples, before (pre-PA) and after (post-PA) the Paris Agreement (PA). The pre-PA period spans from January 31st, 2011, to December 31st, 2015, while the post-PA period spans from January 31st, 2016, to January 31st, 2020.

In our analysis, we have established three primary models. The first model encompasses all variables considered, the second model focuses on stock market-related variables, and the third model concentrates on climate and energy-related variables. With three primary models and two time periods we end up with six models in total. Considering the two distinct time periods and the diversity of models, each model encompasses varying lag lengths for each respective period. To provide clarity, we have opted to present our models using a lag length of 2, which is the most frequently employed lag length across our analyses. Furthermore, we have specified the specific lag lengths utilized in each segment of our analysis.

Model	Period	Dependent Variable	Independent Variables
(1)	Pre-PA	GRNEUR	GRW, STX, ECB, CO1, MO1, CPU
(2)	Pre-PA	GRNEUR	GRW, STX, ECB
(3)	Pre-PA	GRNEUR	CO1, MO1, CPU
(4)	Post-PA	GRNEUR	GRW, STX, ECB, CO1, MO1, CPU
(5)	Post-PA	GRNEUR	GRW, STX, ECB
(6)	Post-PA	GRNEUR	CO1, MO1, CPU

Table 6.1: Description of our six models

Below is the general formula for the Lag-Augmented VAR model containing all variables with 2 lags.

$$\begin{aligned}GRNEUR_t = {} & \beta_{1,1}GRNEUR_{t-1} + \beta_{2,1}GRW_{t-1} + \beta_{3,1}STX_{t-1} + \beta_{4,1}ECB_{t-1} + \beta_{5,1}CO1_{t-1} \\ & \beta_{6,1}MO1_{t-1} + \beta_{7,1}CPU_{t-1} + \beta_{1,2}GRNEUR_{t-2} + \beta_{2,2}GRW_{t-2} + \beta_{3,2}STX_{t-2} \\ & \beta_{4,2}ECB_{t-2} + \beta_{5,2}CO1_{t-2} + \beta_{6,2}MO1_{t-2} + \beta_{7,2}CPU_{t-2}\end{aligned}$$

Below is the general formula for the Lag-Augmented VAR model defined as the market model with 2 lags.

$$\begin{aligned}GRNEUR_t = {} & \beta_{1,1}GRNEUR_{t-1} + \beta_{2,1}GRW_{t-1} + \beta_{3,1}STX_{t-1} + \beta_{4,1}ECB_{t-1} \\ & \beta_{1,2}GRNEUR_{t-2} + \beta_{2,2}GRW_{t-2} + \beta_{3,2}STX_{t-2} + \beta_{4,2}ECB_{t-2}\end{aligned}$$

Below is the general formula for the Lag-Augmented VAR model defined as the climate model with 2 lags.

$$\begin{aligned}GRNEUR_t = {} & \beta_{1,1}GRNEUR_{t-1} + \beta_{2,1}CO1_{t-1} + \beta_{3,1}MO1_{t-1} + \beta_{4,1}CPU_{t-1} \\ & \beta_{1,2}GRNEUR_{t-2} + \beta_{2,2}CO1_{t-2} + \beta_{3,2}MO1_{t-2} + \beta_{4,2}CPU_{t-2}\end{aligned}$$

6.2 Pre-PA analysis

6.2.1 Stationarity and integration

We examine the stationarity and integration of the data with the help of various testing methods, such as the Augmented Dickey-Fuller (ADF) test, Phillips and Perron (PP) test, and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test (Toda and Yamamoto, 1995). P-values from the unit root tests from the pre-PA period are reported in Table 6.2. For CPU we reach inconclusive results on levels data, due to rejecting the null hypothesis for ADF, PP, and KPSS. For first difference data we achieve conclusive results, which holds for all variables. With respect to each variable, the highest observed order of integration is one (I (1)).

	Levels			First differences		
	ADF	PP	KPSS	ADF	PP	KPSS
GRNEUR	0.736	0.756	0.086	0.01***	0.01***	0.06
CO1	0.677	0.660	0.1	0.01***	0.01***	0.10
CPU	0.01***	0.01***	0.04**	0.01***	0.01***	0.10
GRW	0.138	0.242	0.1	0.01***	0.01***	0.10
ECB	0.655	0.668	0.07	0.01***	0.01***	0.10
MO1	0.738	0.910	0.1	0.01***	0.01***	0.10
STX	0.219	0.330	0.1	0.01***	0.01***	0.10

Table 6.2: Integration (unit root) of each variable: Pre-PA. (P-values).

6.2.2 Lag length

The selection of the ideal lag length is crucial for accurately defining the model. To achieve this, we have utilized the Akaike Information Criteria (AIC), choosing the lag length that results in the lowest AIC. In the LA-VAR model we're using the AIC optimal lag length k, plus d_{MAX}, which represents the maximum level of integration in our data (Toda and Yamamoto, 1995). In Table 6.3 we have reported adjusted R-squared, p-values, f-statistics and lag length for each model.

	Model (1)	Model (2)	Model (3)
Adj. Rsquared	0.8984	0.9028	0.8876
P-value	0.0000	0.0000	0.0000
F-stat	37.38	67.17	51.03
Lags	2	2	2

Table 6.3: Fit and significance of pre-PA models

	Model (1)	Model (2)	Model (3)
GRNEURt-1	1.093*	1.224*	0.910*
GRWt-1	-33.400*	-29.204*	-
STXt-1	10.111*	8.768*	-
ECBt-1	-817.663	-855.969*	-
CO1t-1	1.550	-	0.172
MO1t-1	-0.489	-	-7.831
CPUt-1	0.162	-	0.528
GRNEURt-2	-0.416	-0.476*	0.151
GRWt-2	20.136	17.363	-
STXt-2	-4.924	-4.116	-
ECBt-2	1080.041*	794.920*	-
CO1t-2	-3.152*	-	-1.778
MO1t-2	-1.242	-	-6.865
CPUt-2	-0.235	-	0.227

Table 6.4: Coefficient estimates of pre-PA models

**Significant at 5% level*

As seen in table 6.3 all the models demonstrate excellent fit, as evidenced by their adjusted R-squared values of approximately 0.90 or higher. This indicates that the selected variables are highly relevant, and their lagged values contribute significantly to explaining the fluctuations in GRNEUR. Furthermore, the variables collectively exhibit high levels of significance, as indicated by p-values approaching zero. It is worth noting that in the pre-PA period, all models consistently exhibit an optimal lag length of two.

The residuals exhibit normal distribution and we found no evidence of serial correlation or heteroskedasticity in either of the models.

6.2.3 Granger causality

Despite having a good fit with high adjusted r-squared and very low p-value, the variables in model 1 do not Granger-cause GRNEUR. We find it surprising that there is no joint causal relationship between the variables, considering the findings from similar studies done. However, we will continue examining the causal relationship further through this chapter both individually and jointly.

Model (1)	Model (2)	Model (3)
Do not GC GRNEUR	GC GRNEUR	Do not GC GRNEUR

Table 6.5: Joint Granger causality pre-PA

In model 2, containing all market variables, we find that the stock market factors (GRW, STX, ECB) jointly Granger-causes GRNEUR. This is similar to the findings of Henriques and Sadorsky (2008). Although Henriques and Sadorsky (2008) include a technology variable, in contrast to our growth variable (GRW), we believe that our findings indicate a similar relationship. Both these studies have focused on the equity markets of the United States during a period when clean energy companies possessed a comparatively lower market capitalization. We believe that with the development of the clean energy market, the firms within this sector have less in common with technology firms, and more in common with general growth factors. Kumar et al. (2012) and Henriques and Sadorsky (2008) find individual Granger causality from technology to clean energy firms. Employing similar testing for GRW show no individual Granger causality. Nor do we find any individual Granger causality from STX or ECB.

Our decision to include a growth variable instead of a technology variable was done under the assumption that the GRNEUR had more in common with growth stocks compared to technology stocks. However, our findings in the pre-PA period indicated that this is not the case. Fahmy (2022) present similar findings in their article, where they find that technology stocks is not the best regime driver in the pre-PA period, but in the post-PA period.

GRW	STX	ECB
Do not GC GRNEUR	Do not GC GRNEUR	Do not GC GRNEUR
CO1	**MO1**	**CPU**
Do not GC GRNEUR	Do not GC GRNEUR	GRNEUR GC CPU

Table 6.6: Individual Granger causality pre-PA

It is unexpected that both the ECB and STX do not individually Granger cause GRNEUR. We consider these two variables as crucial drivers of clean energy stock movements. We cannot identify a clear reason behind this counter-intuitive finding. One possible explanation could be that the movements in GRNEUR are influenced by numerous small contributions from various factors. Individually, each factor may not have a significant impact, but when combined, they collectively exert a strong influence on GRNEUR.

Continuing our analysis with the energy and climate factors (model 3) we find that they jointly do not Granger-cause GRNEUR. CO1, MO1 and CPU does not individually Granger-cause GRNEUR either. The lack of significance between CO1 and GRNEUR is unexpected, and in contradiction with what Henriques and Sadorsky (2008) find. However, our study is done at a later time-period where the dynamics may have changed and the movements in GRNEUR may be more related to the price of other energy sources such as electricity. Our finding of no causal relationship between MO1 and GRNEUR is in line with the findings of Kumar et al. (2012) that find no link between the price of carbon and the performance of renewable energy firms. Kumar et al. (2012) state that this may be due to the low price of carbon. We believe that our findings is supported by this argument, considering the low price level of MO1 during the pre-PA period.

We find that GRNEUR Granger-causes the CPU. Considering that the CPU index is an American Index this could indicate a random occurring relationship between the two variables, as they operate on different continents. It could also be the case that journalist are observing movements in green assets such as the GRNEUR, which again results in an increased focus on climate uncertainty related topics which again results in more articles being written about the topic. Considering that CPU Granger-causes GRN, and not the other way around, provides evidence supporting the notion that news articles regarding climate uncertainty-related topics in the United States is of limited importance for European investors. A reason behind this may be that Europe, historically, has implemented more stringent climate policies compared to the United States, which could potentially mean that European investors display reduced concern towards news concerning US climate policy uncertainty.

6.2.4 Impulse responses

In this part of our analysis, we move from the LA-VAR methodology, and utilize a standard VAR approach with first differences. This is because the use of impulse response function requires the use of stationary data, since the system needs to be stable for the shock to die out (Brooks, 2019). Ordering of the variables is an important factor in the impulse response analysis, and we have made our ordering based on the decreasing order of exogeneity of our variables. As seen in the plot, we can visually inspect both the direction and size of the movements in the variables (Brooks, 2019).

According to Runkle (1987), the accurate interpretation of both impulse responses and variance decompositions poses a notable challenge. Runkle (1987) suggests that it is essential to construct confidence bands around these responses and decomposition's. However, even with the inclusion of confidence intervals, they tend to be so wide that making precise conclusions remains challenging.

In all the impulse response plots the confidence bands are wide, indicating a degree of uncertainty in the estimation of the plots. The GRNEUR index has an immediate positive effect to a shock to itself, but it is not significant. The shock dies out after the second month. A shock from GRW to GRNEUR is slightly negative, but not significant. Our initial thought was that GRNEUR would exhibit stronger similarities with a growth index (GRW) rather than technology indexes. Interestingly, GRW is the only variable that does not demonstrate a significant individual impact on GRNEUR. This finding suggests that investors may perceive clean energy stocks as being more closely aligned with technology stocks, which is in line with existing literature (Henriques and Sadorsky, 2008; Kumar et al., 2012).

STX and ECB have a significant effect up until the second month which is positive and negative, respectively. This in line with the basic understanding of the CAPM model, beta, and how the cost of capital (interest rates) affect stock performance. This suggests that GRNEUR and other green assets tend to perform well when interest rates are falling and the overall market is experiencing positive growth. Considering the current market conditions characterized by high inflation, rising interest rates, and increased market volatility, this could potentially slow down the pace of the transition towards more clean energy. This is consistent with the findings of Henriques and Sadorsky (2008), which find that a positive shock to the interest rate has a negative effect on the alternative energy index after ten weeks. We can compare these results to our findings in the Granger-causality test, where we find no significance on the mentioned variables individually, but find that they jointly Granger-cause GRNEUR.

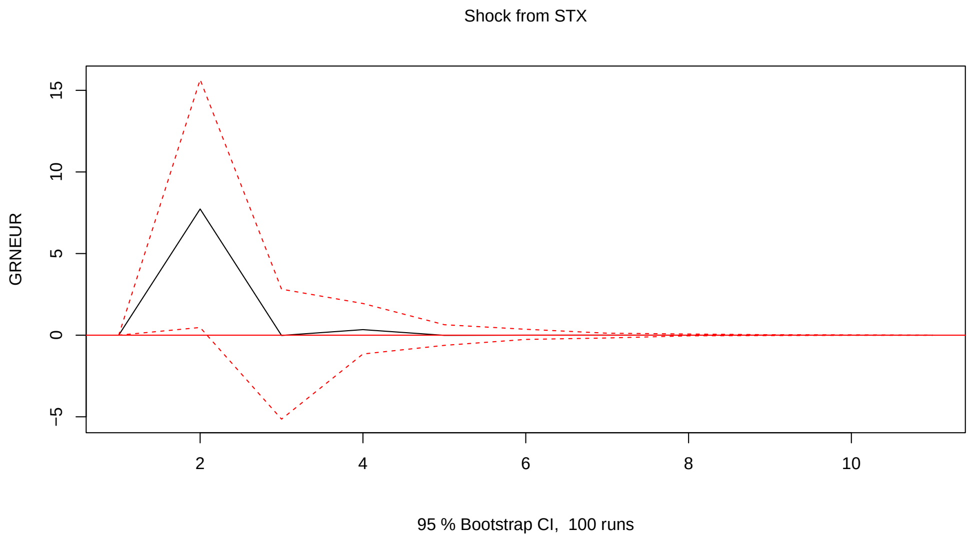

Figure 6.1: Pre-PA: Impulse response function: Shock from STX to GRNEUR

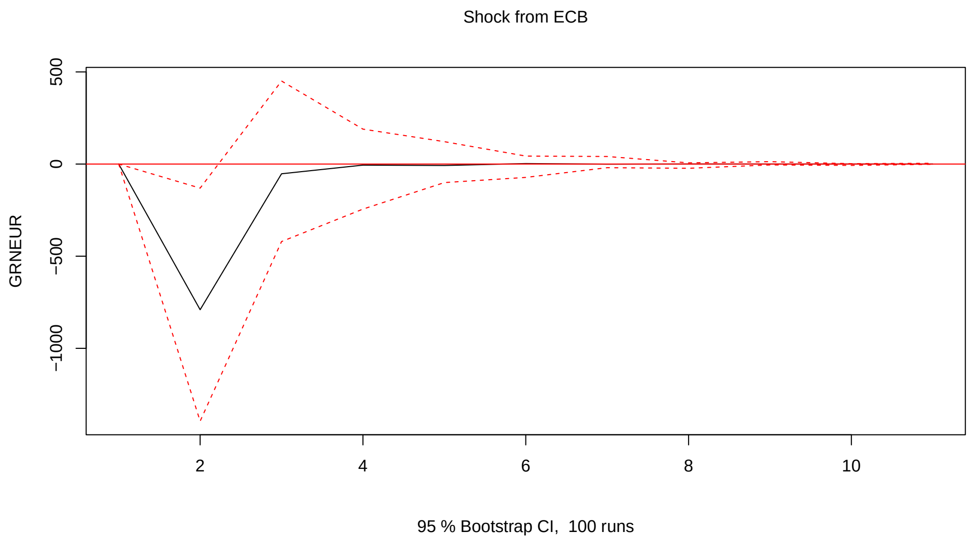

Figure 6.2: Pre-PA: Impulse response function: Shock from ECB to GRNEUR

In the pre-PA period, we observe no significance in any of the impulse response plots for any of the climate and energy factors (CO1, CPU, MO1). Similar to what we found in the test for Granger causality. We have explained our reasoning behind this in the Granger causality section.

6.2.5 Variance decomposition

We have made our variable selection based on our analysis of the GRNEUR index. Therefore, the interpretation of the variance decomposition for the other variables in our analysis is of limited importance. All figures with all variables are included in the Appendix.

As seen in figure 6.3, the contribution of variance from the different variables stays relatively constant over time. There is a minor change to the CPU where the contribution is slightly increasing from period 1 to period 2. As expected, we observe that the stock markets based factors, including GRNEUR are major contributors of the variance in GRNEUR. Further we will examine the variance decomposition of our two other models.

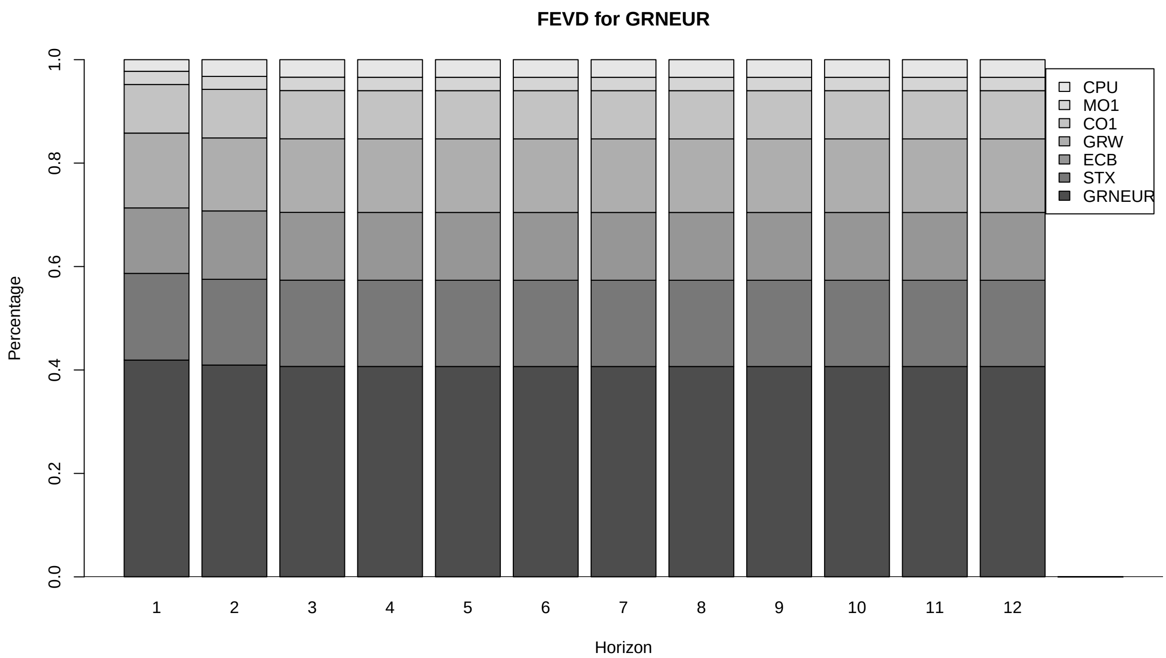

Figure 6.3: Pre-PA variance decomposition of all factors

As mentioned in the previous paragraph, the stock market based factors are the main sources in explaining the variance in GRNEUR. As seen in figure 6.4, GRW, ECB, and STX each account for about similar amounts of variation to GRNEUR. ECB explains less than STX and GRW, which are almost equal in magnitude in the pre-PA period.

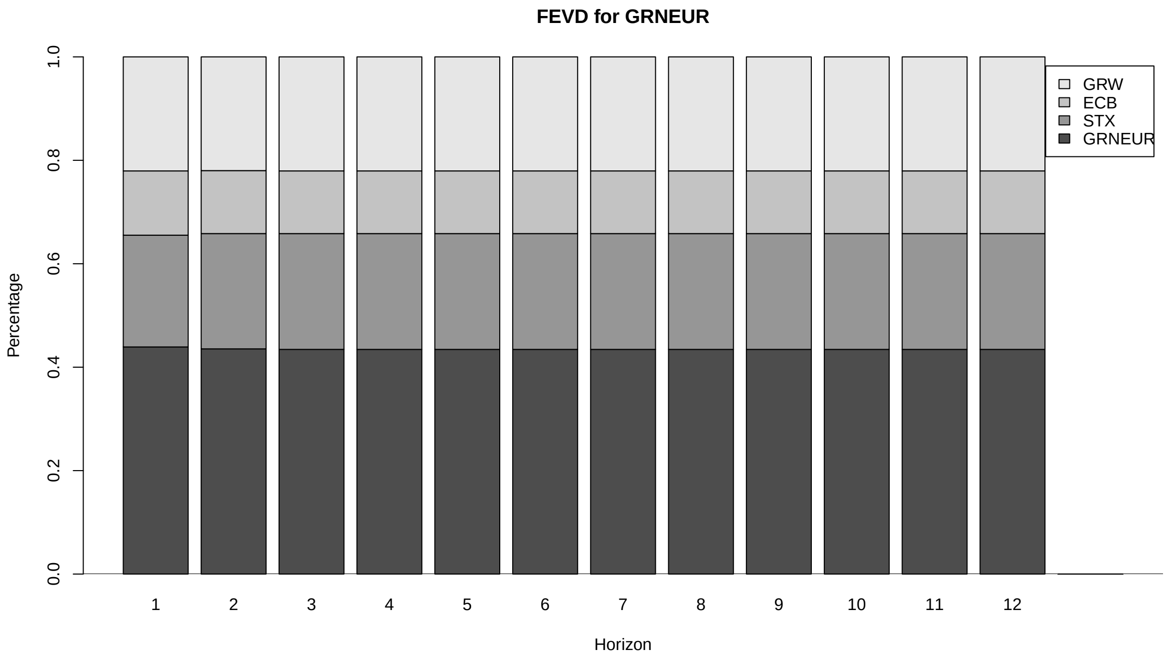

Figure 6.4: Pre-PA variance decomposition of market factors

Figure 6.5 shows that GRNEUR is the majority contributor of variance for GRNEUR in model 3. CO1 is the second largest, and MO1 and CPU has less of an impact. Comparing this to the results from the Granger causality test and figure 6.4 we conclude that during the pre-PA period, the climate- and energy factors explains less of the variation than compared to our other models, and that the relationship between the variables may not be of large significance.

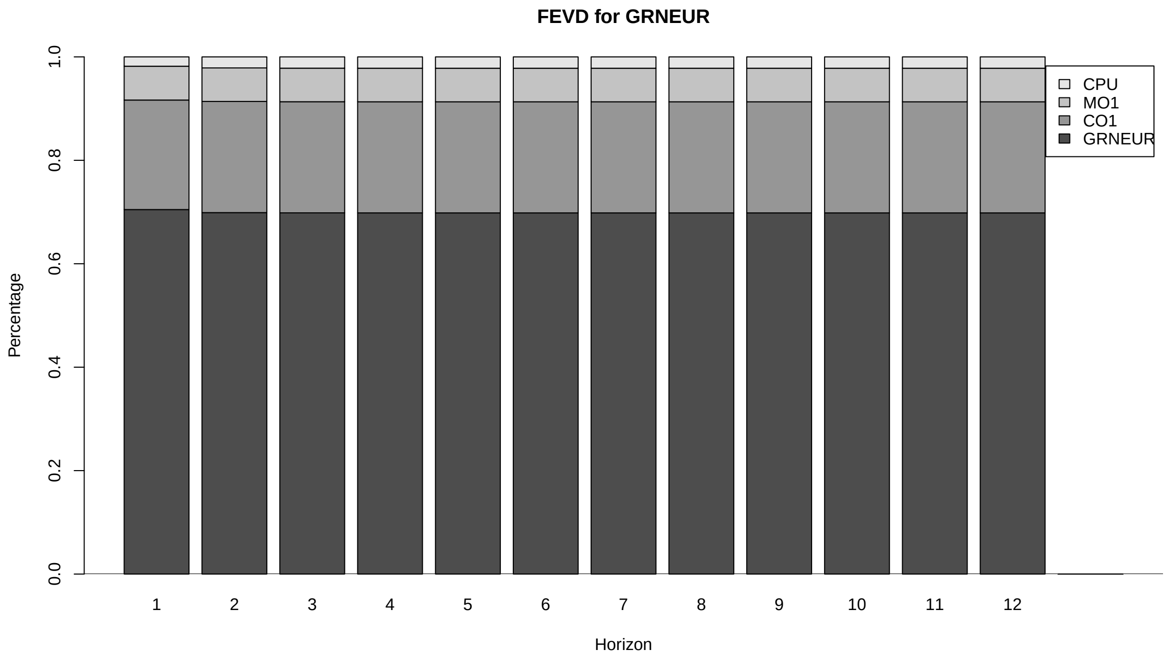

Figure 6.5: Pre-PA variance decomposition of energy- and climate Factors

6.3 Post-PA analysis

6.3.1 Stationarity and integration

We will present this section in the same structure as in the pre-PA section. Table 6.7 reports p-values from the unit root tests for the post-PA period. As we achieve stationarity on first differences for all variables, we can conclude that the highest order of integration is one (I(1)).

	Levels			First differences		
	ADF	PP	KPSS	ADF	PP	KPSS
GRNEUR	0.528	0.491	0.1	0.01***	0.01***	0.10
CO1	0.628	0.614	0.1	0.01***	0.01***	0.10
CPU	0.117	0.083	0.1	0.01***	0.01***	0.10
GRW	0.590	0.409	0.1	0.01***	0.01***	0.10
ECB	0.705	0.687	0.1	0.01***	0.01***	0.10
MO1	0.413	0.637	0.1	0.01***	0.01***	0.07
STX	0.433	0.405	0.1	0.01***	0.01***	0.10

Table 6.7: Integration (unit root) of each variable: Post-PA. (P-values).

Table 6.8 demonstrates that, similar to the pre-PA period, the three post-PA models exhibit good fit, with adjusted R-squared values slightly below or above 0.90. The p-values indicate strong joint significance among the variables.

	Model (4)	Model (5)	Model (6)
Adj. Rsquared	0.9359	0.8864	0.9208
P-value	0.0000	0.0000	0.0000
F-stat	45.8	45.87	31.08
Lags	2	2	4

Table 6.8: Fit and significance of post-PA models

	Model (4)	Model (5)	Model (6)
GRNEURt-1	-0.184	0.513	0.550 *
GRWt-1	18.079 *	10.111	-
STXt-1	-3.997 *	-2.620	-
ECBt-1	750.327	574.820	-
CO1t-1	0.986	-	-0.001
MO1t-1	-15.729 *	-	-14.780 *
CPUt-1	-0.067	-	-0.108
GRNEURt-2	-0.359	0.469	0.072
GRWt-2	-7.112	-9.716	-
STXt-2	4.949 *	2.686	-
ECBt-2	559.118	-1083.888	-
CO1t-2	-5.826 *	-	-4.597
MO1t-2	-3.147	-	16.787 *
CPUt-2	0.038	-	0.357
GRNEURt-3	-	-	0.082
CO1t-3	-	-	5.105
MO1t-3	-	-	-14.301
CPUt-3	-	-	-0.088
GRNEURt-4	-	-	0.205
CO1t-4	-	-	-4.522 *
MO1t-4	-	-	5.379
CPUt-4	-	-	0.312

Table 6.9: Coefficient estimates of post-PA models
**Significant at 5% level*

6.3.2 Lag length

The lag length for most models is two, except for model (6), which has a lag length of four. Overall, the summary of the fit and significance provides compelling evidence of a well-fitting model that proves valuable for further analysis.

We analyzed the residuals of all models and found them to be normally distributed. We also found no evidence of serial correlation or heteroskedasticity in any of the models.

6.3.3 Granger causality

During the post-PA period, we observe a significant joint causal relationship between GRNEUR and all the variables included in the analysis. The stock market- and the climate- and energy factors (Model 4) collectively contribute to Granger-causing GRNEUR. This finding offers valuable insights into factors that influence movements in clean energy assets, and particularly GRNEUR.

Model (3)	**Model (4)**	**Model (6)**
GC GRNEUR	Do not GC GRNEUR	GC GRNEUR

Table 6.10: Joint Granger causality post-PA

Expanding on the findings in Model (4), we find different results in the post-PA period compared to the pre-PA period. What we find particularly interesting is that the Paris Agreement seem to have impacted investors, policy makers and the market. In this period, we find that the stock market factors (Model 5) do not Granger-cause GRNEUR, individually or jointly. This is contrary to our initial belief that the movements in the price of GRNEUR was mainly dictated by movements in the overall stock market, growth, and interest rate. The importance of the interest rate level and expansionary monetary policy became very evident during the Covid-19 pandemic. Zero interest rate and quantitative easing contributed to rapidly increasing asset valuation. However, in our selected time period the interest rate were stable and slightly increasing, which may be a cause to why ECB does not Granger-cause GRNEUR as the interest rate in this period was simply not a deciding factor of movement in GRNEUR.

GRW	**STX**	**ECB**
Do not GC GRNEUR	Do not GC GRNEUR	Do not GC GRNEUR
CO1	**MO1**	**CPU**
Do not GC GRNEUR	MO1 GC GRNEUR	GRNEUR GC CPU

Table 6.11: Individual Granger causality post-PA

As mentioned, contrary to Henriques and Sadorsky (2008) we use a growth index (GRW) instead of a technology index. This choice was based on our hypothesis that the GRNEUR is more closely related to growth stocks than technology stocks. The fact that GRW does not Granger-cause GRNEUR in either of the pre- or post-PA periods indicate that this is not the case. Finding a reasonable explanation for why STX does not individually Granger-cause GRNEUR is challenging considering the correlation of the two assets during the period. We believe that this finding could suggest that the assets included in GRNEUR is viewed differently from the assets included in STX, and that the signing of the Paris Agreement may have contributed to decoupling these assets from the overall market movements.

In the post-PA period, the climate- and energy factors (Model 6) seem to play a more significant role. We find that CO1, MO1 and CPU jointly Granger-cause GRNEUR. Contrary to Kumar et al. (2012) and Henriques and Sadorsky (2008), CO1 does not exhibit individual Granger causality with respect to GRNEUR. Even though oil price is directly linked to energy prices, this might not be a significant determining factor of GRNEUR. One plausible explanation for this is the linkage of clean energy production to long-term Power Purchase Agreements (PPA's typically spanning 15-30 years), which effectively insulates it from the immediate impact of spot oil prices. It is worth mentioning that the prior studies mentioned above were conducted on weekly data in the United States in another time period.

Another interesting finding is the relationship between GRNEUR and MO1. Here we find a univariate relationship, with MO1 Granger-causing GRNEUR. During the post-PA period MO1 has experienced a sharp increase in price. This increase in price is likely due to political pressure, ESG speculation, reduction of allowances and increased focus on carbon risk, which is likely to have increased the visibility of carbon risk to investors (Böhm, 2022). This is consistent with the findings of Bolton and Kacperczyk (2021) and the COP 21 event-study done by Monasterolo and de Angelis (2020). The univariate Granger causality suggests that there is a directional relationship between the price of carbon and the price of clean energy assets. As the price of carbon rises, it is anticipated that the adoption and utilization of clean energy assets will increase.

As in the pre-PA period, we find that GRNEUR Granger-causes the CPU. We believe that the reasoning behind this finding is similar to what we found in the pre-PA period and that the relationship has persisted through both time periods.

6.3.4 Impulse responses

In the post-PA period we find no significant impulse responses from the stock market factors (STX, GRW, ECB) to GRNEUR. This is consistent with the findings of the Granger causality tests, where we find no individual or joint effect to GRNEUR.

As presented in Figure 6.6 we find that a positive shock in MO1 to GRNEUR has a significant negative effect until the second month. This is in contrast to Kumar et al. (2012), which do not find a significant impulse response from carbon price to renewable energy stocks. We find this somewhat surprising, as one would expect clean energy stocks to perform well when the price of carbon increases. A possible explanation for this could be that the EU ETS is politically regulated, whereas the GRNEUR is market regulated. In 2018 the EUA (MO1) prices rose beyond double digit levels and more than trebled since the beginning of the year. The rise was mainly due to the EU ETS Directive published in April 2018 (Roig-Ramos, 2018). The directive of 2018 set new rules for Phase 4 (2021-2030), where they agreed to reduce the current surplus of emission quotas from the market, by 1) introducing a stronger decline in the annual emission cap, and 2) reinforcing the market stability reserve. At the same time the stock market experienced a period of higher risk and lower return, with leading stock indexes ending 2018 with negative returns. We believe that these two simultaneous events may help to explain the somewhat counter intuitive findings in the impulse response plot seen in figure 6.6. In addition in the period before the rapid growth of MO1, MO1 was flat without major variation in price, in the same period GRNEUR experienced significant growth.

It is also important to note, that this model only captures the short-term relationship, and we would expect the long-term effects to be positive. A shock to CO1 and CPU has no significant effect on GRNEUR.

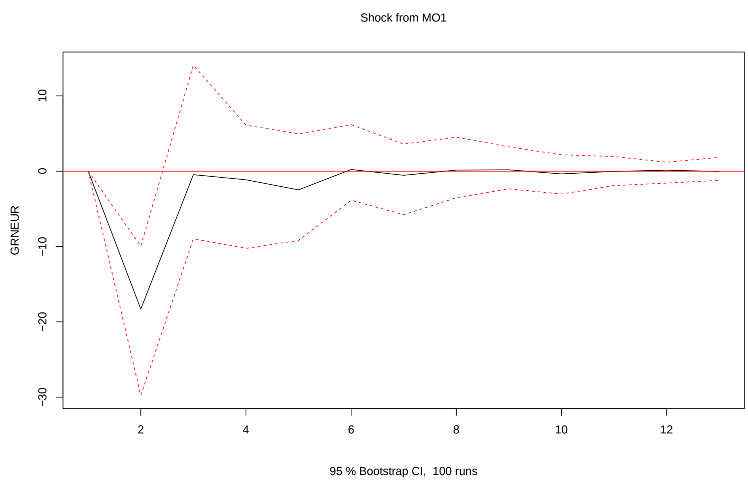

Figure 6.6: Post-PA: Impulse response function: Shock from MO1 to GRNEUR

6.3.5 Variance decomposition

In figure 6.7 we observe an even larger change over time in the variance decomposition plot. In the post-PA period the variables explain more of the variance than in the pre-PA period. CPU has an increasing trend with increasing contribution to GRNEUR´s variance. The same is the case for MO1. CO1 is close to zero in period 1 but increase significantly in period 2. Further analysis of the dynamics will be done in the coming paragraphs.

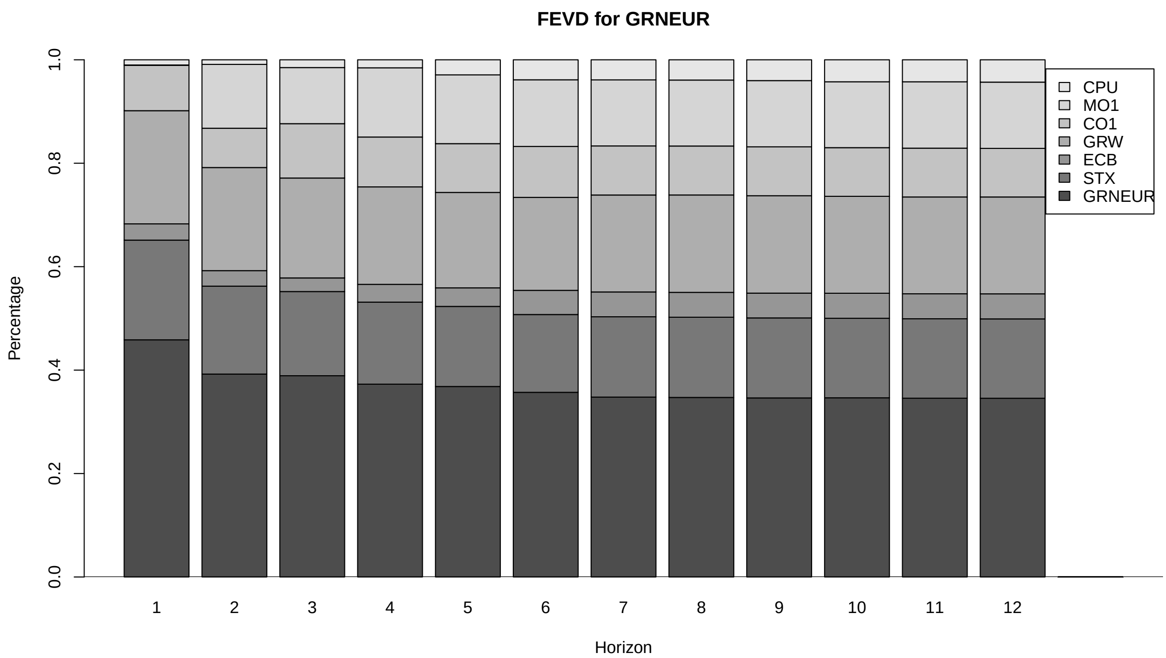

Figure 6.7: Post-PA variance decomposition of all factors

Figure 6.8 reveals that both STX and GRW contribute almost equally to the overall variation, while ECB has the least significant impact. The relationship between the variables does not change over time which is somewhat surprising. It is important to note that the three relevant variables do not jointly Granger cause GRNEUR during this period.

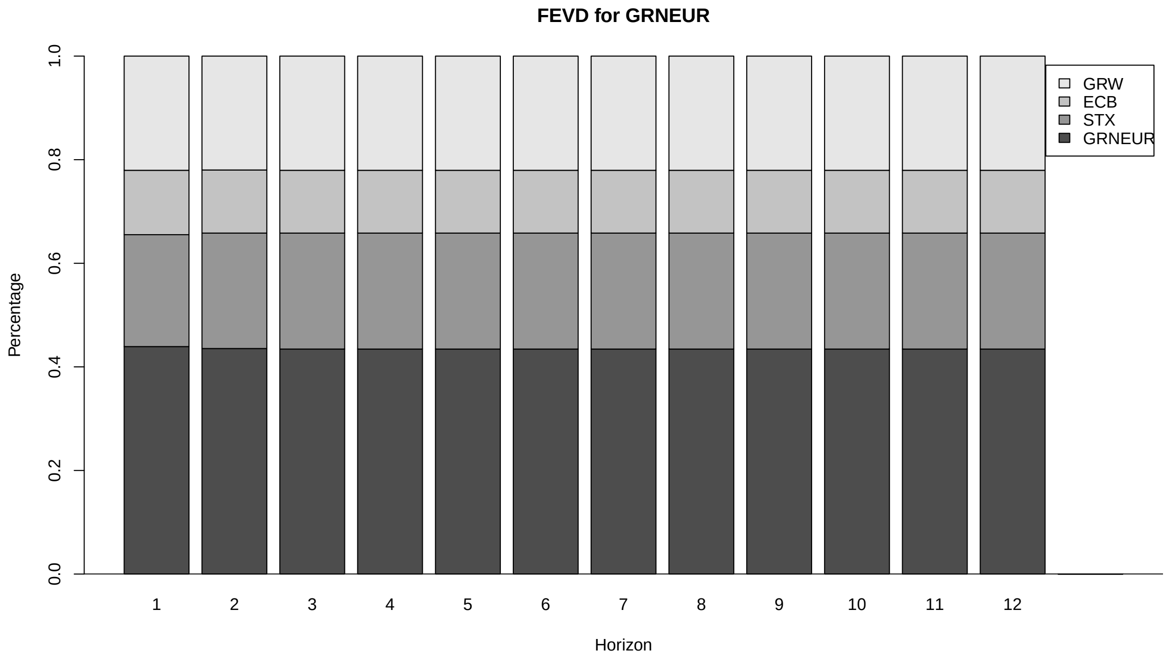

Figure 6.8: Post-PA variance decomposition of market factors

Figure 6.9 for the post-PA period indicates that GRNEUR accounts for over 80% of the variance to itself in period 1, then there is a gradual decline, and the variance becomes increasingly attributable to the other variables. We observe that the MO1 has an increasing explanatory factor from period 1 to period 2 and that the other variables seem to stay constant over the whole period. This may suggest that in the short-term, the effect of MO1 in explaining variation may not be very significant, but in the medium- to long-term the effect is more significant.

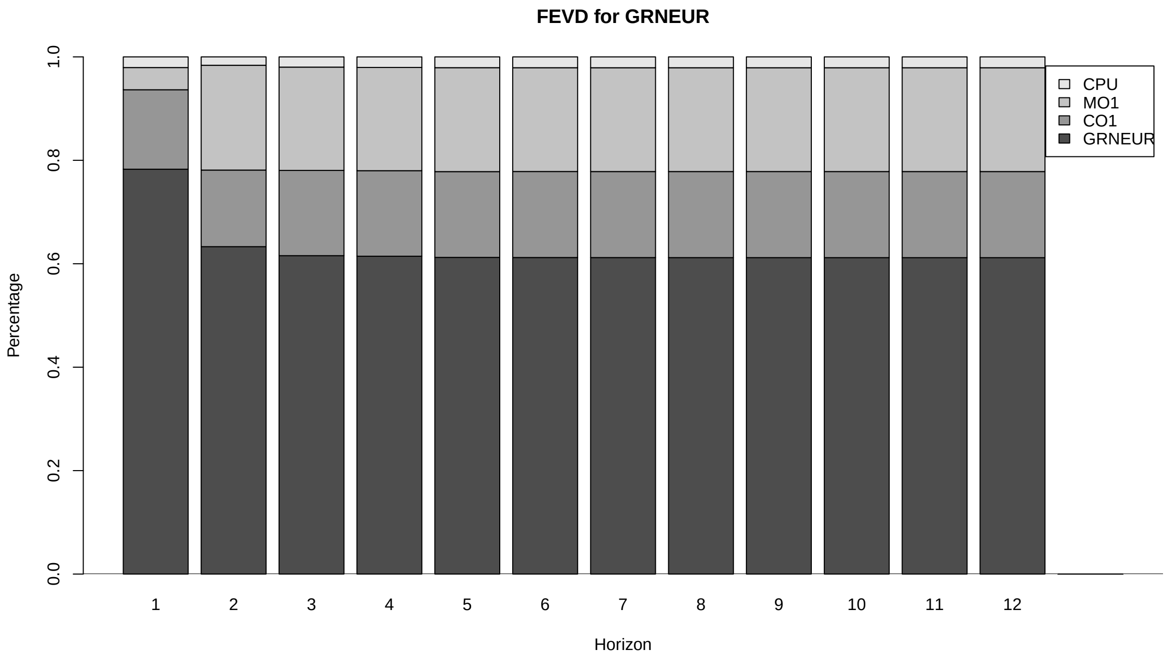

Figure 6.9: Post-PA variance decomposition of energy- and climate factors

6.4 Returns before and after the Paris agreement

Name	Mean	Max	Min	Std	Skewness	Kurtosis	AR*
GRNEUR Pre-PA	0.019	11.186	-17.600	6.334	-0.369	-0.0430	-2.737
GRNEUR Post-PA	1.0423	8.872	-10.450	4.265	-0.470	-0.456	12.890

Table 6.12: Descriptive statistics for monthly log returns pre- and post-PA
**Annualized Return*

To further examine the impact of the Paris Agreement on GRNEUR, we conducted an analysis of the index returns. To account for the difference in the number of months between the two periods, we calculated the annualized return. The annualized return for the pre-PA period was -2.74%, whereas for the post-PA period, it was 11.51%. While multiple factors may have influenced this performance disparity, it is highly likely that the increased focus on climate, energy transition, and the implementation of the Paris Agreement played a significant role. Furthermore, despite the higher annualized return in the post-PA period, we observed a notable improvement in risk-return metrics. The standard deviation of returns was 2.1% lower, and both the minimum and maximum values were lower as well. These findings suggest that the asset's risk-return profile experienced a significant enhancement following the signing of the Paris Agreement.

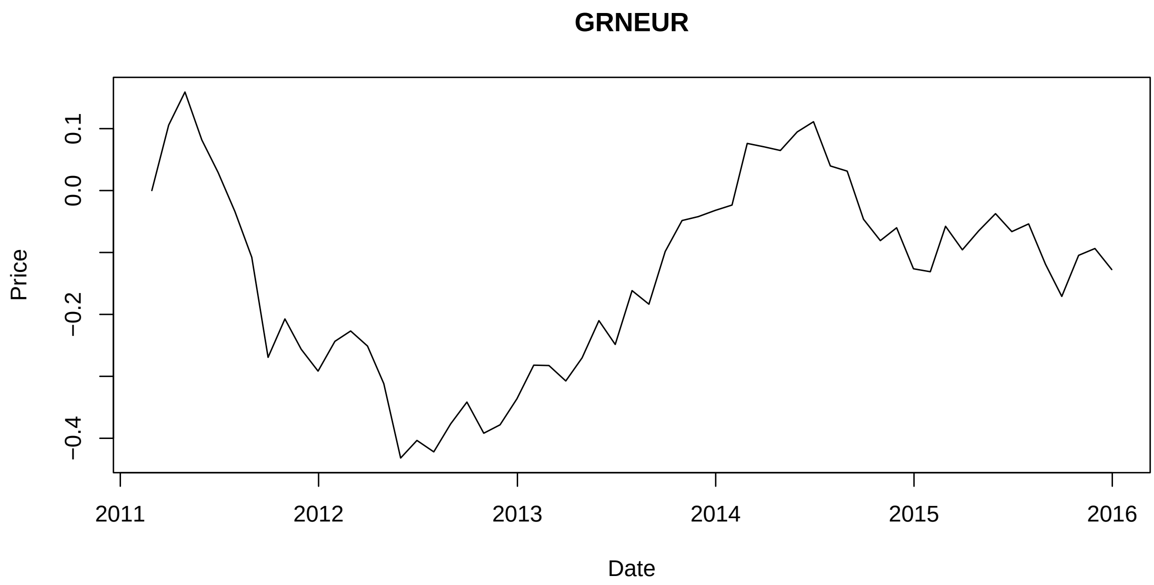

Figure 6.10: GRNEUR accumulated return pre-PA

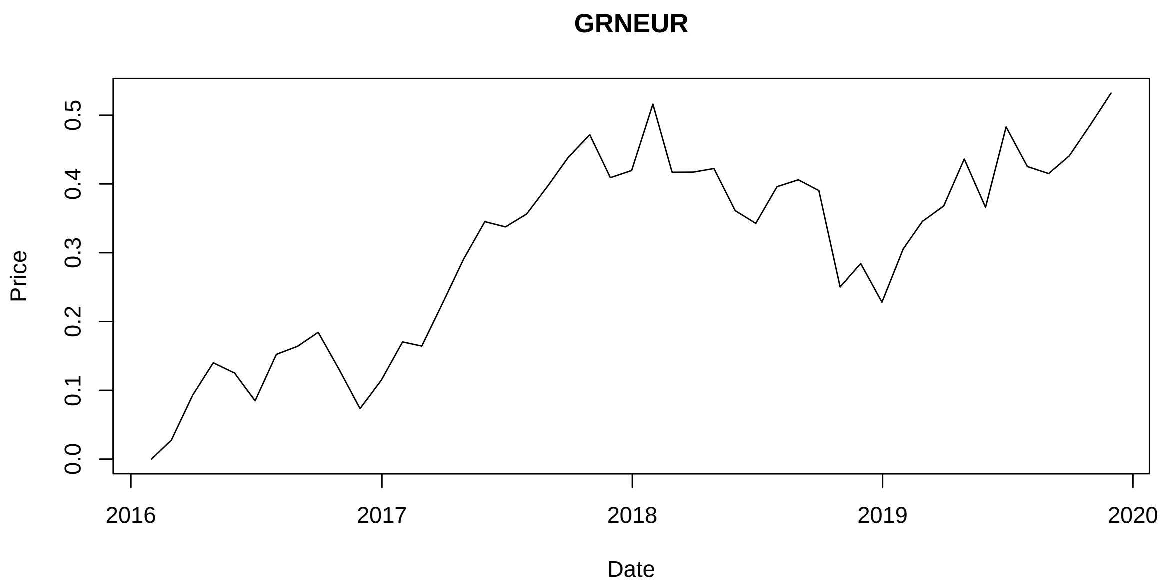

Figure 6.11: GRNEUR accumulated return post-PA

6.5 Robustness checks

To assess the validity of our analysis, we conducted a comparison between the models using common clean energy indexes for the United States and Asia, which represent the two largest markets globally. Due to significant structural changes in the Asian clean energy index (GRNAS) from 2011 to 2012, we excluded the first 15 months of the sample to ensure a Gaussian distribution of the error terms Brooks (2019). Our findings indicate that neither the market factors nor the energy- and climate factors Granger-causes the Asian clean energy index or the US clean energy index. This holds for both the period before and after the signing of the Paris Agreement.

Ticker	Variables
GRNAS	NASDAQ OMX Clean Energy Focused Asia USD
GRNUS	NASDAQ OMX Clean Energy Focused US

Table 6.13: Variables for robustness checks

In the post-PA period we find no Granger causality for any of the models for either US or Asia. Similar to the finding that the market factors do not Granger-cause GRNEUR in the period following the Paris Agreement, a corresponding outcome was observed for GRNAS and GRNUS. However, in contrast to GRNEUR, we find that the energy- and climate variables do not Granger-cause GRNAS or GRNUS following the PA. We assert that this circumstance can be attributed to a multitude of contributing factors. Prior to the implementation of the Paris Agreement, both the European Union and the United States were successful in reducing emissions. Nevertheless, the United States was reluctant to bind itself to any concrete mitigation agreements during this period. On the other hand, the European Union demonstrated its commitment to climate change mitigation by endorsing and signing the Kyoto Protocol, an international treaty that legally binds countries to their pledge of reducing greenhouse gas emissions (UN, 1998). Following the enactment of the Paris Agreement, the European Union has emerged as a leader in climate policy implementation, setting ambitious goals that have influenced policy direction across Europe. Conversely, the United States has adopted a less aggressive stance towards climate change mitigation, rendering climate change a less salient issue in their political discourse. We posit that this divergence in climate policies underpins the differences observed in our findings. Similarly, when comparing Asia and Europe, we suggest that this dynamic continues to be a significant factor.

7 Conclusion

7.1 Conclusion

Climate change, carbon risk, and energy security concerns are increasingly highlighting the urgency for a transition towards clean energy solutions. The Paris Agreement represents the largest legally binding agreement aiming to combat climate change. The energy transition is driven by the need to reduce carbon emissions and ensure energy stability, factors that are becoming more prevalent in economic and political discourse. In this context, clean energy companies are positioned favorably, presenting potential opportunities for growth and innovation in clean energy solutions. Understanding the dynamics between stock market-, climate- and energy variables is critical for market participants and policy makers, to comprehend market behavior.

Using various climate-, energy-, and stock market variables we utilize a LA-VAR and VAR framework to analyze the Granger causality, impulse responses and variance decomposition for the Nasdaq European Clean Energy Focused Index (GRNEUR) in the period from 2011 to 2022. Further we split the sample into two distinct periods, before and after the Paris Agreement, to investigate how the Paris Agreement has affected the market.

In the pre-PA period, we find that the broad market index (STX), growth index (GRW) and interest rate (ECB) has a causal effect on GRNEUR, but the oil price (CO1), carbon price (MO1) and Climate Policy Uncertainty Index (CPU) does not. From this we can understand how investor price and view the clean energy index. These findings are similar to what Henriques and Sadorsky (2008) find in their paper. In the same period the impulse response functions show significance for the market index (STX) and interest rate (ECB) up to two months after the shock. Shocks to oil price, carbon price and climate policy uncertainty have no significant impact on GRNEUR.

In the post-PA period, we find that the oil price (CO1), carbon price (MO1) and the Climate Policy Uncertainty Index (CPU) jointly have a significant causal effect on GRNEUR. However, the broad market index (STX), growth index (GRW) and interest rate (ECB) do not Granger-cause GRNEUR. Interestingly, we find that a positive shock to the carbon price (MO1) has a negative effect to the clean energy index (GRNEUR).

Our findings suggest that the Paris Agreement had an influence on determining factors of clean energy stock performance in Europe. Upon reviewing the return performance of the GRNEUR index before and after the agreement, we observed a notable improvement in performance following its implementation. Additionally, the risk-return relationship has become more favorable during the post-Agreement period. These results highlight the importance of ongoing commitment to climate mitigation efforts and the need for climate policies that support the development of alternative energy sources.

7.2 Limitations

Throughout our research process, we have gained a strong understanding for the limitations of statistical tests. While we have reached conclusions supported by statistical significance, it is important to exercise caution when interpreting these findings.

One potential limitation is that the use of monthly data may not capture a sufficient amount of information or variation within the data. However, we made the deliberate decision to employ monthly data due to its desirable properties that enhance the robustness of our analysis.

Furthermore, we utilized the Climate Policy Uncertainty Index as a proxy for policy uncertainty in Europe, recognizing that it may not perfectly represent the actual state of climate policy uncertainty in Europe.

Another concern is related to omitted variable bias. Instead of the commonly used technology indexes, we opted to include a growth index (GRW). Prior studies have identified individual Granger-causality and statistical significant impulse responses from technology indexes to renewable energy companies. However, we did not observe similar outcomes with our chosen growth index (GRW), which may have introduced limitations to our models.

7.3 Questions for future research

Energy transition, climate change and sustainable development are topics that are experiencing rapid growth and development. Continuous research on these topics are of large importance in understanding the determining factors and mechanisms that help combat climate change. It is also crucial in order to ensure that the pace of the energy transition is sufficient.

Using stock performance as a measure of the development of clean energy capacity might not always provide an accurate representation. Therefore, it would be interesting to investigate the factors that effectively encourage the development of clean energy capacity. Such research would assist policymakers in comprehending the most effective policies to facilitate investments aimed at enhancing clean energy capacity.

Moreover, given our discovery of increased risk-adjusted returns in the period after the Paris Agreement. We suggest exploring what events, with regards to climate mitigation and adaptation, that have had the most significant impact on the risk-reward relationship for clean energy equities.

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Appendix

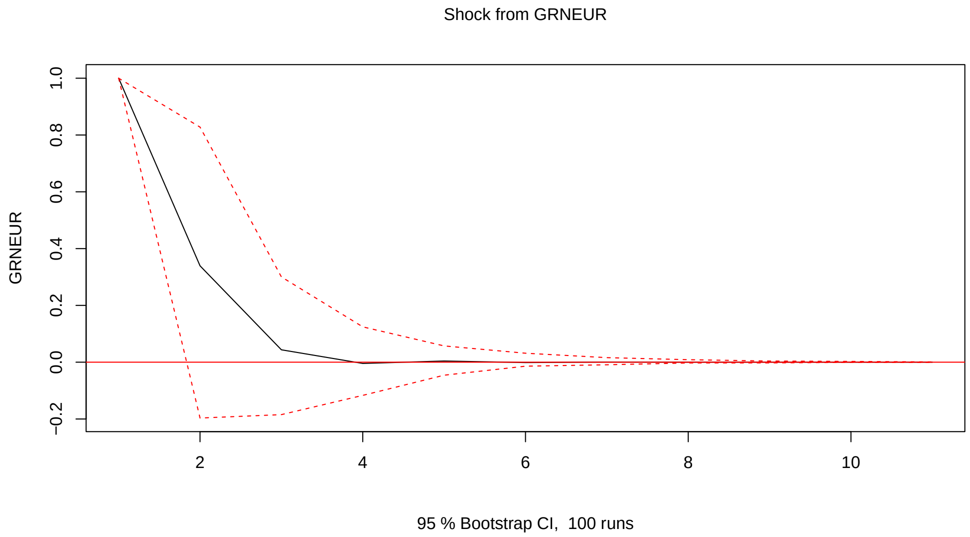

Figure A.1: Pre-PA: Impulse response function: Shock from GRNEUR to GRNEUR

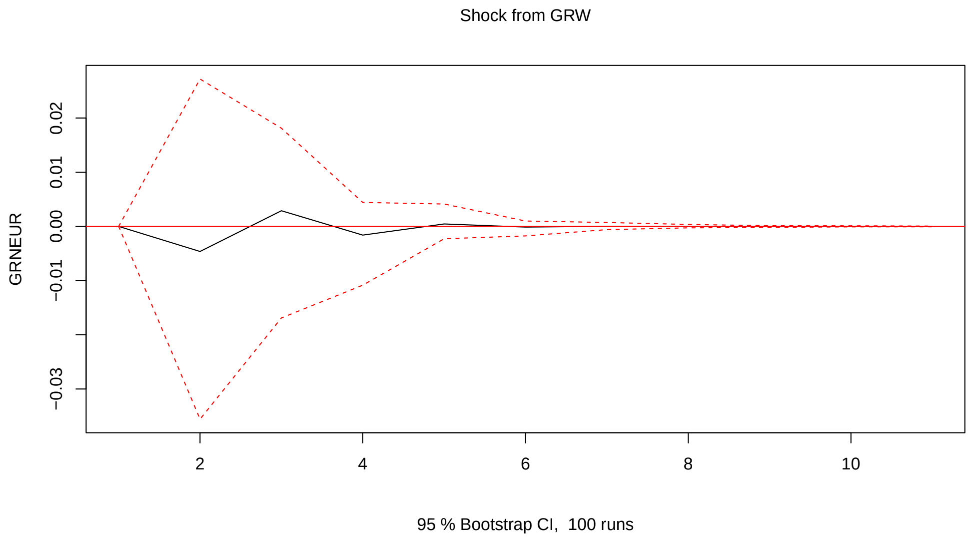

Figure A.2: Pre-PA: Impulse response function: Shock from GRW to GRNEUR

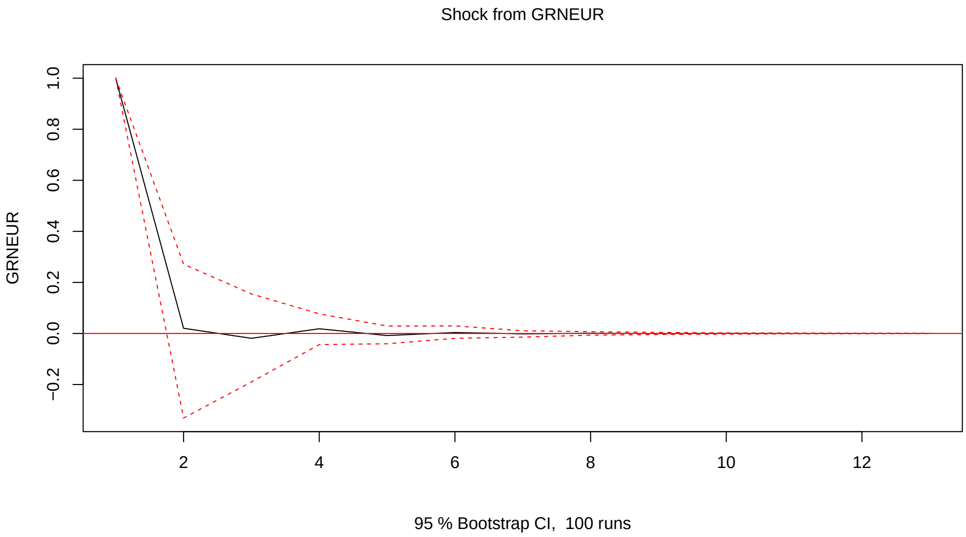

Figure A.3: Pre-PA: Impulse response function: Shock from GRNEUR to GRNEUR Climate/Energy Model

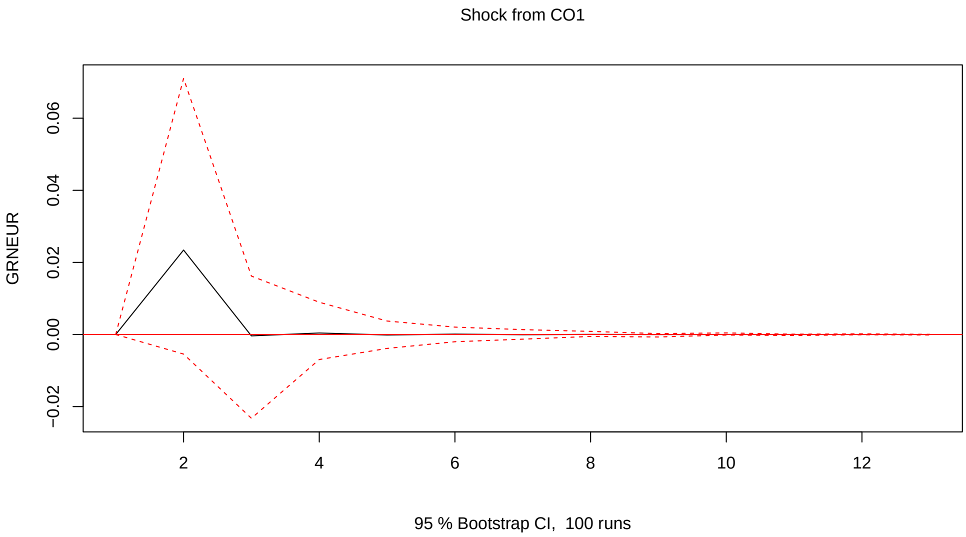

Figure A.4: Pre-PA: Impulse response function: Shock from CO1 to GRNEUR

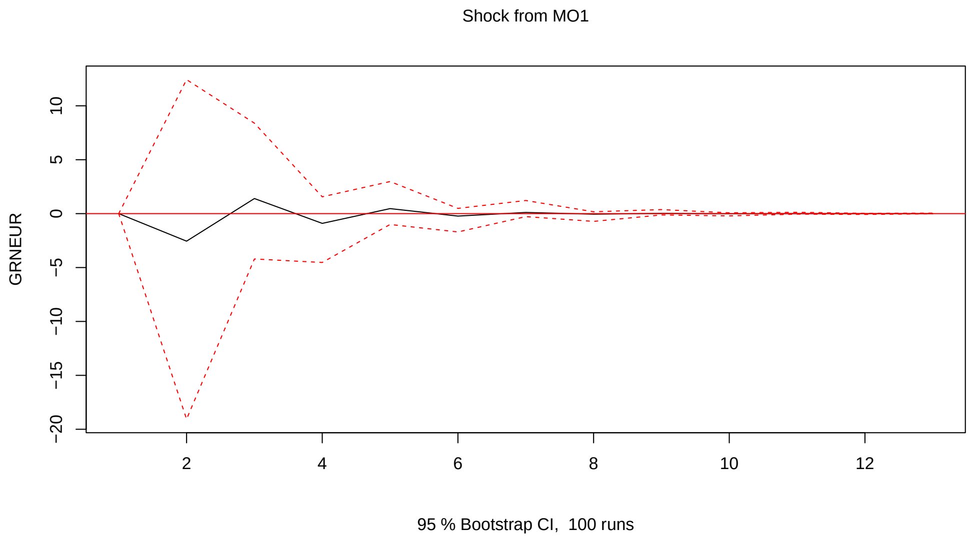

Figure A.5: Pre-PA: Impulse response function: Shock from MO1 to GRNEUR

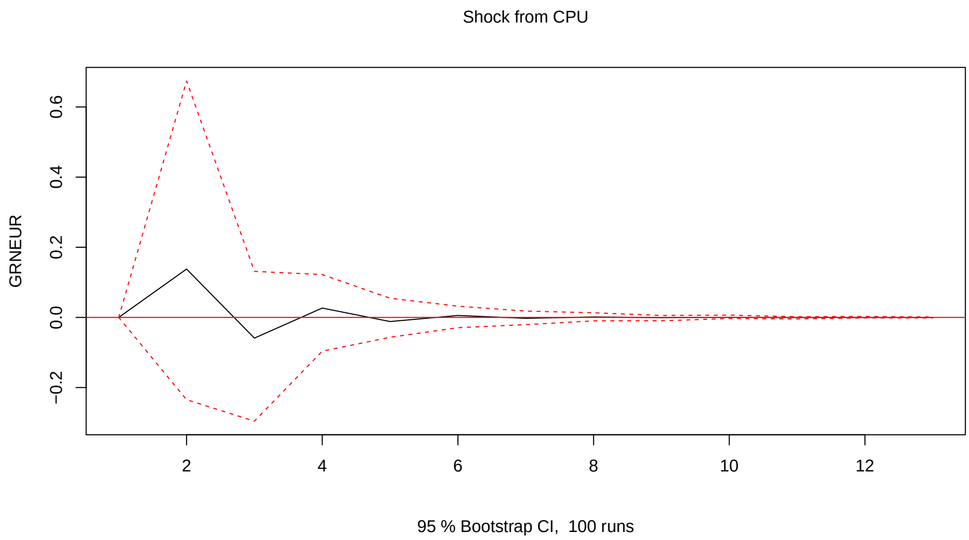

Figure A.6: Pre-PA: Impulse response function: Shock from CPU to GRNEUR

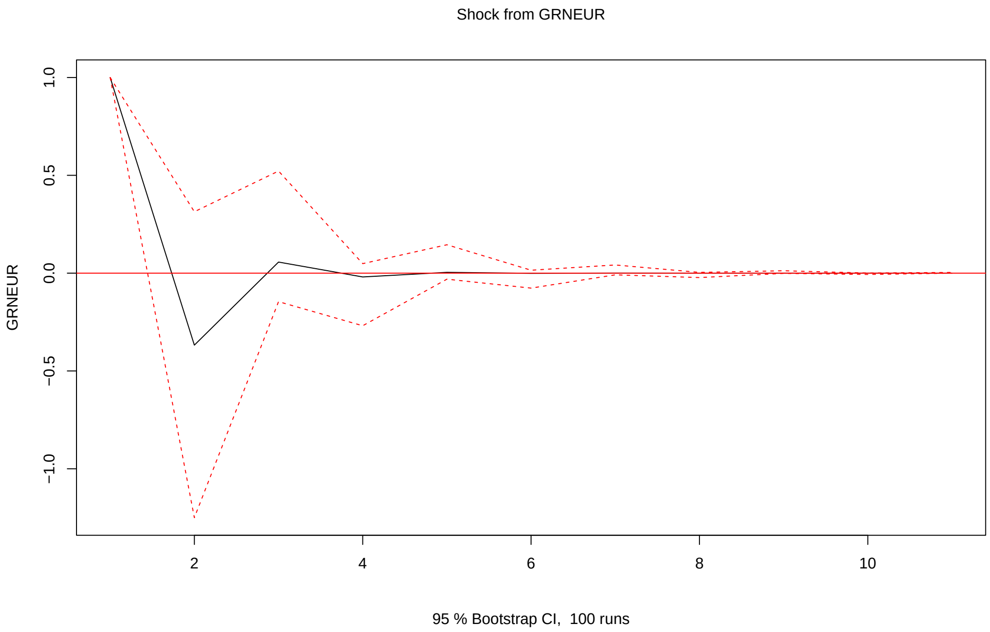

Figure A.7: Post-PA: Impulse response function: Shock from GRNEUR to GRNEUR

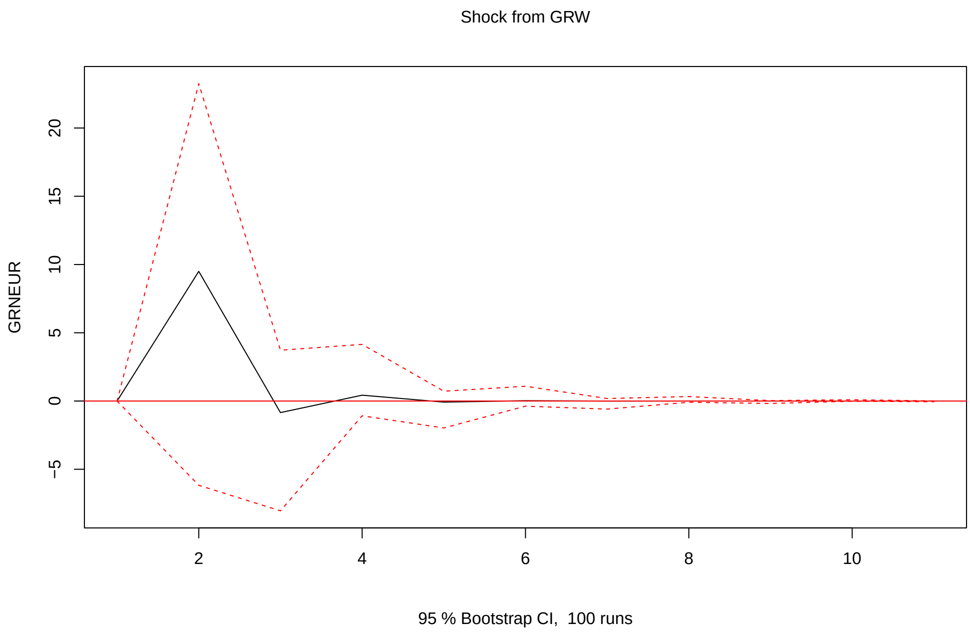

Figure A.8: Post-PA: Impulse response function: Shock from GRW to GRNEUR

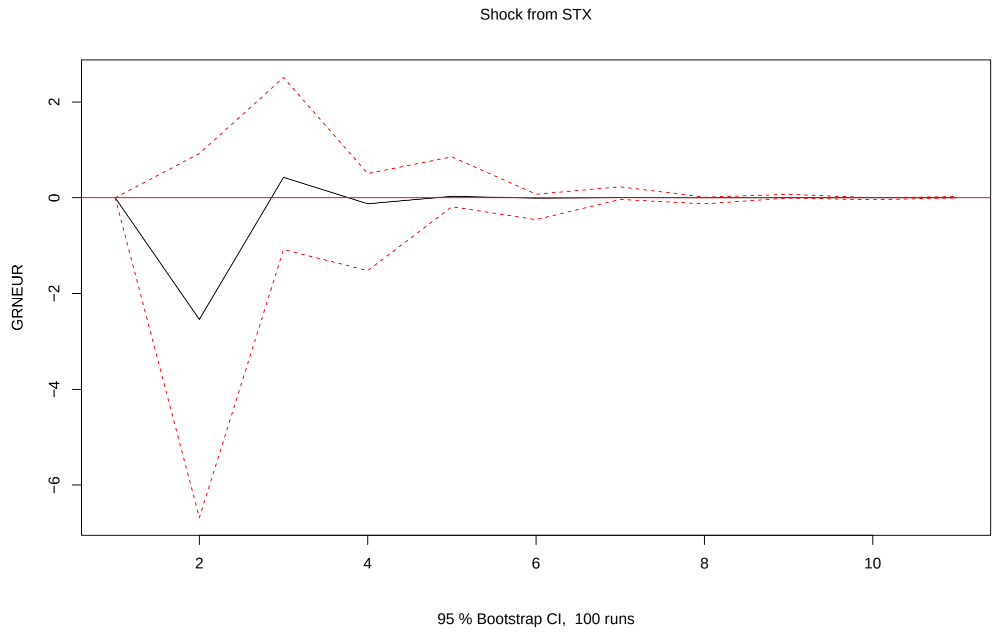

Figure A.9: Post-PA: Impulse response function: Shock from STX to GRNEUR

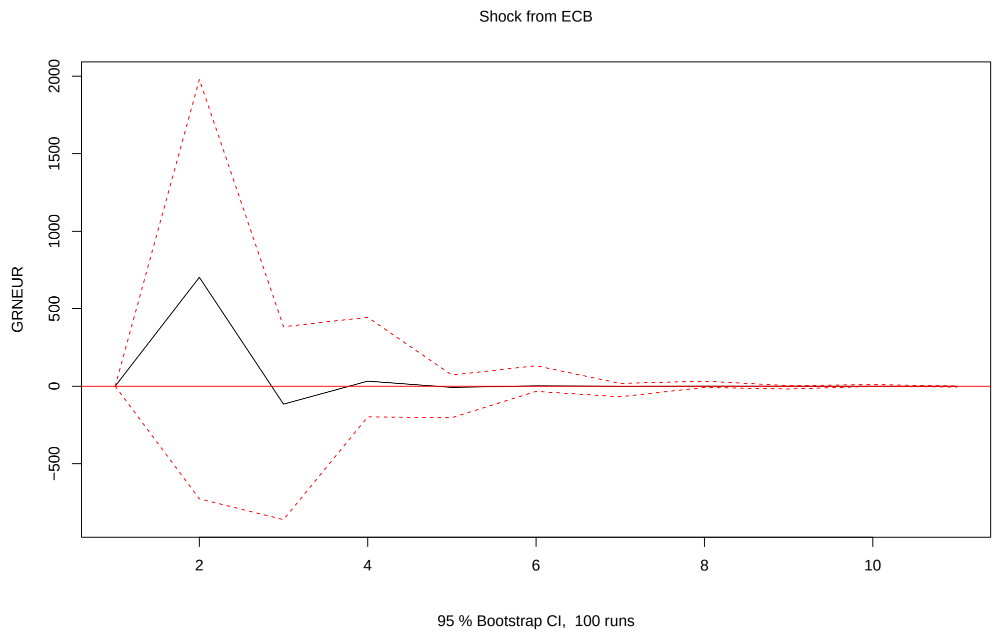

Figure A.10: Post-PA: Impulse response function: Shock from ECB to GRNEUR

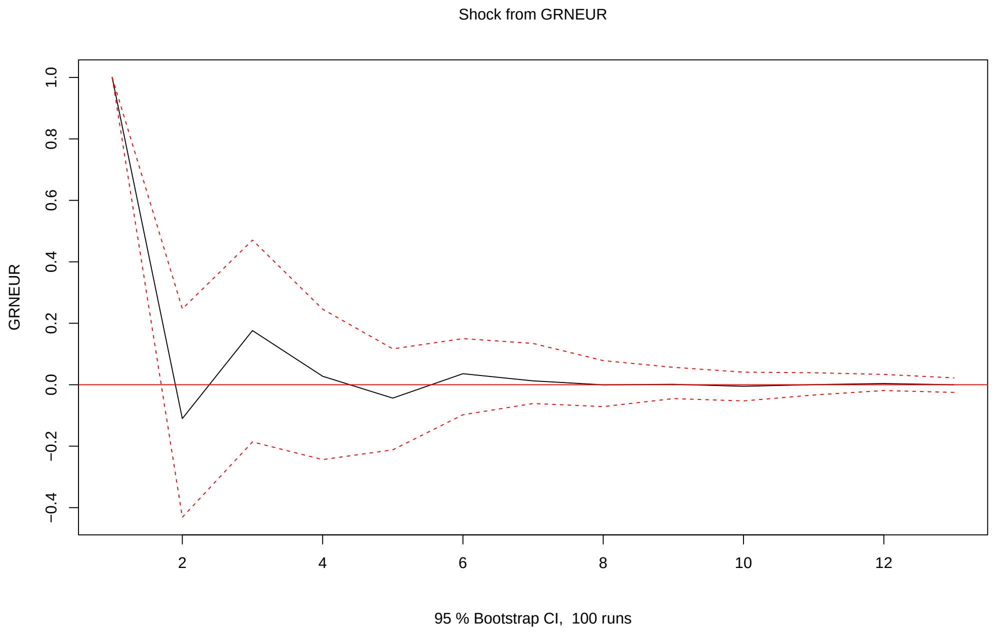

Figure A.11: Post-PA: Impulse response function: Shock from GRNEUR to GRNEUR Energy/Climate Model

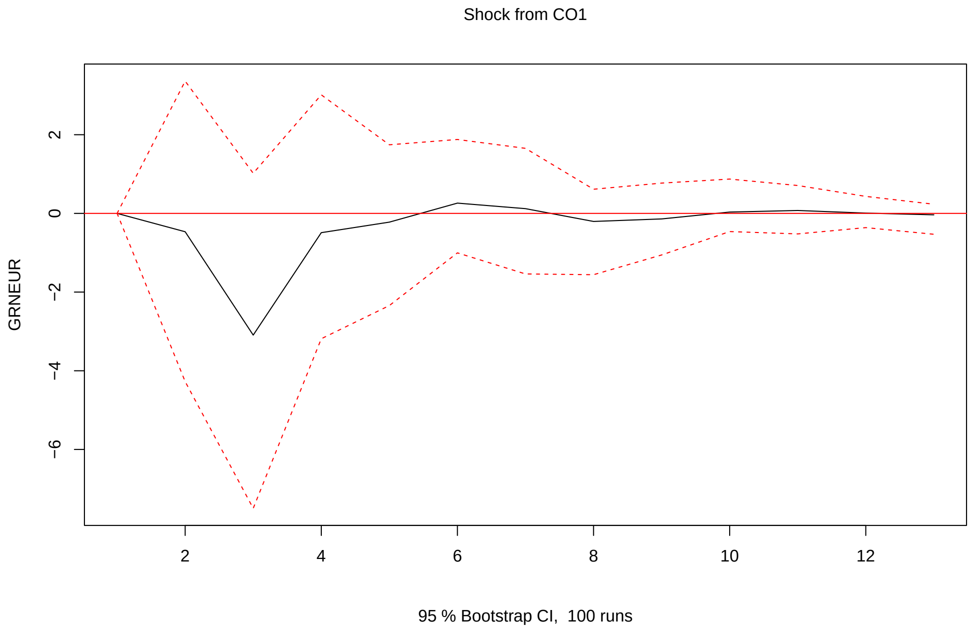

Figure A.12: Post-PA: Impulse response function: Shock from CO1 to GRNEUR

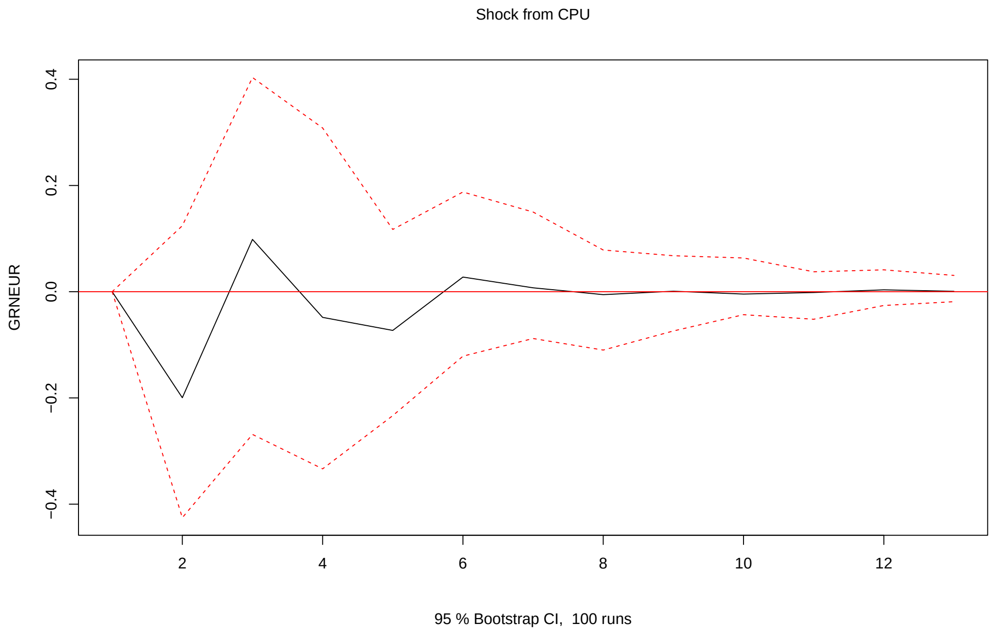

Figure A.13: Post-PA: Impulse response function: Shock from CPU to GRNEUR

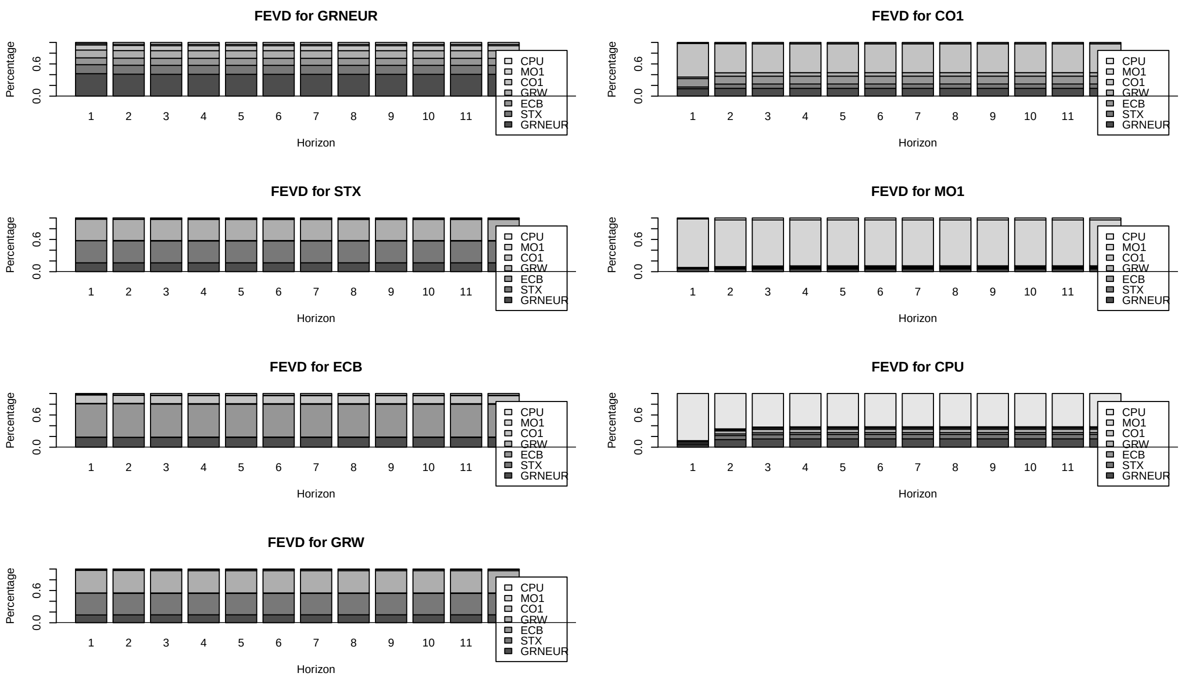

Figure A.14: Pre-PA: Variance decomposition of all factors

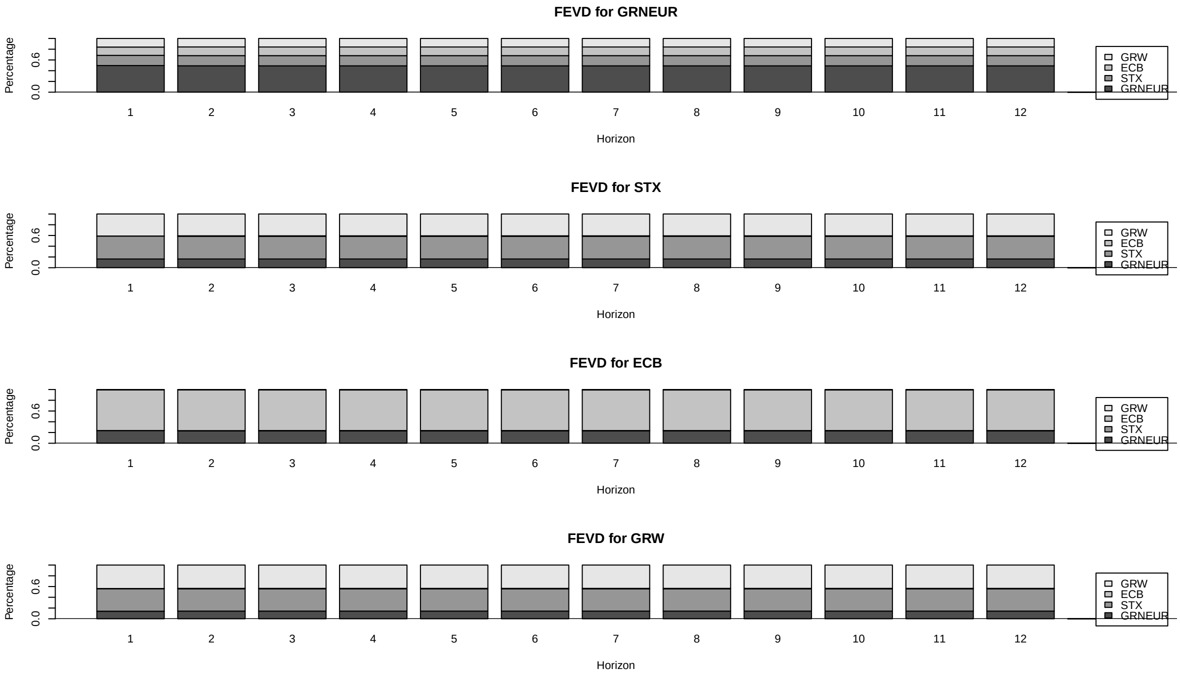

Figure A.15: Pre-PA: Variance decomposition of market factors

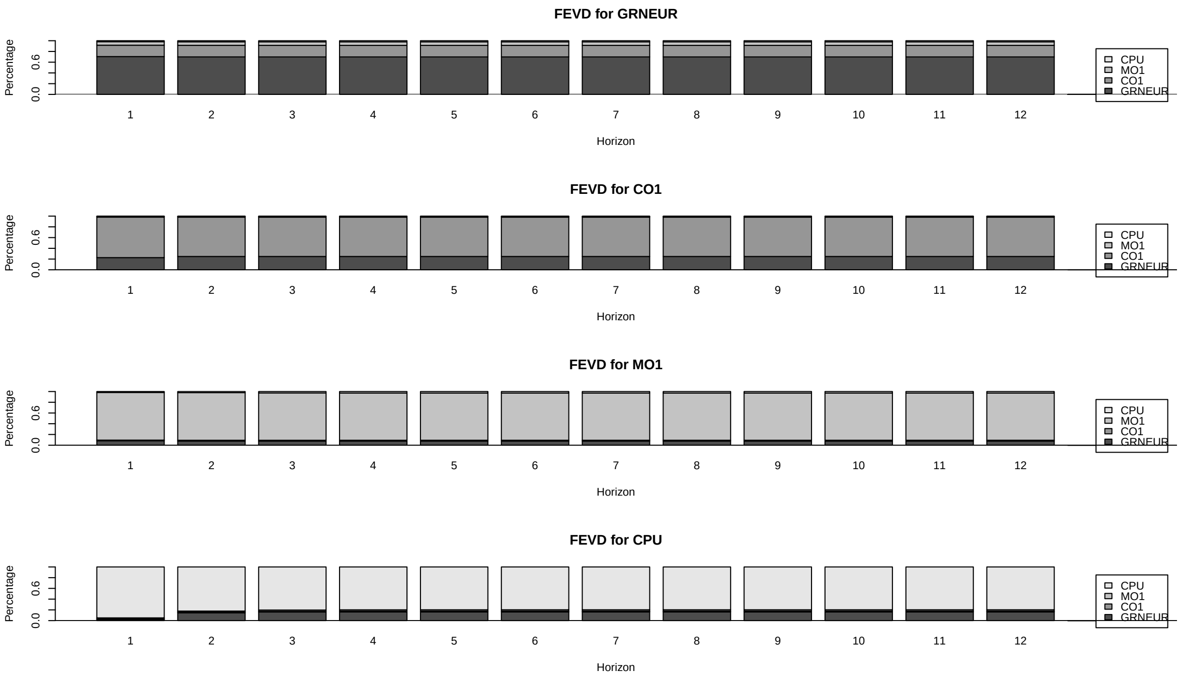

Figure A.16: Pre-PA: Variance decomposition of energy- and climate factors

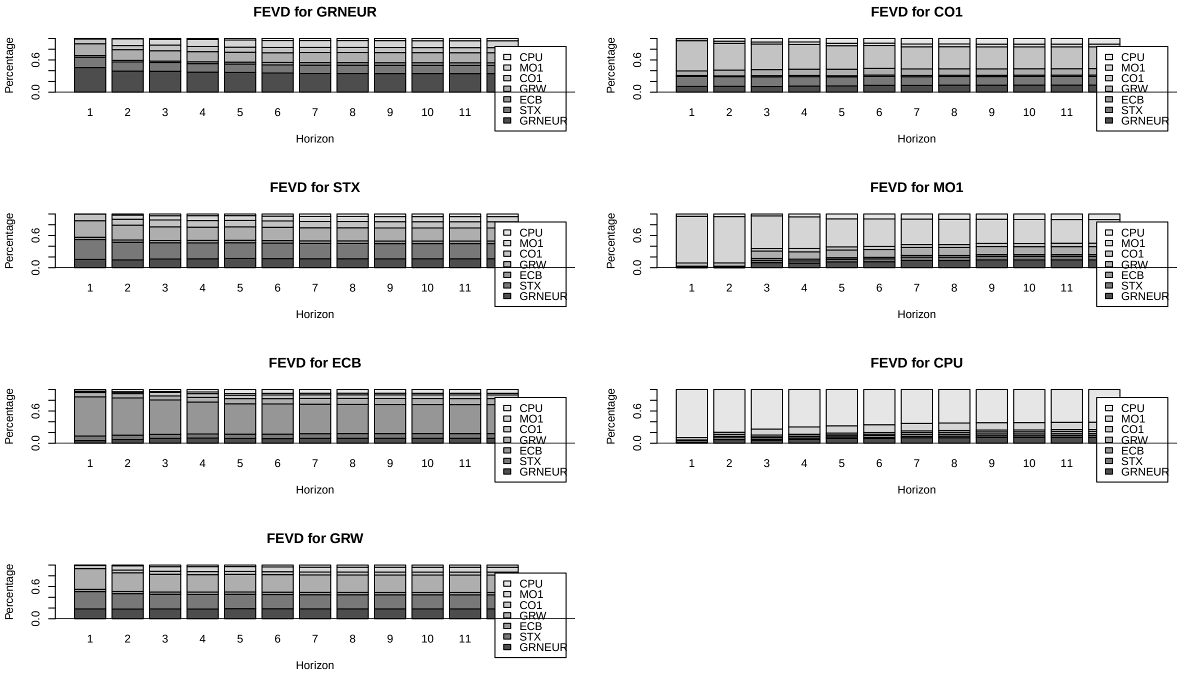

Figure A.17: Post-PA: Variance decomposition of all factors

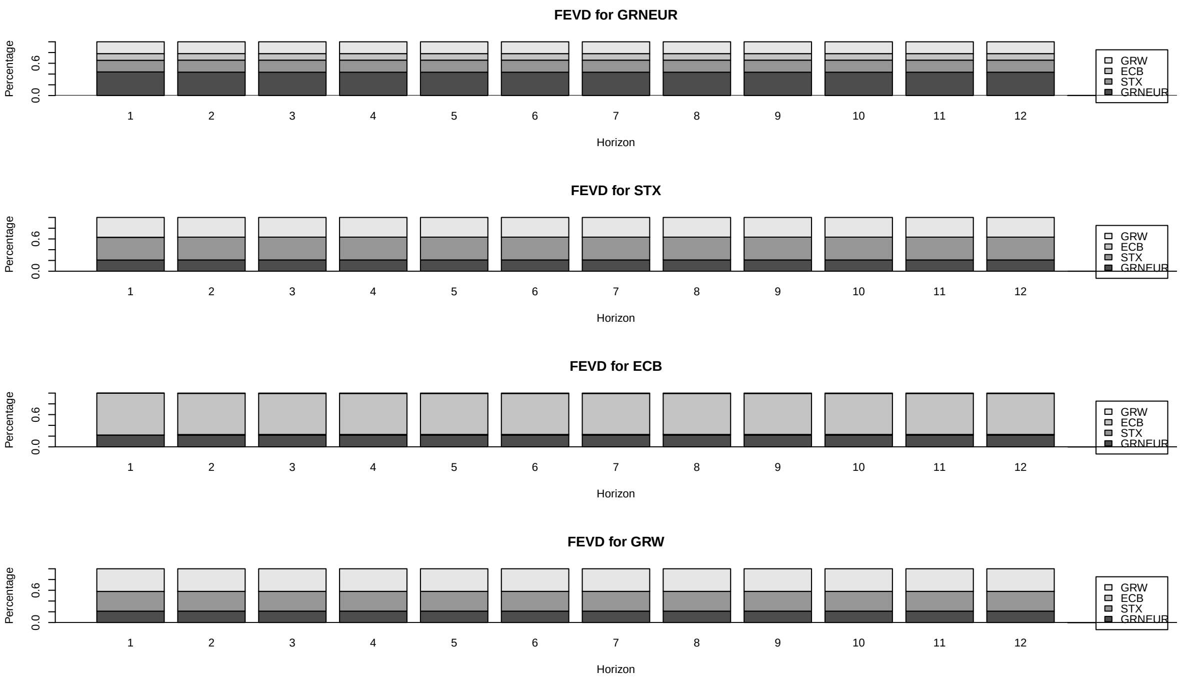

Figure A.18: Post-PA: Variance decomposition of market factors

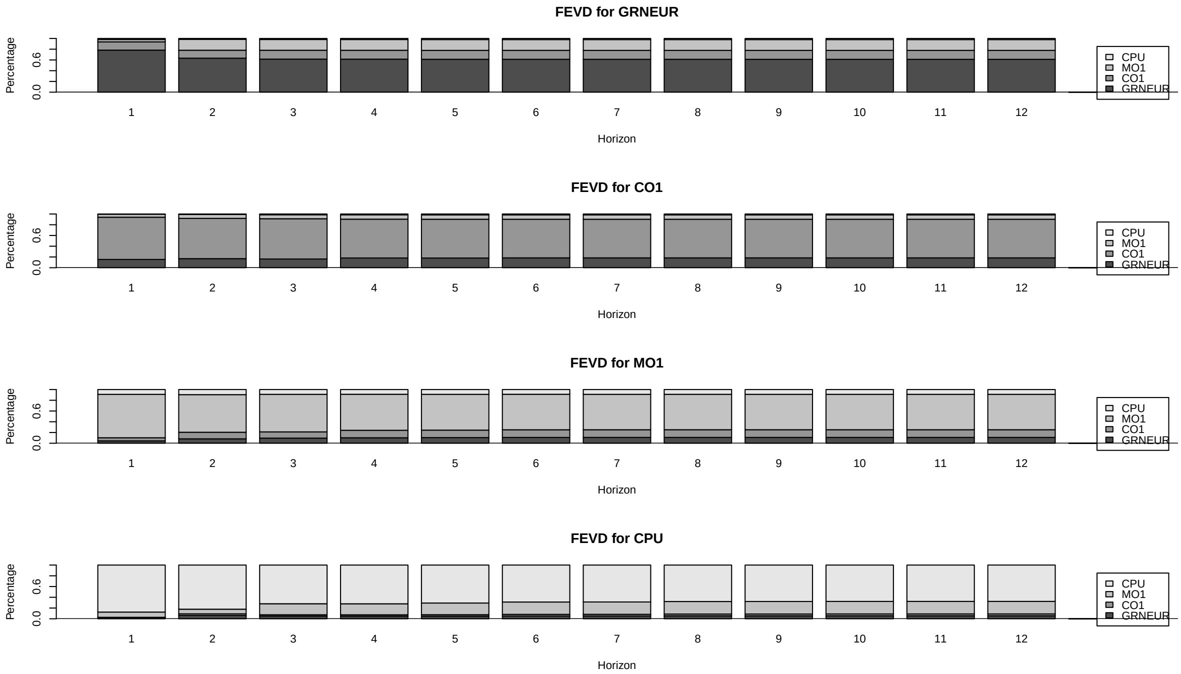

Figure A.19: Post-PA: Variance decomposition of energy- and climate factors