ERASMUS UNIVERSITY ROTTERDAM
ERASMUS SCHOOL OF ECONOMICS
MSc Economics & Business or
Specialization Financial Economics

The Effect of Investor Attention on the Co-movement Between European Clean and Dirty Energy Assets

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Finish date: July 2023

Preface and Acknowledgements

This master thesis is the culmination of my studies in Financial Economics and represents my deep interest in the field. The journey towards completing this thesis has been challenging yet rewarding, as it has provided me with the opportunity to delve into a topic that I am passionate about. It is my hope that this research will contribute to the existing literature and provide valuable insights for policymakers, academics, and individuals interested in the field.

I would like to express my gratitude to my thesis supervisor for providing me with guidance and support throughout the course of my research. The feedback and input have been valuable in taking my research to a higher level.
Finally, I would like to express my deepest appreciation to my family and loved ones for their unconditional support and encouragement throughout my academic journey.

Abstract

Public environmental awareness has increased, prompting traditional investors to invest in clean energy stocks shifting away from fossil fuel investments. To this respect, we examine to what extent investor attention drives the time-varying co-movement of returns between European clean and dirty energy assets while controlling for macroeconomic and uncertainty factors. A two-stage framework consisting of DCC-GARCH and quantile regressions is adopted. Using daily Google Search Volumes we find evidence of a statistically negative effect on the co-movement of clean energy and fossil fuel stocks when common shocks towards the European clean and fossil fuel markets are severe. Additionally, we find evidence for the changing dynamics among the drivers and the co-movement of returns for the European clean and dirty energy sector over the various quantiles of the return correlation distribution. The impact of investor attention on the DCC between the clean energy and fossil fuel sector is fully attributable to the post-COVID period.

Keywords: Clean energy, Fossil fuel, Investor attention, European, Co-movement

JEL Classification: G11, G4, Q42

Table of contents

List of Tables

List of Figures

1 Introduction

In an effort to combat climate change and the growing concerns about energy security issues, the world has been increasingly turning towards cleaner sources of energy over the past ten to fifteen years (Kumar et al., 2012). To accomplish the objective of reaching net-zero emissions and mitigating climate change, there must be a shift from traditional carbon-intensive energy sources towards low-carbon clean energy. Within the literature this raised a new field of study that focusses on the relationship between clean and dirty energy stocks. Many studies relate to connectedness or spillover but few can be regarded as studies on dynamic conditional correlation (DCC) which has practical relevance for investors and portfolio managers regarding diversification and hedging opportunities.

Among others, Ahmad (2017), Song et al. (2019) and Reboredo and Ugolini (2018) study spillover effects between clean and dirty energy markets using the framework of Diebold and Yilmaz (DY) (2012, 2014). However, their model assumes a time-invariant covariance matrix neglecting the presence of volatility clustering (Gamba-Santamaria et al., 2019). Multivariate Generalized AutoRegressive Conditional Heteroscedasticity (MGARCH) models can account for this time-varying clustering and capture the time-varying correlations. Financial time series are prone to shocks and during these periods volatility in asset returns tends to rise for a prolonged period after which a period of lower volatility follows, indicating the conditional variance. Hence the series exhibits varying levels of volatility throughout time and a model that assumes constant variances is not suitable. The series studied in this report experience volatility clustering as a result of major shocks such as COVID and the Russian invasion of Ukraine. In addition, during times stress and high levels of uncertainty, financial markets are more connected to each other resulting in a time-dependent link between them (Ahmad, 2017; Kocaarslan & Soytas, 2019; Gosh et al., 2023). This is reflected in varying levels of correlation among markets throughout time. For these reasons we are interested in conditional variances and correlations, i.e. variances and correlations that vary over time.

As noted by Kumar et al. (2012) an increase in public environmental attention may raise the environmental awareness of traditional investors and thereby prompt them to invest in clean energy stocks shifting away from fossil fuel investments. Hence attention regarding clean and renewable energy investments increases as well. Investor attention may therefore be regarded as a driver behind the co-movement dynamic between clean and renewable energy assets. However, this relation has never been examined. Existing studies regarding investor attention mainly focus on predicting returns or study the connectedness among various assets and investor attention using the DY framework. Results are however not consistent with each other. The study of Prange (2021) is the only one that investigates the relation between investor attention, measured through ticker volumes, and the co-movement dynamics between various financial assets using an MGARCH model. They find a positive relation. The clean and dirty energy sector are however not included. In addition, they study the effect of investor attention on the co-movement at the mean of the distribution and do not include control variables. While based on existing literature (Liu & Hamori, 2021; Gao et al., 2021), we suspect a change in relation at the tails of the distribution of the time-varying co-movement of returns due to major shocks. The Russian Ukraine war is the most recent shock that led to a Western ban on the supply of Russian oil and gas, making these commodities extremely expensive. This has accelerated the transition towards sources of cleaner energy.

Given the rapid development and investments in the clean energy sector and its connection to the fossil fuel sector it is essential for investors and policymakers to extend their understanding of the return dynamics between the two and get insight into potential drivers of this interdependency, in particular investor attention. The purpose of this paper is to fill this gap.

To what extent does investor attention drive the time-varying co-movement of returns between European clean and dirty energy assets?

This study aims to answer the question of whether investor attention, measured through the Google Search Volume Index (GSVI), has explanatory power for the dynamic correlation for the European market while controlling for macroeconomic variables.

The literature regarding drivers behind the time-varying co-movement of clean and dirty energy assets is scarce (Kocaarslan & Soytas, 2019; Saeed et al., 2020; Saeed, et al., 2021; Liu et al., 2021a). They vary in used methods, omit variables such as investor attention, do not account for evolving relations and they all focus on indices and none of them examines the dynamics at the stock level. Within an index movements of the individual stocks' returns may cancel each other out which could lead to making wrong inferences about the existing relations. In addition the study of Saeed et al. (2020) and Liu et al. (2021a) who apply the DCC-GARCH model do not implement an ARMA process for the mean model. It is recommended to include a mean model in an MGARCH framework when there is evidence of conditional mean effects in the data. To sum up, little is known about the drivers behind the time-varying co-movement dynamics of clean and dirty energy assets, hence there is lack of understanding within this field. More specifically the effect of investor attention towards clean and renewable energy has never been investigated in relation to the time-varying co-movement of returns among clean and dirty energy assets. To the best of our knowledge, no study incorporates a behavioral perspective on investor attention in the modelling of time-varying co-movement. Besides, the changing relation between investor attention and the co-movement of returns over the various quantiles of the correlation distribution is overlooked within the literature. In addition, existing literature mainly focusses on the oil market as a proxy for the dirty energy sector whereas there are fossil fuel indices available. Finally, research on the co-movement dynamics within the European market has, to the best of our knowledge, never been conducted.

A two-stage framework is used to provide an answer to the research question. First the Dynamic Conditional Correlation General AutoRegressive Conditional Heteroscedasticity (DCC-GARCH) model as introduced by Engle (2002) is used to model the dynamic correlation between the clean and dirty energy indices for the European market. Secondly, quantile regressions are applied in order to examine the dynamics of potential drivers of this co-movement at different quantiles of the distribution. In particular the relation between investor attention and the dynamic correlation is examined while controlling for macro-economic conditions.

Our study provides new findings to the literature in light of the changing effects of drivers of the return co-movement, especially for the effect of investor attention. Using daily Google Search Volumes we find evidence of a small negative effect on the DCC of clean energy with dirty energy when common shocks towards the clean and fossil fuel markets are severe. The previous day value of DCC, stock- and oil market uncertainty are found to be most important in driving the co-movement. The impact of the drivers increases at the tails of the return correlations distribution indicating more importance for the drivers in times of crisis. Additionally, we show the presence of time-varying dynamics among the drivers and the co-movement of returns for the European clean and dirty energy sector. Furthermore, an analysis conducted on the stock level shows no differences in effects with the index level analysis indicating uniformity in the return series for the clean energy stocks.

Understanding DCC among markets holds practical importance for various market participants such as investors, speculators, and policymakers. This study sheds light on possible diversification or hedging strategies within the European market for which correlation is a critical factor (Engle, 2002; Begiazi et al., 2016). Also, the changing dynamics between clean and dirty energy stocks impacts financial and environmental sustainability. By recognizing the relation between these assets, it can benefit clean investments. Our results show that, for the last three years, the downside risk of dirty energy stocks can be mitigated by investing in renewable energy making clean energy investments more attractive to investors. This has implications for both social and economic development and can help policymakers in developing effective policies and strategies for transitioning to a low-carbon economy.

The remainder of this study is organized as follows. Section 2 covers existing literature on what is known about the time-varying relation as well as potential drivers. The data that is being used and a preliminary inspection is covered in section 3. Section 4 describes the methodological framework used, followed by section 5 results and section 6 conclusion and implications of our study.

2 Literature Review

The objective of this section is to provide an overview of what is known in the literature concerning the relation between green and dirty energy markets. In addition, literature is scanned on potential drivers that explain the co-movement of stock returns between these energy markets and the position of investor attention in explaining this relation.

2.1 Outperformance of green or brown assets

Table 1 provides a brief overview of the existing literature on the ongoing debate about the existence of a premium for either dirty or clean stocks.

Table 1: Literature overview regarding debate concerning Carbon premium or Greenium

Author(s) (Publication year)	**Frequency & time period**	**Region**	**Method**	**Control variables**	**Results**
Bolton & Kacperczyk (2021)	Monthly 2005 to 2017	US	Panel regression CO2 emissions (total, change, intensity (sales))	Industry, FF-5, LIQ & firm char.	CO2 (total & change) ***+ CO2 heavy industries account for carbon premium
Bolton & Kacperczyk (2022)	Monthly 2005 to 2018	Global	Panel regression CO2 emissions (total, change)	Country, Industry, FF-5, LIQ & firm char.	Carbon premium ***+ Domestic factors matter
Pástor et al. (2022)	Monthly 2012 to 2020	US	Panel regression on GMB portfolio returns MSCI ESG ratings	Inv.sent, Earnings news, FF-5, LIQ, RMW, ME & firm char.	GMB 174% Shocks to climate ***+
Bauer et al. (2023)	Monthly 2010 to 2021 & 2022	G7-countries	Panel Regression & Parallel Panel Regression CO2 emissions (total, intensity (size))	Fixed effects & firm char.	Green > Brown (till 2021) Green < Brown (2022)

*Note: GMB indicates Green minus Brown portfolio returns. FF-5 Fama French 5-factor model including MKTRF, SMB, HML, MOM, CMA. CMA is the investment factor. LIQ is liquidity factor. RMW is the profitability factor. ME is the market equity factor, Banz (1981). ***+ significantly positive relation at 1% level.*

According to Bolton and Kacpercszyk (2021, 2022) there exists a carbon premium that is due to the carbon transition risk a company faces when it operates in a polluting industry. Accordingly, the returns of companies operating in CO2-heavy industries such as oil and gas companies exceed those of green stocks. After the Paris Agreement, the carbon premium is argued to be more pronounced due to increased investor awareness concerning climate change. In addition to this, the tightness of a countries climate policy matters for the magnitude of the carbon premium as well. This is intuitive as the firms operating in these countries are more subject and exposed to the transition away from fossil fuels. Europe is the frontrunner in this transition towards more renewable sources of energy. The European Union has come up with a set of rules concerning the subject of climate change that all member states have to comply with to speed up the transition, one of them being the Paris Agreement.

Therefore, all EU member states pursue a tight climate policy and as a result experience a larger carbon premium.

In addition to the realized returns, Pástor et al. (2021) model the expected returns of green and brown assets and argue that the expected returns of green assets are lower than those of brown assets for two main reasons. 1) investors get more utility from holding green assets and 2) green assets mitigate carbon transition risks making them a better hedge against climate risk. Due to these favorable characteristics investors accept a lower return compared to brown assets. When one looks at realized returns Pástor et al. (2022) show that green assets can have higher realized returns due to unexpected shifts in investors' or consumers demand to greener assets or products. The unexpected shifts in demand are likely due to an unanticipated increase in climate concerns, as measured by a media index created by Ardia et al. (2022), which boosts demand for greener products and stocks. At the same time and through the same mechanism demand for brown firms' assets and products is reduced due to the substitution effect lowering the realized returns of brown assets. The distinction between expected and realized returns is an important one to make and one could argue that the reasoning behind the lower expected returns for green assets drives demand for green assets and hence increases the realized returns. Even if the expected return model predicts a positive carbon premium, green stocks will outperform brown stocks if preferences for green assets and therefore their demand rises.

The results of Pástor et al. (2022) conflict with previous studies of Bolton and Kacpercszyk (2021, 2022). Possible explanations for this are the differences in their used sample period and the classification of clean and dirty assets. Pástor et al. (2022) use a sample that contains more recent data and the period after the Paris Agreement is more pronounced putting more weight on this new dynamics. Pástor et al. (2022) classify clean stocks based on MSCI ESG ratings while Bolton and Kacpercszyk (2021) make a distinction based on total CO2 emissions.

Contrary to the paper of Bolton and Kacpercszyk (2022), Bauer et al. (2023) adjust emissions from companies according to their size. The reason behind this is that a large company emits more by definition than a small company. Their results are in line with those of Pástor et al. (2022) supporting the fact that green stocks generally outperform brown stocks and hence conflict with the results of Bolton and Kacpercszyk (2021, 2022) making the existence of a carbon premium during the past decade questionable. In the case of a carbon premium it was unlikely to be very large. Related to this, Lontzek et al. (2023) imply that investors only need a minor carbon premium for retaining brown assets until climate tipping points have been crossed.

Furthermore, Pástor et al. (2022) examine the effect of climate change concerns on the returns of the green minus brown portfolio (GMB) measured via a media index. With this they examine the effect of general market sentiment on stock returns and find a positive relation on GMB. This so called market sentiment may lead to searches for green financial assets among investors and via this mechanism stock returns are affected. One could postulate that they therefore study an indirect relation between climate concerns and stock returns. Searches for green financial assets are a more direct way of measuring attention but this has not been studied before.

2.2 Co-movement clean and dirty energy markets

Table 2 shows a snapshot of recent and relevant studies regarding the dynamic relation among renewable and dirty energy markets and assets.

Table 2: Literature overview regarding co-movement of clean and dirty energy assets

Author(s) (Publication year)	Method	Frequency & time period	Data series	Results
Sadorsky (2012)	MGARCH models (BEKK, Diagonal, CCC, DCC)	Daily 1-1-2001 to 31-12-2010	ECO, PSE, WTI	DCC-MGARCH best model ECO - WTI (-0.3 to 0.6) ECO - PSE (0.45 to 0.91) WTI - PSE (-0.4 to 0.6)
Ahmad (2017)	Connectedness framework of DY (2012) MGARCH models (BEKK, CCC, DCC)	Daily 1-5-2005 to 1-4-2015	PSE, ECO, WTI	Strong returns spillovers ECO-PSE. DCC ECO-WTI (-0.25 to 0.7) DCC ECO-PSE (0.4 to 0.9) Effect of major economic events
Ahmad et al. (2018)	DCC, ADCC and GO-GARCH	Daily 3-3-2008 to 31-10-2017	ECO, WTI	ECO-OIL (0.0 to 0.5) OIL effective hedge for ECO
Reboredo & Ugolini (2018)	Multivariate VAR model Connectedness framework of DY (2014)	Daily 1-1-2015 to 1-8-2017	Twitter as inv. Sent., ECO	Twitter no big impact on returns/volatility
Song et al. (2019)	Connectedness framework of DY (2014)	Daily 15-6-2009 to 26-10-2018	GSVI, WTI, ECO, S&PGCE, ERIX	GSVI highest explanatory power for S&PGCE (0% to 10.39%) lowest for ERIX (0 to 4.49%)
Kocaarslan & Soytas (2019)	DCC-GARCH(1,1) ARDL-model	Daily 1-5-2004 to 18-1-2018	ECO, PSE, WTI	Time-dependent link between US dollar appreciation main driver
Saeed et al. (2020)	Corrected DCC-GARCH(1,1)	Daily 3-1-2012 to 29-11-2019	ECO, IEO, WTI	ECO - IEO (0.4 to 0.75) Clean energy assets are effective hedge
Saeed et al . (2021)	Quantile-based VAR model for connectedness	Daily 3-1-2012 to 29-11-2019	ECO, IEO, OIL prices	Return connectedness mean/median 29%, tails 65%
Tang & Aruga (2022)	Bayesian DCC-MGARCH(1,1)	Daily 1-2-2019 to 26-2-2021	WTI, ECO	ECO and WTI (-0.75 to 0.75) positive correlation after 2020
Tang et al. (2023)	Bayesian DCC-MGARCH(1,1)	Daily 30-6-2014 to 18-10-2021	Coal, gas, oil, ECO	Time-varying conditional correlation present
Ghosh et al. (2023)	Quantile-based VAR model for connectedness	Daily 31-12-2019 to 19-1-2022	ICLN, IXC	Clean energy and dirty energy markets highly connected. COVID-19 pandemic in extreme quantiles

Note: Due to conciseness the most relevant parts from the studies to ours are summarized. WilderHill Clean Energy Index (ECO). NYSE Arca Technology Index (PSE). West Texas Intermediate crude oil futures contract (WTI). Google Search Volume Index (GSVI). S&P Global Clean Energy Index (S&PGCE). European Renewable Energy Index (ERIX). iShares U.S. Oil & Gas Exploration & Production ETF (IEO). iShares Global Clean Energy ETF (ICLN). iShares Global Energy ETF (IXC).

Estimates from Bloomberg New Energy Finance (2023) suggest that the amount of money invested in renewables in 2022 achieved a new record of 470 billion euro, up 73% since 2015. In contrast, investments in the fossil fuel market show a downward trend since 2015 while still being high compared to investments in renewables. From an investment perspective this shift in capital investments may indicate a substitution effect between clean and dirty energy assets. This substitution effect can be explained by the high correlation among the two asset classes (Henriques and Sadorsky, 2008; Sadorsky, 2012; Kocaarslan & Soytas, 2019; Saeed et al., 2020). Rising fossil energy prices create demand for alternative sources of energy as fossil energy becomes expensive, thus promoting the development of renewable energy sources (Song et al., 2019). This encourages the switch to sustainable energy sources by energy investors which results in increasing profits of the clean energy sector and good performances in the equity markets. This mechanism is based on the demand side for clean energy. On the supply side it can be argued that clean energy adoption is associated with technological innovation. This in combination with decreasing oil prices, which are often associated with less favorable economic conditions putting a halt on technological innovation, lowering the growth of the clean energy industry (Ferrer et al., 2018). So due to decreasing oil prices stock returns for oil- and clean energy firms both decrease resulting in co-movement. The second view that prevails in the literature is regarded as the decoupling hypothesis creating portfolio diversification benefits (Ahmad, 2017). When the correlation among the two markets is low they are not found to be comparable and hence no substitution effect exists. The main reasons for this are the high costs associated with constructing and installing clean energies (Farid et al., 2023).

Over the past decade, there has been a growing strand of literature concerning the relation between clean and dirty energy stocks. Diebold and Yilmaz (2012, 2014) proposed a framework for studying the connectedness among assets which consist of VAR models. Their approach, and variations of it, are adopted numerous times to analyze the relation between clean and dirty energy assets. The DY framework is used by Song et al. (2019) who study the connectedness between fossil and renewable energy markets. According to their results the fossil energy market is closely related to the global-, European- and US based renewable energy market. Furthermore, by using a rolling-window method they report that the total spillover varies across time indicating a dynamic relation. Saeed et al. (2021) study return spillover effects between, among others, the WilderHill Clean Energy Index (ECO), iShares U.S. Oil & Gas Exploration & Production ETF (IEO) and crude oil prices. They apply a variation of the Diebold and Yilmaz (DY) framework which enables them to study the spillover effects in the upper and lower quantiles. Their quantile-based VAR model indicates a significant difference between the return connectedness at the mean and at the tails, 29% and 65% respectively for the total spillover index. With this, they show that mean based connectedness measures are not suitable to use when examining the relation between clean and dirty energy markets. Ghosh et al. (2023) find strong connectedness among the global clean and dirty energy market during times of the

COVID-19 pandemic by applying wavelet coherence tests and quantile-based VAR models. The quantile analysis reveals sharp increases in connectedness in the tails of the distribution just after the pandemic started.

Another part of the literature focuses on practical relevance for investors and portfolio managers regarding hedging opportunities of clean energy and oil prices using DCC-GARCH models. Existing works from Sadorsky (2012), Kocaarslan and Soytas (2019), Ahmad (2017), Ahmad et al. (2018), Tang and Aruga (2022) and Saeed et al. (2020) study the dynamic conditional correlations of ECO with oil prices as proxied by WTI oil and indicate a time-dependent link between them. Sadorsky (2012) finds that there exist hedging opportunities in a portfolio constructed of clean energy stocks and oil due to low correlation. The results of Ahmad (2017) and Ahmad et al. (2018) show low dynamic correlation, confirming the findings of Sadorsky (2012). Kocaarslan and Soytas (2019) find evidence of decreasing diversification opportunities during economic downturns when correlation tends to increase. Tang and Aruga (2022) focused on the effect of the COVID-19 pandemic and showed that the correlation went from negative to positive at the beginning of 2020 reaching a peak of 0.75. Hence, there are short term risks associated with the hedging potential of ECO and WTI oil.

These studies focus on the oil market as a proxy for the dirty energy market regardless of the existence of indices that track the performance of dirty energy companies. In addition, the DY framework is applied multiple times but it fails to account for the presence of volatility clustering (Gamba-Santamaria et al., 2019). Hence, DCC-GARCH models are better suited. In addition, all above mentioned studies focus on the US market and to the best of our knowledge the dynamic conditional correlation among the European clean and dirty energy market has never been studied before. This is surprising as Europe is the frontrunner in the fossil fuel transition regarding adoption and regulation therefore it is expected that investor attention is more pronounced. Based on existing literature we expect time-varying co-movement of returns between the European clean and dirty energy sector.

H1: There exists a time-varying relation between the returns of the European clean and dirty energy sector.

2.3 Investor attention

Selecting stocks to invest in is a time-consuming exercise and ranking all thousands of stocks available is non-trivial, hence making investment decisions can be regarded as a search problem. In accordance with the limited attention theory, to make this more manageable the choice set of the investor is determined based on a topic that attracted their attention and hence this motivates their investment behavior (Pham & Huynh, 2020; Barber & Odean, 2008). Over the past decade climate change has been a hot topic and is discussed broadly in the news. Over the years this has led to increased public environmental attention and increasing concerns over climate change. This affects the investment decisions of sustainable investors, traditional investors and opportunistic investors who may favor stocks of sustainable firms and divest stocks of conventional energy firms hence increasing returns of sustainable stock indices (Gutsche & Ziegler, 2019; Derwall et al., 2011; El Ouadghiri et al., 2020; Kumar et al., 2012). Fear for climate change among investors drives them to actively search for information which in the literature is referred to as 'attention' or 'sentiment' (Han & Yin, 2017; Lemieux & Peterson, 2011; Vozlyublennaia, 2014). These two terms are used interchangeably.

A lot of research has been done regarding investor sentiment in the energy and financial markets across different continents for which a variety of methods has been applied. A general distinction can be made between studies that look at the relation between investor sentiment and the clean and dirty energy markets separately and research that explain the co-movement of these two markets with investor sentiment or attention based measures. Results are however not consistent with each other due to the inherent difficulties in assessing investor sentiment mainly because of differences in sampling methods, time spans, and methodology.

Table 3: Literature overview regarding investor attention and investor sentiment

Author(s) (Publication year)	**Method**	**Time period & Frequency**	**Data series**	**Results**
Reboredo and Ugolini (2018)	Connectedness framework of DY (2014)	Daily 1-1-2015 to 1-8-2017	Twitter data, ECO	Limited capacity of Twitter sentiment on renewable returns
Song et al. (2019)	Connectedness framework of DY (2014)	Daily 15-6-2009 to 26-10-2018	GSVI, WTI, GAS, COAL, ECO, S&PGCE, ERIX	Inv. sentiment dynamic spillover (S&PGCE 0% to 10.39%, ERIX 0% to 4.49%)
El Ouadghiri et al. (2020)	OLS cont. for Carhart 4-factor model and GARCH(1,1)	Weekly 9-1-2004 to 29-6-2018	GSVI, Media index, DJSI US, 4GUS.FGI, FTSE USA	Sustainable: GSVI ***+ Conventional: GSVI ***-
Wang et al. (2021)	SVAR model Panel data model	Daily 1-5-2015 to 31-12-2019	Inv.sent from CSMAR, SSEEPII	Inv.sent ***+ Return green comp
Liu & Hamori (2021)	TVP-VAR	Daily 1-2-2005 to 20-12-2019	S&PGCE, Henry Hub, WTI, Tech, News headlines	Inv.sent weak impact on clean energy stock Inv.sent significant during economic events
Gao et al. (2021)	Connectedness framework of DY (2014)	Daily 14-9-2017 to 14-9-2020	Baidu index, China's green stock market	Significant time-varying and asymmetric effects. Investor attention affects the green stock market
Prange (2021)	DCC-GARCH DCCX	Daily 1-1-2015 to 1-9-2020	GSVI, IYY, fossil fuel futures	Investor attention ***+ Reversal after covid
Liu et al. (2021b)	Mediating effect model	Daily 1-1-2016 to 2-9-2020	Baidu Index, AQI (pollution) China's A-share market	Baidu ***+ to clean and polluting companies AQI ***- to polluting companies

Note: Due to conciseness the most relevant parts from the studies to ours are summarized. WilderHill Clean Energy Index (ECO). West Texas Intermediate crude oil futures contract (WTI). Google Search Volume Index

(GSVI). S&P Global Clean Energy Index (S&PGCE). European Renewable Energy Index (ERIX). FTSE 4Good US Index (4GUS.FGI). Dow Jones Sustainability Indices (DJSI US). FTSE USA Index (WIUSA). Shanghai Stock Exchange Environmental Protection Industry Index (SSEEPII). iShares Dow Jones U.S. ETF (IYY). Air Quality Index (AQI). Carbon Emission Trading (CET). Baidu Index is equivalent to GSVI for the Chinese market.

Song et al. (2019), Reboredo and Ugolini (2018), Liu and Hamori (2021), Gao et al. (2021), El Ouadghiri et al. (2020), Wang et al. (2021) and Liu et al. (2021b) all study the effect of investor sentiment on the returns of clean and dirty energy stocks separately using different proxies to measure investor sentiment. Song et al. (2019) and Reboredo and Ugolini (2018) use the DY framework and find contradicting results. Song et al. (2019) use GSVI as a proxy for investor sentiment towards renewable energy and investigate its connectedness with fossil fuel and clean energy markets for the European, US and global markets. According to their results investor sentiment has dynamic explanatory power for renewable indices to a certain degree, highest for S&PGCE (10.39%) and lowest for ERIX (4.49%). Gao et al. (2021) confirm these results in the Chinese market and find that investor attention substantially affects the green stock market. They also report that the spillover is affected by overall market performance. These results contradict the results of Reboredo and Ugolini (2018) and Liu and Hamori (2021) who find limited explanatory power for their Twitter based investor sentiment measure in predicting renewable energy companies returns. Liu and Hamori (2021) however find that investor sentiment affects the stock market significantly during economic shocks.

Liu et al. (2021b) adopt a more direct way of measuring investor attention by using an index that reflects search volumes for ticker or company name. They find a significant positive relation between green stock returns and dirty energy companies while controlling for general market performance. This finding is in line with existing literature that generally speaking, greater investor attention is associated with better stock performance (Bank et al., 2011). Liu et al. (2021b) further find that on days when pollution is high stock returns of polluting firms are affected negatively. On these days environmental awareness among investors might increase which may explain this negative effect on dirty energy stocks. El Ouadghiri et al. (2020) find evidence that investor sentiment, as measured via GSVI on keywords concerning climate change and pollution, has a significantly positive (negative) effect on clean (dirty) stocks while controlling for the 4 factors of Carhart (1997). Wang et al. (2021) use another proxy for investor sentiment based on online investor reviews and find a significant positive effect on clean stock returns while controlling for the lag return, book to market factor, market value and market beta in order to isolate the effect of investor sentiment.

Prange (2021) also states that online investor attention for stocks, measured by ticker volumes with Google searches, may provide valuable information for the assessment of the co-movement between financial assets. He finds that online investor attention is a statistically significant positive determinant of the time-varying correlations between stocks and several other financial assets. There is however a reversal effect present during times of common shocks to the stock market. This indicates a dynamic relation. Also, the robustness of the results may be questioned as no control variables are incorporated into the model.

2.3.1 Google Search Volume Index

Recently, online search queries have been associated with investors' demand for information (Prange, 2021). The Google Search Volume Index (GSVI) was initially introduced by Da et al. (2011) to directly measure investor sentiment, and has since been widely employed to measure investor sentiment or attention within financial and economic fields (El Ouadghiri et al., 2021; Gupta & Banerjee, 2019; Joseph et al., 2011; Rao & Srivastava, 2013; Vozlyublennaia, 2014). By capturing internet searchers' attention through relevant keywords, the GSVI can directly reflect investor sentiment regarding a given topic (Ji & Guo, 2015). Da et al. (2011) report that GSVI captures investor attention more promptly than existing proxies and it is likely to measure the attention of retail investors. Thus, it can be argued that the GSVI has advantages over alternative sentiment measures such as market- and questionnaire-based indicators which are either indirect proxies or do not classify as real time measures and hence miss practical applications. Additionally, Rao and Srivastava (2013) demonstrate that the GSVI outperforms Twitter sentiment in predicting market indices and commodities. The results of Yuan (2015) add to their finding by providing evidence that GSVI can help avoid errors stemming from indirect proxies, such as news and headlines. This would also explain the differences in results from the studies of Song et al. (2019) and Reboredo and Ugolini (2018).

As noted by Ding et al. (2022) and Kumar et al. (2012) an increase in public environmental attention may raise the environmental awareness of traditional investors and thereby prompt them to invest in clean energy stocks and shift away from fossil fuel investments. Hence attention regarding clean and renewable energy investments increases as well and affects the returns of both the clean and dirty energy markets. The effect on the dynamic correlation has however never been studied before. Given the rapid development and investments in the clean energy sector and its connection to the fossil fuel sector it is essential for investors and policymakers to extend their understanding of the return dynamics between the two and get insight into potential drivers of this interdependency. In this regard, it is interesting to examine the relation of investor attention measured through GSVI on the dynamic conditional correlation among clean and dirty energy markets. Based on previous research it is expected that investor attention concerning the renewable energy market has a positive (negative) effect on the returns of clean (dirty) energy companies indicating a negative effect on the dynamic conditional correlation.

H2: Investor attention measured through GSVI has a negative effect on the time-varying co-movement between the clean and dirty energy market.

2.4 Driving factors behind the co-movement

Few studies dive deeper into the time-varying co-movement between clean and dirty energy markets and examine which macroeconomic factors explain this dynamic conditional correlation. The study of Kocaarslan and Soytas (2019) is the only study that we are aware of at this point in time that can be regarded as closely related to this topic. They use MGARCH models to model the dynamic nature of the relation between clean and dirty energy markets after which they apply various regression models to study the potential drivers. Liu et al. (2021a) only report findings of total market integration among multiple markets and not specifically the time-varying co-movement between clean and dirty energy assets as we are interested in. With this we should interpret their results with caution. Saeed et al. (2021) apply quantile-based VAR models in combination with OLS regressions to study the drivers of connectedness at the mean and tail of the distribution. With their approach, they relate to a certain extent to our study and hence can be used to get insight into driving factors behind the co-movement of clean and dirty energy assets. The same holds for the study of Saeed et al. (2020) who investigate potential drivers of the dynamic hedge portfolio returns constructed on the output of a DCC-GARCH(1,1) model. High correlation translates into lower returns for the hedged portfolio. All of these studies make use of indices and none of them examine the dynamics at the stock level. Within an index movements of the individual stocks' returns may cancel each other out which could lead to making wrong inferences about the existing relations. In addition the study of Saeed et al. (2020) and Liu et al. (2021a) who apply the DCC-GARCH model do not implement an ARMA process for the mean model. This is however recommended in an MGARCH framework when there is evidence of conditional mean effects in the data.

Table 4: Literature overview drivers of co-movement between clean and dirty energy markets

Author(s) (Publication year)	**Method**	**Time period & Frequency**	**Data series**	**Results**
Kocaarslan & Soytas (2019)	DCC-GARCH ARDL model	Daily 1-5-2004 to 18-1-2018	ECO PSE WTI	DEF ** (+) TERM (+) TED * (-) FFR (+) DXY *** (+)
Saeed et al. (2020)	DCC-GARCH OLS on hedge ratio returns	Daily 3-1-2012 to 29-11-2019	ECO WTI IEO	VIX *** (+) OVX *** (-) EPU (+) DXY (-) TERM ** (+) Inflation *** (+)
Saeed et al. (2021)	Quantile-based VAR model for connectedness (DY) OLS	Daily 3-1-2012 to 29-11-2019	ECO Crude oil prices IEO	Dummy2014 (-) OVX (-) VIX * (-) EPU ** (+) PSE *** (-) DXY *** (+) TERM spread *** (-) FFR *** (+)

Liu et al. (2021a)	DECO OLS & Quantile regressions	Daily 1-12-2008 to 8-10-2020	ECO PSE S&P 500 EURO STOXX 50 Brent crude oil prices	VIX *** (+) OVX (-) EPU ** (0) DXY (+) FSI ** (-) TERM (-) DCOVID INT *** (+)

*Note: Only the data series and factors relevant to our research are presented here. This means, dirty and clean energy related equity markets. Default spread is the difference between yields of various debt instruments (DEF), difference between short-term and long-term bonds (TERM), difference between the three-month Treasury bill and the three-month LIBOR (TED), Federal Fund Rate (FFR), US dollar index (DXY), Oil market volatility (OVX), Chicago Board Options Exchange's Volatility Index (VIX), Economic Policy Uncertainty (EPU), NYSE Arca Tech 100 Index (PSE), interaction term for COVID (DCOVID INT). *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.*

2.4.1 Uncertainty measures

Uncertainty in general has a negative impact on firms investments and household consumptions, hence on the behavior of investors as they react to this contraction. It is common knowledge that the equity market underperforms during times of uncertainty. Investors sell their shares which causes an oversupply in the market which results in falling share prices leading to possible negative returns. Therefore it is important to account for uncertainty surrounding certain information (Scotti, 2016).

Stock market uncertainty is measured as the market's expectation of 30-day volatility on a certain index. Because both indices under study are related to the stock market, an increase in equity market uncertainty will result in both returns to decline and hence a positive relation is expected with the dynamic conditional correlation. Research by Liu et al. (2021a) indicates that at lower quantiles the coefficient for the Chicago Board Options Exchange's Volatility Index (VIX) is negative and simultaneously not found to be significant. At the upper quantiles it is positive and significant indicating that during times of high levels of correlation, stock market uncertainty has a bigger impact on the co-movement than at the lower quantiles. While at stable times their correlation decreases. European stock market uncertainty is reflected by the VSTOXX.

According to Saeed et al. (2021), Oil market volatility (OVX) affects the connection between clean and dirty energy investments. It relates to the expected volatility in the oil market for the coming 30-days. Increases in the level of the OVX have an inverse relation with dirty energy stock prices (Ji & Fan, 2016) and this effect is larger compared to the effect on clean energy stocks. Saeed et al. (2020) find evidence for the following rationale: increases in the OVX make investors nervous and therefore they tend to reduce dirty energy positions rather than clean ones. So at the mean of the distribution, the effect of OVX on the DCC should have a negative sign. The results of Liu et al. (2021a) show that at different levels of the co-movement the effect of OVX changes. At the bottom 20% of the dependent variable there exists a positive relation indicating that at low levels of correlation an increase in OVX leads to an increase in correlation. At the 80%-quantile the sign switches to negative meaning that an increase in oil market uncertainty lowers the correlation.

EPU is a newspaper based frequency measure constructed by Baker et al. (2016) which is only available for the US on the daily and weekly frequency. It is based on approximately 1500 US newspapers and for an article to be counted it must contain at least one keyword in each of the three topics related to 'uncertainty', 'economic' and 'policy'. Liu et al. (2021a) study dynamic correlation among different asset classes across the globe, US and Europe and use the US based EPU on all three markets. The rationale behind the use of this US based measure for European assets follows from the fact that the US economy is considered the locomotive for the world economy. In addition, Piljak (2013) states that US macroeconomic factors represent the global economy, which Europe is part of. High levels of EPU are associated with lower returns for crude oil (Aloui et al., 2016), hence reducing the profits for oil companies. Equity returns are also found to be negatively related to increasing levels of EPU (Brogaard & Detzel, 2015). As a result, we anticipate a positive sign for the EPU on the level of dynamic correlation.

Kocaarslan and Soytas (2019) are the first to analyze the effect of the US dollar index (DXY) on the time-varying correlation using an autoregressive distributed lag (ARDL) model for the US market. The DXY measures the performance of the US dollar against six major currencies: the Euro, the Swiss franc, the Japanese yen, the Canadian dollar, the British pound, and the Swedish krona. While accounting for DEF, TERM, TED and FFR they find a significant positive relation for the DXY indicating that this drives the co-movement between Eco, PSE and WTI. Thereafter, other studies (Liu et al., 2021a; Saeed et al., 2020, Saeed et al., 2021) all incorporate the DXY in their analysis and find a positive relation on the dynamic co-movement and connectedness, except the study of Saeed et al. (2020) who study hedge ratios. Two possible reasons for the dollar to appreciate are times of lower economic prospects outside of the US or when global uncertainty rises. Due to the safe haven perception of the US dollar among investors the demand for the dollar may rise, resulting in an appreciation of the dollar (Brunnermeier & Pedersen, 2009; Maggiori, 2017). An appreciating dollar therefore shifts away demand for risky assets such as clean energy stocks and prices go down (Kocaarslan & Soytas, 2019). From a dirty energy perspective the following can be argued. An appreciating US dollar implies low economic activity resulting in a demand reduction for oil, oil prices will fall, hence profits of oil companies will reduce lowering the stock price. Based on this mechanism it is expected that there exists a positive relation between the DXY and the dynamic conditional correlation between clean and dirty energy markets.

Existing literature suggests that financial shocks affect the time-varying relation among oil and stock markets (Smyth & Narayan, 2018; Martín-Barragán et al., 2015). Tang and Aruga (2022) and Ghosh et al. (2023) showed the impact of COVID-19 on respectively the dynamic correlation and connectedness among the clean and dirty energy sectors. During the pandemic, business cycle and uncertainty measures rose which are reported to significantly affect the time-varying relation between clean and dirty energy markets. However, they did not account for macroeconomic factors that already drive the dynamics in co-movement. Due to this their results may not be accurate or trustworthy as there are no other variables that could have explained the variance in the data.

2.4.2 Business cycle measures

The TERM spread serves as a proxy for short-term business conditions indicating recession probabilities. Increasing TERM spreads indicate a shift towards long term investments which point towards growth prospects as investors only want to invest long term if economic conditions are certain (Greenwood & Vayanos, 2014; Löffler et al., 2021). Hence boosting the performance of growth stocks. The price of clean energy stocks, which are characterized as growth stocks, are expected to rise. At the same time, favorable long term economic conditions are associated with higher economic activity rising the demand for oil. It is expected that during periods of increasing TERM spread DCC increases as well, hence a positive relation is expected.

Gross domestic product (GDP), the three-month interbank interest rates (IIR), Consumer price indices (CPI) and the industrial production indices (IP) tend to proxy the business cycle, hence previous research incorporates them in their analysis to explain co-movement between markets (Pham et al., 2021; Piljak, 2013). However, measuring the business cycle is complex and is best captured by the dynamics between multiple macroeconomic variables (Lucas, 1977). The Aruba Diebold and Scottie index (ADS) (Aruoba et al., 2009) is created specifically to cater this need. It takes into account the dynamics between the term premium, unemployment insurance, employees on non-agricultural payrolls and GDP due to their strong cyclical behavior. Berge and Jordà (2011) study which business cycle measure is best at capturing the unobservable state of the business cycle. Their results show that the ADS index accurately captures the current state of the business cycle. The ADS index is regularly used as proxy for economic activity (Andreou et al., 2013; Fei et al., 2012; Diebold, 2020). This index is however not available for the European market. Based on the same argument as for the EPU, this US measure can be used to explain the dynamic conditional correlation for European based stocks. During times of recessions the ADS index decreases and falls out of pattern. It is at these times that we expect the DCC to increase therefore an inverse relation is expected and a negative sign is anticipated.

2.4.3 Monetary conditions

The monetary policy measure that is used by Kocaarslan and Soytas (2020) and Saeed et al. (2021) is the US Federal Fund Rate (FFR) which accounts for interest rate impacts. An increase in FFR indicates a contractionary monetary policy which slows down economic activities. This can be due to three reasons: 1) rising interest rates, 2) increasing banks' reserve requirements or 3) selling government securities. It is common knowledge that interest rates have an inverse impact on stock prices. Accordingly, investments in the equity market become less appealing resulting in an increase in correlation, thereby a positive relation is expected for a monetary policy measure.

The relations between macroeconomic variables and the co-movement of clean and dirty energy markets may vary across different levels of the DCC distribution. The following is therefore hypothesized.

H3: The effect that the explanatory variables have on the DCC changes over the various quantiles of the distribution of the return correlation.

The literature review points out some interesting findings that can be summarized as follows. Green stocks have been outperforming[1] brown stocks for the last decade potentially due to increasing concerns over climate change. Drivers of the time-varying co-movement between clean and dirty energy markets remain understudied, especially in the European market and is limited to macroeconomic features. In addition, only the co-movement between market indices is studied and no research has been conducted on the stock level. To the best of our knowledge, no study has been conducted that examines the effect of investor attention as measured through GSVI on renewable energy on the time-varying co-movement between clean and dirty energy markets while controlling for macroeconomic variables and incorporating a behavioral perspective.
Control variables that have to be taken into account are summarized below in Table 5.

Table 5: Anticipated effect of control variables on the DCC

Increase in explanatory variable	**Anticipated effect on co-movement**	**Rationale behind relation with co-movement**
VSTOXX	Increase	Investors close out on risky positions lowering returns.
EPU	Increase	Lower returns for crude oil and equity market assets.
OVX	Decrease	Effect on dirty energy stocks is larger compared to clean energy stocks.
ADS	Decrease	Good business conditions have a bigger impact on clean energy investments.
FFR	Increase	Contractionary monetary policy slows down economic activities.
TERM	Increase	Favorable long term economic conditions rising oil demand and investments in growth stocks
DXY	Increase	Low economic activity decreasing oil demand and equity market investments.

Note: Expected effect on DCC between clean and dirty energy assets at the median of the distribution. European stock market uncertainty (VSTOXX). Economic policy uncertainty (EPU). Oil market uncertainty (OVX). Aruba Diebold and Scotti business cycle measure (ADS). Federal Fund Rate (FFR). Difference between 3-month treasury bond yield and 10-year treasury bond yield (TERM). US dollar index (DXY).

[1] Based on existing literature for the period before the Russian Ukraine war.

3 Data

3.1 Return series

The European Renewable Energy Index (ERIX) and MSCI Europe Energy Index (EUR) are used to track the performance of respectively the clean- and dirty energy sector. Daily price data for the indices as well as the underlying stocks composing the index are retrieved from Datastream for the period ranging from the 1st of January 2012 to the 30th of April 2023 and expressed in Euros, leaving us with 2889 observations per time series. Stock price data for Siemens Gamesa Renewable Energy (SGRE) is not available via Datastream or Bloomberg and is therefore left out. ERIX comprises ten European companies operating in the renewable energy sector. These companies are selected based on their involvement in one or more of the following investment clusters: biofuels, geothermal, marine, solar, water and wind. For potential inclusion in the index the company must generate their biggest share of revenue from one or several of these areas. The EUR tracks the performance of 11 large and mid-cap European equities in the oil and gas sector in developed markets. Returns of the ERIX and EUR indices are constructed as $\log\left(\frac{P_t}{P_{t-1}}\right)$, where P_t represents the daily closing price in period t.

From Figure 1 one can see periods of certain co-movement and periods at which the returns tend to move in the opposite direction. Also, the magnitude of the effect may differ from period to period. The oil crisis of 2014-2016 is clearly visible in the return series and both series are prone to shocks reflected in the clear periodic drops in returns. A clear co-movement pattern is noticeable during the COVID pandemic whereas the series tend to move in the opposite direction during the Russian invasion of Ukraine.

Figure 1: Normalized Cumulative return series ERIX and EUR

Note: Blue line ERIX, Green line EUR. Cumulative return is calculated as $R_t = R_{t-1} * (1 + R_t)$. Return series are normalized by min max scoring as the series have very different ranges of cumulative returns which makes comparing difficult. The cumulative return series for ERIX varies between 1 and 6 indicating a peak of 500% return on investment and EUR between 0.3 and 1.1. For individual cumulative return series see Appendix A Figure 5.

3.2 GSVI

This study uses the daily Google Search Volume Index (GSVI) to measure worldwide investor attention on renewable stocks. Within the literature the most direct way of measuring this is via ticker searches however this does not apply to the ERIX as it results in low data quality. Therefore the suggested keywords of Song et al. (2019) are used as the best available proxy for investor attention regarding renewable energy stocks. The keywords related to renewable energy in Google trends are: ‘renewable energy’, ‘solar energy’ and ‘wind energy’. An additional keyword is added to this, namely ‘clean energy’ because the terms renewable and clean energy are seen as synonyms of each other and used interchangeably (Shinn, 2022). By using these keywords a behavioral perspective is incorporated to approximate investor attention (Da et al., 2011). To ensure that our designated keywords are associated solely with financial requests, we utilize the exclusion feature within Google Trends’ settings to remove any queries that are not related to the financial domain from our data.

Google Trends assigns a value ranging from 0 to 100 based on the relative frequency of search queries over a specific time period and region. Google Trends excludes repeated searches from the same user over a short period of time for greater accuracy. Google continues to be the most favorite search engine around the world accounting for 92.9% of the market share as of January 2023 (Statcounter, 2023), except for the Chinese market. According to the data of Statcounter global database in January 2023, the Baidu search engine occupied 65.2% of the Chinese market share, much higher than Google which accounts for 2.4% of searches in the Chinese market. Due to this, we can postulate that Chinese investor attention is not well represented in the GSVI statistics. This has implications for the generalization of the results for the global investor. The market share of the Google search engine has been steady over the years from 2009 to 2023 while the number of searches grew rapidly from 3.5 billion searches per day in 2012 (Search Engine Land, 2012) to almost 8.5 billion daily searches as of 2023 (Oberlo, 2023). The volume of searches needs to be large enough for it to be economically significant. To overcome the possibility that the GSVI is based on too few searches we use data ranging from the 1st of January 2012 to the 31st of March 2023.

As we are interested in a daily time series spanning over roughly 12 years and Google trends does not provide data on the daily frequency for data requests exceeding 270 data points we need to convert multiple series into a coherent time series. The algorithm of Bleher and Dimpfl (2019) is used to convert the time series to the daily frequency which makes use of 30 overlapping data points to estimate a linear regression and knit the estimated separated data sets together, see Appendix B.

3.3 Control variables

Following previous studies six explanatory variables are selected based on their availability at the daily frequency, significant relation and presence in at least two papers: the US dollar index (DXY), term spread (TERM), European equity market volatility index (VSTOXX), Economic Policy Uncertainty (EPU), Fed Fund Rate (FFR) and Crude Oil ETF Volatility Index (OVX). In addition to this, the ADS index created by Aruba, Diebold and Scotti (2009) is added. The selected variables account for business cycles, monetary conditions, and uncertainty.

The VSTOXX is used which measures uncertainty based on EURO STOXX 50 real-time options prices. The CBOE Crude Oil ETF Volatility Index (OVX) is a forecast of crude oils 30-day volatility as priced by the United States Oil Fund (USO) and used to proxy oil market uncertainty. The US EPU is used as this is the only metric available at the daily frequency. The TERM spread is captured by subtracting the 3-month treasury bond yield from the 10-year treasury bond yield. US dollar index (DXY) is used to measure global uncertainty by appreciation or depreciation in the dollar value against major currencies. Single macroeconomic variables are often measured on frequencies lower than the daily frequency and hence cannot be used during our analysis. The ADS index resolves this issue and provides a metric for the business cycle on the daily frequency. The European equivalent for the FFR, the LIBOR discontinued in 2022 which brings data availability limitations; hence the Federal Fund Rate (FFR) is used as a proxy for the European monetary policy market. Data for VSTOXX, OVX and DXY is sourced from Datastream, EPU and FFR are obtained from the Federal Reserve Bank of St. Louis, and lastly data for the ADS index is sourced from the Federal Reserve Bank of Philadelphia.

3.4 Statistics

Return series are known for their low mean-variance ratio which is also the case for our data, see Table 6. Also the returns tend to be widely spread with heavy outliers. The Augmented Dickey-Fuller (ADF) test results for unit root of all series except TERM and DXY show that the null hypothesis of non-stationarity is rejected at a 5% level of significance.

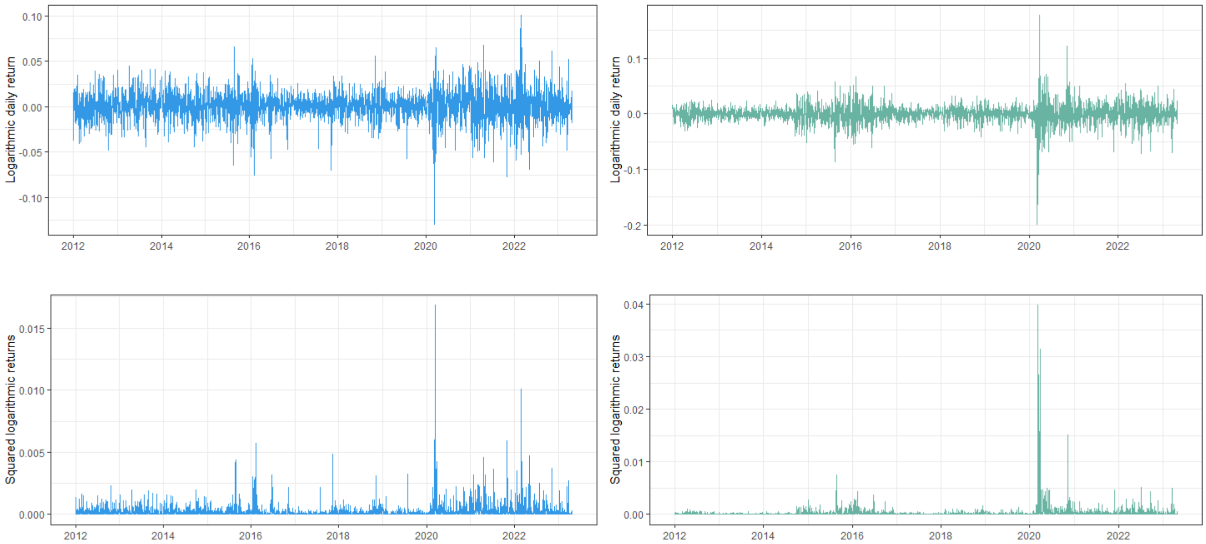
Table 6: Summary statistics and test results indices and explanatory variables

	ERIX Return	**EUR Return**	**VSTOXX**	**EPU**	**ADS**	**OVX**	**FFR**	**TERM**	**DXY**	**GSVI**
mean	0.00056	0.00001	20.99	118.67	-0.19	37.75	0.84	1.03	92.83	22.31
sd	0.016	0.016	6.98	86.23	2.62	18.17	1.10	0.66	7.87	16.49
median	0.0009	0.0003	19.79	94.65	-0.12	34.67	0.16	1.04	94.68	21.00
min	-0.130	-0.199	10.68	3.32	-26.49	14.67	0.00	-0.59	78.27	0.00
max	0.100	0.177	85.62	807.66	9.14	234.66	4.83	2.78	114.11	151.00
skew	-0.257	-0.605	2.34	2.52	-6.36	4.13	1.70	0.30	-0.26	1.06
kurtosis	3.96	18.62	12.62	9.27	58.97	29.09	2.55	-0.56	-0.60	2.73
ADF	0.010***	0.010***	0.010***	0.010***	0.010***	0.023**	0.99	0.266	0.578	0.010***

*Note: ADF test with lag length of 14. ARCH test with 12 df. Ljung-Box test with 10 df. Jarque-Bera test with 2 df. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.*

A financial time series is usually characterized by its non-normal distribution and the series clearly exhibit volatility clustering with the presence of ARCH effects (Tsay, 2005). When a series exhibits varying levels of volatility throughout time the use of a homoscedastic model leads to suboptimal results. In this case, Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are encouraged to be used to study the dynamic conditional correlation between the clean and dirty energy indices (Andersson- Säll & Lindskog. 2019; Kocaarslan & Soytas. 2019). The statistical characterizations of the return series are examined and presented in Appendix E Table 10. Skewness and kurtosis for the returns series indicate non-normal distributions as these are respectively negative and bigger than three. This non-normality property is supported by the Shapiro-Wilk (SW) and Jarque-Bera (JB) test results that reject the null hypothesis of normality. As the return series are stationary the Engle's Lagrange multiplier (LM) test can be applied (Engle, 1982) which indicates the presence of ARCH effects for the return series. For robustness, to show the presence of ARCH effects the squared residuals from a mean model are tested on serial autocorrelation. Based on the Akaike Information Criterion (AIC), the mean models ARMA(5,3) and ARMA(2,1) are fitted on respectively the ERIX and EUR series, see Appendix E Figures 7 and 8 for model diagnostics. The (P)ACF plots, Appendix C Figure 9, of squared residuals show significant lags and indeed ARCH effects are present according to the Ljung-Box test that rejects the null hypothesis of no autocorrelation at a 1% confidence level. This encourages us to model the volatility, Figure 2.

Figure 2: Returns and squared returns ERIX and EUR



Note: Blue ERIX, Green EUR. The squared residuals show some periods of high peaks that persist for a short time indicating the presence of an ARCH effect.

The explanatory variables that are being transformed with the first order difference according to their stationarity properties are FFR, TERM, DXY and ADS. This results in diffFFR, diffTERM, diffDXY and diffADS for variable abbreviations. Graphical representation of the explanatory variables can be found in Appendix D Figure 10. A static correlation analysis and stepwise VIF selection procedure among the transformed explanatory variables indicate no signs of multicollinearity with a threshold value of 2.5, see Table 9 of Appendix D for the correlation matrix.

4 Method

To come up with an answer to the hypotheses a framework consisting of two steps is adopted. First a DCC-GARCH model is estimated on the returns of the clean and dirty energy assets after which quantile regressions are applied to examine the effect of investor attention on this dynamic and whether there are differences to be observed at the different levels of the distribution.

4.1 Hypothesis 1 – DCC-GARCH model

To investigate whether there exists a time-varying relation between the ERIX and EUR index returns the DCC-GARCH model proposed by Engle (2002) is applied. As argued by Engle (2002), the DCC-GARCH model accounts for heteroscedasticity in a direct way by measuring the correlation coefficient on standardized residuals and hence the heteroscedasticity bias is avoided (Forbes & Rigobon, 2002; Le & Tran, 2021) resulting in no bias from volatility. The DCC-GARCH model from a bivariate perspective is denoted by:

$$H_t = D_t R_t D_t \tag{1}$$

$$D_t = diag\left[\sqrt{h_{1t}}.\sqrt{h_{2t}}\,\right] \tag{2}$$

$$R_t = diag[Q_t]^{-\frac{1}{2}}\,Q_t\;diag[Q_t]^{-\frac{1}{2}} \tag{3}$$

where H_t Equation (1) is the conditional covariance matrix. The diagonal matrix of time-varying standard deviations from the univariate GARCH models is denoted by D_t Equation (2). R_t, Equation (3), is the (2x2) time-varying correlation matrix. Before one can estimate H_t, univariate GARCH models are fitted for each of the return series resulting in estimates of the conditional variance, D_t. Thereafter correlations are estimated resulting in estimates for R_t.

A GARCH(1,1) model is depicted by Equation (5). The residuals from Equation (4), u_t, are input for Equation (5) and are obtained from estimating the returns with a mean model, μ_t, according to an ARMA process. For simplicity we assume that u_t follows a normal distribution.

$$r_t = \mu_t + u_t. \tag{4}$$

$$h_t = \omega_0 + \alpha u_{t-1}^2 + \beta h_{t-1} \tag{5}$$

ω_0 is a constant term, u_{t-1}^2 is the lag of the squared residuals indicated as the ARCH term, h_{t-1} is the lag of the conditional variance indicated as the GARCH term, α and β measure these ARCH and GARCH effects respectively. Estimates of $\sqrt{h_{it}}$, the conditional standard deviations, are obtained. During the second step the DCC parameter is estimated, R_t, for which Q_t serves as input.

$$Q_t = (1 - a - b)\bar{Q} + a u_{t-1} u_{t-1}^T + b Q_{t-1} \tag{6}$$

a and b are non-negative scalars that have to satisfying $a + b < 1$ to ensure stationarity and positive definiteness of Q_t. If this is the case, there exists a time dependent relation. $\bar{Q}$ is the unconditional variance matrix of standardized residuals u_t obtained from the GARCH models. From this the DCC series can be obtained from Equation (7).

$$\rho_t = \frac{Q_{12.t}}{\sqrt{Q_{11.t}Q_{22.t}}} \tag{7}$$

The residuals of the univariate GARCH models are evaluated on serial autocorrelation with the Ljung-Box test. If either one of the models exhibits serial autocorrelation the model does not adequately capture the information present in the return series and hence the DCC-GARCH model cannot be regarded as adequate.

4.2 Hypotheses 2 and 3– Quantile regressions

Whether investor attention measured through GSVI has a negative effect on the DCC between clean and dirty energy assets at the median of the distribution, a quantile regression approach is adopted. In addition, this method allows us not only to examine the relation at the median but also at the various quantiles of the return correlation. With this we can answer hypothesis 3, whether the effect that the explanatory variables have on the DCC changes over the various quantiles of the distribution of the return correlation. This has implications for portfolio managers as this gives more insight into how particular relations evolve. This method was proposed by Koenker and Bassett (1978) and in its most basic form is expressed as a linear relation between independent variables and a specified quantile of the dependent variable. The main benefit of quantile regression over OLS regression is that it can estimate the coefficients in the presence of skewness, heteroskedasticity and outliers (Yahya et al., 2023). At the τ^{th} conditional quantile of the DCC distribution the regression equation is denoted as:

$$Q_{DCC_t|X_t}(\tau) = X_t\beta(\tau) + \varepsilon_t \tag{8}$$

Where $Q_{DCC_t|X_t}(\tau)$ denotes the τ^{th} conditional quantile of the time-varying correlation obtained from the DCC model Equation (7), X_t is a vector containing the intercept and explanatory variables; GSVI, VSTOXX, EPU, OVX, diffDXY, diffTERM, diffFFR, and diffADS. The coefficients at quantile τ are denoted by $\beta(\tau)$ and estimated by minimizing the weighted absolute deviation as follows:

$$\beta(\tau) = \min\left(\tau \textstyle\sum_{DCC_t > X_t\beta'(\tau)} |DCC_t - X_t\beta'(\tau)| + (1-\tau) \sum_{DCC_t < X_t\beta'(\tau)} |DCC_t - X_t\beta'(\tau)|\right) \tag{9}$$

When estimated coefficients change over the various quantiles of the distribution one can postulate that the existing relation is dynamic of nature. Koenker and Machado (1999) describe R^1 as a local measure of goodness of fit at the particular quantile which is the natural analog of the familiar R^2. It is defined as $R^1(\tau) = 1 - V(\tau)/\hat{V}(\tau)$, where $V(\tau)$ corresponds to the error terms of the unrestricted quantile regression model at quantile τ Equation (8) and $\hat{V}(\tau)$ are the error terms of a restricted quantile regression model at quantile τ that only includes an intercept.

As for the control variables, they do not have to be statistically significant as the primary purpose is to account for any confounding variables that could affect the relation of interest. Therefore, it may be crucial to include a control variable in the model even if it is not statistically significant in order to obtain accurate and unbiased estimates of the regression coefficients of the relevant independent variables.

4.3 Robustness checks

Two robustness checks are performed in order to verify the empirical results. The first one relates to the unit of analysis being individual stocks and the second robustness check relates to the sample period.

Individual stocks

Because an index tracks the performance of an aggregation of different stocks, price fluctuations of underlying stocks may cancel each other out. To eliminate this effect the DCC-GARCH and quantile regression analyses are performed at the individual stock level, something that has never been done within the literature. The search terms used that make up the GSVI remain the same. This way results can be compared with the index-level analysis.

Time-varying dynamics

The magnitude and direction of relations found with the DCC may vary across time. Gao et al. (2021) and Pham and Huynh (2020) both find evidence for this time-varying behavior. Whether the results change due to differences in sample period is examined by conducting the quantile regressions analysis on three subsamples; 1) January 2012 to March 2016, 2) April 2016 to October 2019 and 3) November 2019 to April 2023. The first period covers the aftermath of the financial crisis of 2008 and includes the oil crisis. The second period characterizes itself as the recovery of oil crisis and signing of the Paris agreement. However, the five years after the Paris agreement the average growth rate in clean energy investment was just over 2% (IEA, 2022). The final period is marked by increasing political will, cost-competitiveness of renewables with fossil fuels and awareness among consumer that demand the transition as they are voting with their feet (IEA, 2022). During this period the average annual growth rate of renewable investments has risen to 12%.

5 Results

5.1 Hypothesis 1: Time-varying co-movement ERIX-EUR

Due to numerical challenges in the estimation process of the multivariate model parameters GARCH (1,1) is utilized. To fit the DCC-GARCH(1,1) model a mean and variance model need to be estimated. As discussed in Chapter 3 the mean models are reflected by ARMA(5,3) and ARMA(2,1) for respectively the ERIX and EUR. Based on the AIC score an ARMA(3,4) and ARMA(5,5) model is obtained as variance model for ERIX and EUR respectively, for model diagnostics see Appendix E Figures 11 and 12. The Ljung-Box test reveals no autocorrelation in residuals of the variance models indicating a good model fit. See Figures 10 and 11 of Appendix E for model diagnostics of the fitted DCC-GARCH(1,1) model. The individual GARCH series fulfill the criteria that $\alpha + \beta < 1$ this holds for ERIX as well as EUR. In addition it holds that $a + b < 1$ which indicates that dynamic correlation is present. All α and β coefficients are greater than 0. The univariate GARCH series show no presence of serial autocorrelation in residuals, therefore the model is adequate. Hence there is substantial time-varying co-movement between the log returns of the ERIX and EUR index and we accept hypothesis 1. We will not go into further detail on the estimated coefficients as this is beyond the scope of this research. The primary objective is to extract the DCC series according to Equation (7) and analyze the time-varying behavior in relation to investor attention and macroeconomic variables.

Figure 3: DCC between ERIX-EUR

Also, Figure 3 clearly shows evidence of time-varying correlation between the ERIX and EUR with an average correlation of 0.38. The correlation varies between -0.02 and 0.75. It peaked during October 2015 and during the beginning of the COVID-19 pandemic in March (0.72) it almost hit the same level, attributable to temporary declines in stock prices. A trough is noticed in December and late January just before the COVID19 pandemic. The high co-movement during late 2014 comes from poor stock performance on Asian markets that triggered herd behavior among investors. As there is more uncertainty in the financial market, oil prices crashed, and equity indices declined which resulted in increased co-movement between the indices. In 2016 the oil sector benefitted from the agreed upon OPEC deal to tackle worldwide oil glut which led to confidence in the market. During the pandemic, both sectors experienced a sharp decline but the clean energy sector experienced a fast recovery while the oil sector lagged behind and never fully recovered from it resulting in a sharp decrease in co-movement and low dynamic correlation for over a year. During this period awareness over climate change grew which spurred clean energy investments while simultaneously the economy was down which had a big impact on the fossil fuel sector as there was less demand for oil. The period after February 2022 is characterized by high volatility in the DCC. Following the Russian invasion of Ukraine in February 2022 correlation dropped sharply due to stronger returns for clean energy stocks over fossil fuel stocks. Because Russia is a major supplier of oil to Europe there was increased uncertainty about the energy security, this led to extra attention for diversifying the energy supply with renewable and clean energy sources spurring the demand for clean energy stocks. In line with the findings of Bauer et al. (2023) the fossil fuel sector outperformed the clean energy sector during the period after the Russian invasion of Ukraine but there are still short periods to be observed were the clean energy sector outperforms the fossil fuel sector resulting in a decrease in correlation. This contradicts their suggesting that preferences for green assets have declined to some extent. One of those periods is the gas cut off from Russia to Europe in June that decreased correlation sharply from 0.4 to 0.05. At first, investors were uncertain about how this would affect the oil market and people turned to alternative sources of energy generation as energy still needs to be provided. This resulted in a decrease (increase) in returns for the fossil fuel sector (clean energy sector). Soon after, oil was seen as a scarce product still in high demand and with limited supply, this caused a sharp rise in oil prices. This was amplified by the arrival of winter which inherently stands for more energy consumption.

These results contradict the general assumptions stated in the literature on the luxury nature of green investments and their underperformance during crisis periods (Dreyer et al., 20223; Bauer et al., 2023). Clean- and renewable energy sources are becoming more prominent and are replacing traditional sources of power generation as a result of the COVID pandemic and the ongoing conflict in Russia and Ukraine. Whereas COVID has raised awareness on climate change, The war has emphasized the necessity of the energy transition even more to find alternatives to fossil fuels, primarily oil where Europe depends on Russia, to diversify and reduce the energy security risk.

Overall it looks like the correlation series can be split up into three sections regarding the range it fluctuates between. The first period comprises of January 2012 up to November 2016 with a range of 0.25 to 0.6. Thereafter the correlation fluctuates between 0.15 and 0.5 for the period December 2016 to October 2019. The last period seems to have started from the beginning of COVID-19 where the correlation pattern seems to recover between the limits of 0.05 and 0.45.

5.2 Hypothesis 2 & 3: Quantile regression ERIX-EUR

A quantile regression approach is used to answer hypotheses 2 and 3. Quantile regressions are estimated according to Equation (8) for the DCC between ERIX and EUR at the following quantiles of the co-movement of returns distribution indicated by τ; 0.10, 0.20, 0.50, 0.80 and 0.90. See Appendix F Figure 14 for a graphical representation. The one day lagged value of DCC (DCC_{t-1}) is added as extra explanatory variable during the quantile regression analysis due to the presence of serial autocorrelation in the errors of the quantile regressions at each quantile violating the independency property, see Appendix F Table 12. Results of the corrected quantile regressions that take DCC_{t-1} into account are presented in Table 7. These results show no signs of autocorrelation in residuals indicated by the Ljung-Box test at 5% confidence level. As tested in Chapter 3, there are no signs of multicollinearity between the explanatory variables, Appendix F Table 9. For answering hypothesis 2, whether investor attention measured through GSVI has a negative effect on the time-varying co-movement between the clean and dirty energy market, we look at the estimates of the quantile regression at the median of the DCC distribution, τ equal to 0.5.

Table 7: Quantile regressions ERIX-EUR

Coefficient	$\tau = 0.1$	$\tau = 0.2$	$\tau = 0.5$	$\tau = 0.8$	$\tau = 0.9$	***Anticipated effect on DCC***	***Found relation at*** $\tau = 0.5$
Intercept	-0.008*	-0.001	0.007***	0.012***	0.024***		
VSTOXX	0.0002	0.0001	0.0001***	0.001***	0.001***	+	+
EPU	0	0	0	0*	0	+	-
OVX	0	0	0	-0.00008**	-0.0002**	-	-
diffADS	0.007	0.003	0.002*	0.004	0.005	-	+
diffFFR	0.001	0.001	-0.003	-0.014	-0.011	+	-
diffTERM	-0.007	-0.008	0.001	0.022*	0.024	+	+
diffDXY	-0.003	-0.002	0.0002	0.0012	-0.001	+	+
GSVI	-0.00024***	-0.00013**	-0.00002**	-0.00007	-0.0002**	-	-
DCC_{t-1}	0.974***	0.972***	0.968***	0.951***	0.932***		
R^1	0.86	0.89	0.90	0.87	0.84		
Ljung-Box test	0.618	0.911	0.992	0.304	0.1		
Obs.	2888	2888	2888	2888	2888		

Note: Graphical representation of quantile lines in DCC plot for ERIX-EUR can be found in Appendix F Figure 13. European stock market uncertainty (VSTOXX). Economic policy uncertainty (EPU). Oil market uncertainty (OVX). First order difference Aruba Diebold and Scotti business cycle measure (diffADS). First order difference Federal Fund Rate (diffFFR). First order difference between 3-month treasury bond yield and 10-year treasury bond yield (diffTERM). First order difference US dollar index (diffDXY). 3-day SMA Google Search Volume Index (GSVI). One day lagged value DCC (DCC_{t-1}*)* R^1 *goodness of fit. Ljung-Box test shows no signs of first order autocorrelation in error terms (reported p-value). *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.*

Looking at the median, τ equal to 0.5, several findings stand out. First of all the biggest effect is noticed for the previous day DCC value which is close to 1 suggesting that one can best explain the time-varying co-movement according to the value of yesterday, indicating an AR(1) model. However, the significance of the GSVI coefficient at 5% confidence level indicates that investor attention has explanatory power as well. The negative sign is as hypothesized meaning that higher levels of investor attention regarding renewable- and clean energy lowers the co-movement of returns, hence H2 is accepted. Potentially due to divestments in fossil fuel stocks and investments in clean energy stocks. This reasoning is in line with El Ouadghiri et al. (2020) and Pástor et al. (2022). Yet, with an estimated coefficient of -0.00002 and the value of GSVI ranging between 0 to 105 with a mean of 22.3 there is no economic importance. The GSVI needs to reach a value of 500 in order to lower the DCC by 0.01, all else equal. So the impact of investor attention at the mean of the distribution of the dynamic conditional correlation between ERIX and EUR is very limited. In addition, at 10% confidence level the control variables VSTOXX and diffADS show a significant estimation but the economic importance compared to the economic importance of DCC_{t-1} is rather small. When taking the range a variable fluctuates between into account, diffADS seems most important in explaining the DCC while diffDXY, diffTERM and diffFFR have the least impact. However, the significance level of 10% for diffADS is not very sufficient and can be explained by the fact that the ADS index sharply declined during the beginning of COVID after which it quickly increased to a new all-time high. The model tries to capture this effect as otherwise the errors are counted heavily in the loss function. This suggests that the diffADS variable only captures the effect that COVID had on the DCC, all else equal. Regarding the direction of the effects we observe an opposite sign as expected for EPU, diffADS and diffFFR. The validity of these estimated coefficients with their corresponding signs can be questioned as they are all not statistically significant at 5% level. For control purposes it is recommended to keep them in the model although they do not add significant value.

Next, we move to the drivers of dynamic conditional correlation across lower and upper quantiles in order to provide an answer to hypothesis 3, whether the effect that explanatory variables have on the DCC changes over the various points of the distribution of the return correlation. The results of Table 7 show some interesting findings starting with the fact that the magnitude and direction of the coefficients is not uniform across the quantiles. Equity market uncertainty, oil market uncertainty and investor attention show significant effects on the DCC at 5% confidence level. OVX and VSTOXX have the biggest impact on the DCC at the 80% and 90% quantiles. The impact of GSVI on explaining the co-movement of ERIX and EUR returns is increasing and statistically significant when moving away from the median quantile. At the lowest and highest quantile, the coefficients are -0.00024 and -0.0002 respectively. This yields that all else equal, a 0.01 decrease in DCC is established with a value of 42 and 50 for GSVI indicating some degree of economic significance. The magnitude of impact that the equity market uncertainty and oil market uncertainty have on the DCC increases as we move away from the median quantile, $\tau = 0.5$, to the upper quantile. In this regard, it may be claimed that the macroeconomic environment during recessions has a greater impact on the pattern of the dynamic correlations than it does during stable times, a finding that is supported by Kocaarslan and Soytas (2019) and Saeed et al. (2021). To our surprise EPU, diffADS, diffFFR, diffTERM and diffDXY show no statistically significant effect for any quantile at a 5% confidence level. There is no economic significance either for these variables. The direction of the effects for increasing business conditions represented as an increase in TERM spread and decreases in US dollar value changes are however similar to what Kocaarslan and Soytas (2019) found at the mean of the dependent variables' distribution. This gives us confidence that these variables correctly capture some part of the variance in the data and including them as control variables is useful. That economic policy uncertainty EPU is not found to be significant which may be due to the following. EPU has a negative effect on R&D investments (MengDie, 2023) and hence on the returns of clean energy firms as they rely heavily on R&D. However, subsidy moderates this effect in a positive sense indicating that subsidies alleviate this effect. As the clean energy market is heavily subsidized the impact of EPU on clean energy returns may be tempered and hence the effect on the DCC may cancel out.

Apart from this, in line with the findings of Saeed et al. (2021) the OVX shows a change in sign of the coefficient from zero (positive) to negative at the upper quantiles which is statistically and economically significant. When oil market uncertainty is high investors tend to close out positions that are exposed to this risk, e.g. oil and fossil fuel stocks. Simultaneously, there tends to be an increase in stock prices of clean energy firms resulting in a decrease in conditional correlation as these asset classes are seen as substitutes (Sadorsky, 2012; Saeed et al., 2020; Dutta, 2017). As a result of COVID the economy was halted to a complete stop resulting in an increase of oil market uncertainty as never seen before while the clean energy sector flourished resulting in a negative effect on the co-movement. Lastly, the impact of the previous day correlation slightly decreases, while the impact of all other variables increases when moving to the upper quantile, $\tau = 0.9$. This dynamic shows that during times of high co-movement macroeconomic variables and investor attention become more important in explaining this co-movement behavior.

As expected, our findings demonstrate that higher levels of investor attention are to some extent related to a decrease in correlation which is in line with Prange (2021) and Song et al. (2019). The impact is greater at the upper and lower quantile of the distribution. During periods of common shocks, when the correlation is at its upper quantile, we do observe an amplification effect which is contrary to the findings of Prange (2021) who finds evidence for a reversal. This may be due to the way investor attention is measured as we adopted a more behavioral perspective. It is at the COVID period, where correlation is at its highest quantile, that the effect of investor attention is more pronounced. During this period public awareness about climate change and global warming increased, resulting in increased investor attention concerning clean investments which has a positive (negative) effect on clean (dirty) stocks (El Ouadghiri et al., 2020). This finding is also in line with Liu and Hamori (2021) and Gao et al. (2021) who indicate that investor sentiment significantly affects the stock market during economic events. The stronger negative effect at the lowest quantile indicates that investor attention regarding clean energy investing has an even bigger impact on decreasing the dynamic correlation resulting in more diversification benefits. In addition, higher levels of stock market uncertainty increase the level of dynamic correlation between the European clean energy and fossil fuel indices. Thus reducing the hedging potential. Increases in oil market uncertainty on the other hand decrease the level of correlation as expected. The impact of oil market uncertainty is higher than the impact of investor attention which is in line with the findings of Song et al. (2019) that indicate that the oil market is more strongly connected to the renewable energy market compared to their used investor sentiment index.

Some differences with existing literature are also noted. We find a positive relation for the equity market uncertainty measure, VSTOXX, at the median of the conditional correlation distribution were Saeed et al. (2021) find a negative impact for US stock market uncertainty measured by the VIX. When we substitute the VIX for VSTOXX, our results do not change and the positive relation remains. Showing robustness of our results and points to possible differences between the the US and European clean energy market. Kocaarslan and Soytas (2019) report that changes in the US dollar value have the highest importance in driving the co-movement between oil and US clean stocks, an effect that we do not observe for the co-movement between the European clean and fossil fuel sector. We do however observe a stronger impact of US dollar value changes on the co-movement in the 80% quantile, τ equal to 0.8, which is in line with the reasoning of Kocaarslan and Soytas (2019). During times of recession both sectors tend to move together more strongly and during these times an appreciating dollar signals worsening economic conditions pushing investors to close out positions in the global oil and stock market and invest in the US dollar due to its safe haven property. This explains the more pronounced impact of changes in de US dollar value at the 80% quantile. Our results are more in line with those of Liu et al. (2021a) who also do not find a significant relation for changes in the dollar value.

Based on the results we can conclude that the effects of the drivers on the time-varying co-movement of returns between ERIX and EUR changes across the various quantiles, hence we accept H3.

5.3 Robustness check: Individual stocks

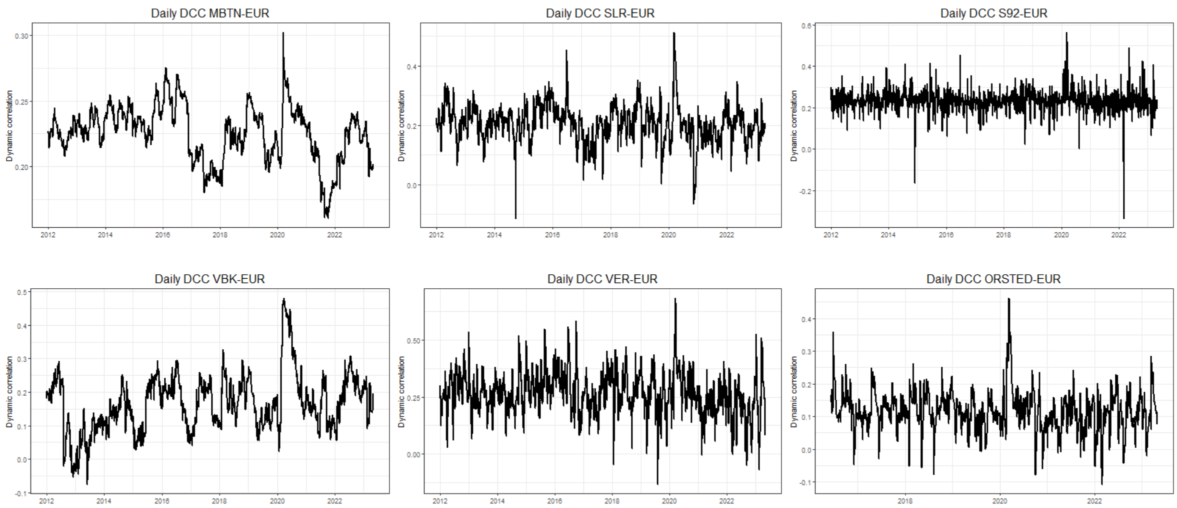
Before we examine the dynamics on the cross-section of clean and dirty energy stocks the correlation among each asset group is examined, Tables 13 and 14 Appendix G. Results show that the individual stocks in the EUR index are highly correlated with each other except for NESTE. This can be explained by the fact that NESTE is a top producer of sustainable aviation fuel, renewable diesel and renewable feedstock solutions which may be more related to the renewable energy sector than the traditional fossil fuel sector. Due to the high static correlation among the fossil fuel stocks it can be argued they behave the same way. This makes conducting the analyses on each combination of clean and dirty energy stock redundant, hence the fossil fuel index EUR is used instead. Even though

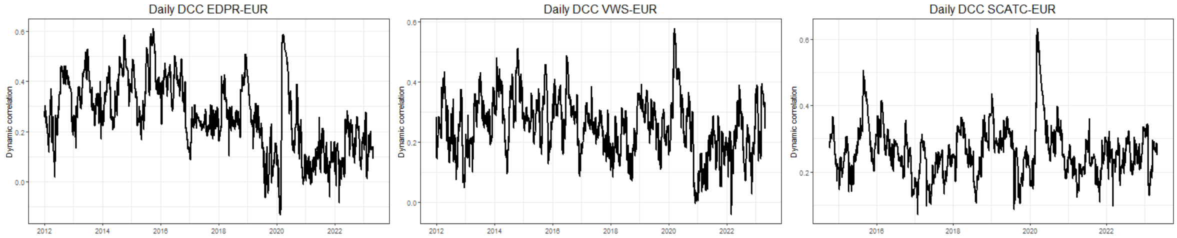
NESTE is then still represented in the EUR index its return will have a limited effect on the total return of the index as it has a weight of just 3.25%.

The static correlation analysis for the clean energy stocks shows that on average correlations are rather low for the renewable energy stocks. Grouping the stocks according to their industry classification or energy cluster they operate in increases the correlations slightly for the utility industry and solar and wind cluster. The highest correlation is observed between ORSTED and EDPR, both operating in the utility sector and wind cluster. These low correlations make it interesting to study the correlation dynamics between the dirty energy index and the individual stocks that comprise the ERIX index.

Table 11 of Appendix E shows summary statistics of the DCC at the stock level. The EDPR-EUR DCC tends to be the most volatile. The individual stocks show a lower average correlation compared to the average correlation on the index level, ERIX-EUR. This is due to the fact that company specific effects that impact the co-movement of returns with fossil fuel firms are canceled out. When one looks at the dynamic conditional correlation patterns, Figure 4, between the individual clean energy stocks and the EUR index we immediately notice very spikey patterns for some stocks with some stocks showing a relatively similar movement, e.g. EDPR, VWS and SLR. The spikey pattern of S92 and VER can be explained by the relatively low levels of average trading volume in these assets of respectively 166.000 and 135.000 compared to 23.41 million for MBTN. This makes the return series of the individual stocks more exposed to individual investors that want to either sell or buy a position. Secondly, a sharp increase in correlation is seen for all correlation series during the COVID pandemic indicating the effect of shocks on the co-movement.

Figure 4: DCC individual clean energy stocks and fossil fuel index EUR





Note: Mean and variance model for EUR correspond to respectively ARMA(2,1) and ARMA(5,5). For the fitted model specifications at individual stock level see Appendix E Table 10. MSCI Europe Energy index (EUR). Meyer burger technology ag (MBTN). Solaria energia y medio ambiente (SLR). Sma solar technology ag (S92). Verbio vereinigte bioenergy (VBK). Verbund ag (VER). Orsted a/s (ORSTED). Edp renovaveis sa (EDPR). Vestas wind systems a/s (VWS). Scatec asa (SCATC).

Results of the quantile regressions on the stock level can be found in Appendix G Tables 15 to 23. We can categorize two energy clusters, wind and solar. The wind cluster includes EDPR, SLR, ORSTED and VWS. The solar cluster includes MBTN, S92 and SCATC. We observe the same direction and magnitude of effects for the DCC between stocks of the same cluster and the EUR index with no clear differences in effects. This leads us to conclude that the DCC between stocks operating in the same cluster, wind or solar, and the fossil fuel index EUR behave similarly to the exogeneous environment. A significant effect of investor attention on the DCC between VWS and EUR is observed more often. The average daily trading volume for VWS is 1.9 million which is the second highest among the clean energy stocks under study. This high average trading volume may be an effect of increased investor attention, hence explaining the more pronounced effect.

When looking among the two clusters, some notable differences in effects exist. At the 10% and 20% quantiles of the correlation distributions, we see a bigger positive impact of stock market uncertainty for the wind cluster compared to the solar cluster. The same holds for economic policy uncertainty at the 90% quantile. This may stem from the fact that according to IEA (2021) under the stated policies the solar cluster will increase more strongly than the wind cluster making investments in the wind cluster more prone to uncertainty and a stronger co-movement with the fossil fuel sector during times of stress is expected. In addition, there is a notable effect of investor attention on both clusters in the same order of magnitude as observed at the index level for ERIX-EUR. However, the effect is more often statistical for the wind cluster. The wind cluster comprises more mature companies, based on market cap, making them more familiar compared to the solar cluster making them more likely to receive attention from investors and hence experience an effect of investor attention (Ding & Hou, 2015). Secondly, the DCC between EDPR and SLR with EUR, both part of the wind cluster, are the only two that are significantly affected by increases in federal fund rates. This effect holds for the quantiles 0.5, 0.8 and 0.9 for which a negative effect is observed. Meaning that in times of stress the correlation decreases. Increasing interest rates have a direct impact on the cost of capital which impacts smaller growth stocks in the wind cluster more heavily. Lastly, an opposite effect is seen for increases in term spreads among the solar and wind clusters. Better economic conditions, reflected by an increase in term spreads, result in a decrease in dynamic correlation among solar stocks and the fossil fuel sector. For stocks that are included in the wind cluster the opposite effect on the DCC is observed. So during better economic conditions returns for clean energy companies operating in the wind energy market will more strongly co-move with the fossil fuel market which is known to perform better during these times. This sheds light on the maturity of the wind energy cluster as this cluster is seen as a better substitute for fossil fuel energy than solar.

When one compares the effects found for the DCC at the individual stock level with the index-level analysis we observe the same dynamics in effect for VSTOXX, GSVI and OVX but one additional relation stands out. Economic policy uncertainty is found to have a significant negative effect on the DCC for most of the individual stocks at the 80% quantile indicating that during times of high correlation economic policy uncertainty lowers the correlation. The DCC between ERIX and EUR is not affected by this uncertainty measure at 5% confidence level. Individual stocks are therefore found to be more prone to uncertainty in the political environment regarding economic regulation when correlations are rather high.

The analysis shows that no major differences can be seen with the observed relations at the index level. This suggests that the stocks in the index are subject to the same effects even during economic downturns. However, a slight distinction can be seen between the two clusters wind and solar where the co-movement relation between wind energy stocks and the fossil fuel sector are more affected by uncertainty in times of crisis.

5.4 Robustness check: Time-varying dynamics

In order to verify whether investor attention shows signs of time-varying dynamics on the co-movement of returns between the European clean and dirty energy sector proxied by the ERIX and EUR index the DCC-GARCH model and quantile regression analyses are conducted on three subsamples. Each subsample is marked by the ending or beginning of a political or economic event related to the clean or dirty energy sector. The results are presented in Table 24 to 26 in Appendix H.

Overall the tables show the same relations among each other with notable some exceptions. First of all, oil market uncertainty is statistically and economically significant for the period containing the oil crisis of 2014 after which its effect disappears for the two sample periods thereafter. Therefore the effect found for OVX at the upper quantiles in Table 7 can completely be assigned to this period. Secondly, FFR is found to be statistically significant at 5% confidence level at the 50% and 80% quantile for the period April 2016 to October 2019, but it lacks economic significance. However, the negative effect shows that contractionary monetary policy, reflected in an increase in federal fund rates due to increases in interest rates, lowers the correlation. This dynamic can be explained by the common knowledge that clean energy stocks are growth stocks and rely heavily on R&D. These stocks are more affected by interest rate increases lowering their returns as these companies now need to borrow at higher costs. The negative effect for FFR is also present in the other two subsamples, but not significant. The same is found in Table 7 for the index analysis. Lastly, results for investor attention for the period ranging from October 2019 to April 2023 differ in two ways from the previous two periods. First of all, there is a significant effect obtained at 5% level at the 90% quantile compared to no significant effect for the previous periods. Secondly, the obtained effect is negative across all quantiles compared to a merely positive effect seen at the preceding periods. These results show that the explanatory power of investor attention on the dynamic conditional correlation among European clean and dirty energy index returns is related to the sample period. The significance found during the last sample period can be attributed to the impact that COVID had on public awareness. Because investor attention is only significant at the 90% quantile and at this point correlation was at its peak due to increased uncertainty the effect of investor sentiment was of short notice potentially due to the limited attention theory and herding behavior (Pham & Huynh, 2020; Barber & Odean, 2008). It is believed that since COVID the clean energy sector shows signs of overvaluation as market caps outrun intrinsic values in some cases (S&P Global Market Intelligence, 2021) making investment in clean energy stocks less appealing for shorter term investors. This may be reflected by lower stock returns as of 2021 for the clean energy sector, reducing the correlation among the clean- and dirty energy market for the last period.

This analysis shows the presence of time-varying dynamics among the explanatory variables and the return correlation, especially the effect of investor attention is interesting as it became significant during the last sample period indicating an increasing demand for clean energy investments. This is consistent with the limited attention theory that in the short term investors make adjustments to their investment strategies according to what is trending in the news, thus affecting returns. In the long run the effect is less pronounced. The magnitude of the effect of investor attention is in the same order of magnitude as found during the index analysis indicating that the long-run effect can be completely attributed to the impact of COVID.

6 Conclusion

To what extent does investor attention drive the time-varying co-movement of returns between European clean and dirty energy assets?

This study is the first that captures the effect of investor attention towards clean energy investing on the dynamic conditional correlation among clean and dirty energy assets while incorporating a behavioral perspective. For this three hypotheses are constructed.

H1: There exists a time-varying relation between the returns of the European clean and dirty energy sector.
We document the presence of time-varying co-movement between the returns of the European clean and dirty energy sector. Times of low and high correlation alternate, increasing (decreasing) diversification and hedging opportunities. Hence accepting H1.

H2: Investor attention measured through GSVI has a negative effect on the time-varying co-movement between the clean and dirty energy market.
Using daily Google Search Volume Index and data for European clean and dirty energy indices and stocks we find evidence of a small negative effect on the DCC at the median of the return correlation distribution, hence H2 is accepted.

H3: The effect that the explanatory variables have on the DCC changes over the various quantiles of the distribution of the return correlation.
The impact of all drivers increases at the tails of the return correlations distribution indicating more importance in times of crisis. The previous day value of the DCC, stock- and oil market uncertainty are found to be most important in driving the co-movement. The effect of investor attention on explaining the co-movement of returns between the clean and dirty energy sector strengthens when common shocks to both markets are severe. The presence of changing dynamics results in accepting H3. Our results provide new findings to the literature in light of the changing effects of drivers of the return co-movement, especially for the effect of investor attention.

The answer to the research question is that investor attention regarding clean energy investing has a limited impact on the time-varying co-movement dynamics of the clean and dirty energy sector. However, during times of high uncertainty investor attention reveals some economic importance in explaining the time-varying co-movement of returns and increases diversification benefits. In addition, diversification opportunities have increased since the COVID-pandemic. With the Russian invasion of Ukraine, a period of new dynamics has begun with higher levels of investor attention regarding clean energy investing magnifying the explanatory power of investor attention on the time-varying co-movement.

Robustness tests indicate the presence of time-varying dynamics among the drivers and the co-movement of returns for the European clean and dirty energy sector. The observed effect for investor attention is a result of the COVID-19 pandemic and the Russian Ukrainian War that increased renewable energy investments. In addition, the effect and impact of the drivers on the co-movement of returns is examined on the individual stock level where the results indicate that stocks in the ERIX index are subject to the same effects with a slightly more pronounced impact for stocks included in the wind cluster. Also, the effects found for the co-movement between the individual stocks and the fossil fuel index are the same as those found during the index level analysis. Indicating uniform return series for the clean energy stocks.

Our study has several practical implications as well. First, investors should be aware of the changing dynamics in drivers at the various points of the return correlation which may impact their investment decisions. Secondly, during times of high uncertainty investor attention can be useful in adjusting portfolio as diversification benefits rise. Secondly, to increase diversification benefits and the hedging potential of clean energy stocks and consequently drive investors to invest in them, it is important for policy makers to diminish the vulnerability of clean energy stocks to equity market uncertainty and increase investor attention towards clean energy investing. Therefore it may be useful for policy makers to inform investors that clean energy stocks are, and will be, heavily subsidized by the government and fossil fuel energy will be taxed more heavily as this increases the substitution motives for consumers and thereby investors.

Limitations and Future research

The daily GSVI series includes a lot of days for which search requests are not sufficiently high enough to being reported. This makes the pattern very spikey with no clear periods of sustaining levels of search volumes, influencing the results concerning the explanatory power of investor attention on the co-movement of returns. This problem can be overcome by conducting the analysis on a lower frequency e.g. weekly, smoothening out the randomness. Attention towards clean and renewable energy investing may not be associated with daily trading but rather longer term which relates to longer term investing. Sudden shocks that spurs attention towards clean and renewable energy investing on a daily level are less common as investor attention is driven by momentum regarding public awareness (Pham & Huynh, 2020; Barber & Odean, 2008). Hence, it is of interest for further research to redo the analysis on a higher frequency. This simultaneously tackles the problem of spikey patterns for the other explanatory variables and return series. A challenge that comes with this is the amount of available datapoints to estimate a model on. Weekly data for our sample period results in roughly 600 datapoints which can be regarded as few when incorporating the control variables as proposed during this research to obtain a reliable model.

Our results may be influenced by the global measure of GSVI that is used in this study to proxy investor attention. With this, the effect of US investor attention towards clean energy investing is also reflected into the GSVI. In this regard it is of interest to further examine the presence of region-specific effects of investor attention on the European market. This way one can state whether the co-movement of returns between the European clean and dirty energy sector is influenced by regional or global investor attention. This sheds light on the home bias hypothesis stating that investors favor stocks from their home nation, in this regard European stocks.

As we observe small differences in the magnitude of the drivers of the co-movement for the solar and wind cluster it is interesting to further examine the effects at this cluster level. Building on the work of Pham (2019), who uses US based clean energy stocks, one can examine the influential drivers of the clusters at the different quantiles of the distribution of the co-movement of returns. His results indicate varying relations across the different clean energy clusters showing the importance of portfolio management at a disaggregated level. However, drivers behind these relations are not examined.

We assumed that error terms for the univariate GARCH process follow a normal distribution for the sake of simplicity and interpretability. This assumption is however violated which means that the error terms of the mean model follow a different distribution than normal. Implementing a different distribution for the error terms may influence our results for the quantile regression as this depends on the DCC-GARCH model which now assumes normality. Hence, considering a different distribution behind the error term of the GARCH model will be interesting for future work. Also, different functional forms for modeling the volatility in the DCC-GARCH model could be done for future research.

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Appendix A Individual cumulative return series ERIX and EUR

Figure 5: Cumulative return series

Note: ERIX (blue) and EUR (green). Periods of shocks are clearly visible. Note the difference in range for the y-axis.

Appendix B Creating a coherent GSVI series

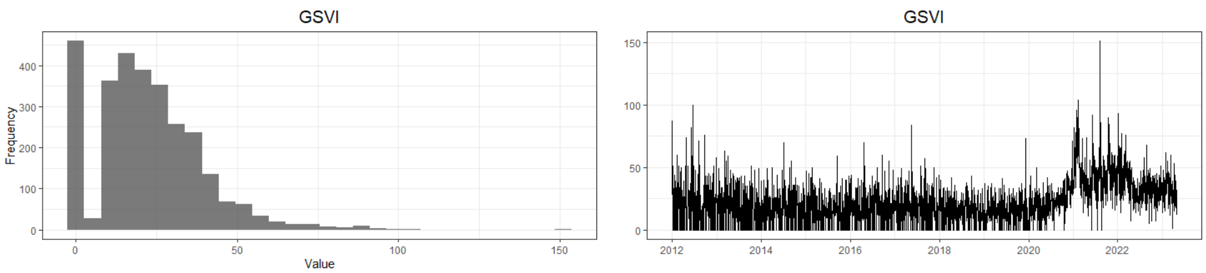
Bleher and Dimpfl (2019) advise on 30 days in the overlapping window. Using this approach allows values to exceed the initial upper limit of 100.

The following steps summarize the regression-based building algorithm:

1) Download data sets comprising of 270 days covering the full sample period with 30-days of overlap between two consecutive data sets.
2) Set the oldest data set (starting point) as A and the consecutive set comprising 270-days as B. values in these sets are denoted by subsequently $GSVI_{A,t}$ and $GSVI_{B,t}$
3) Estimate the following regression equation for the overlapping 30 points: $GSVI_{A,t} = \alpha + \beta GSVI_{B,t} + \varepsilon_t$
4) Test if the hypothesis for the intercept H0 : α = 0 can be rejected. If so, estimate $GSVI_{B,t}$ with estimated parameters of this equation. If not estimate $GSVI_{A,t} = \beta GSVI_{B,t} + \varepsilon_t$ and with this equation estimate values of $GSVI_{B,t}$.
5) Join the original set A and the predicted set for B to one data set. This data set replaces data set A, whereas B is replaced by the next data set to be added.
6) Repeat step 2 to 5 until one data set is obtained.

Weekend days are however included in this series. Deletion of these days results in potential information loss. For this reason the following is implemented for search volumes on Mondays: $MAX(SVI_{sat}; SVI_{sun}; SVI_{mon})$. This way a potential lagged effect of google searches in weekends is captured in Monday returns. Also there are a large amount of 0-values present in the GSVI series. Fitting a model on this data will not be sufficient. In order to overcome this problem a three day simple moving average is applied to the GSVI series.

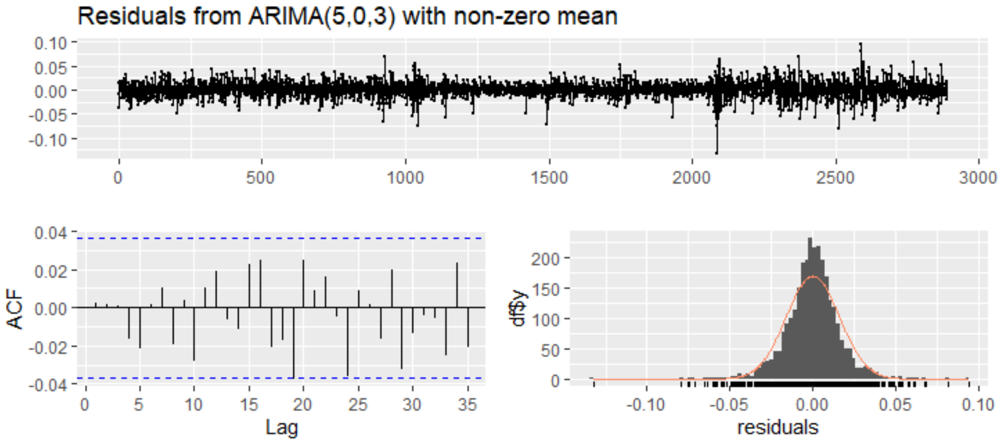
Figure 6: GSVI series unmodified, histogram and timeseries



Note: There are numerous days with insufficient data indicated by 0-values.

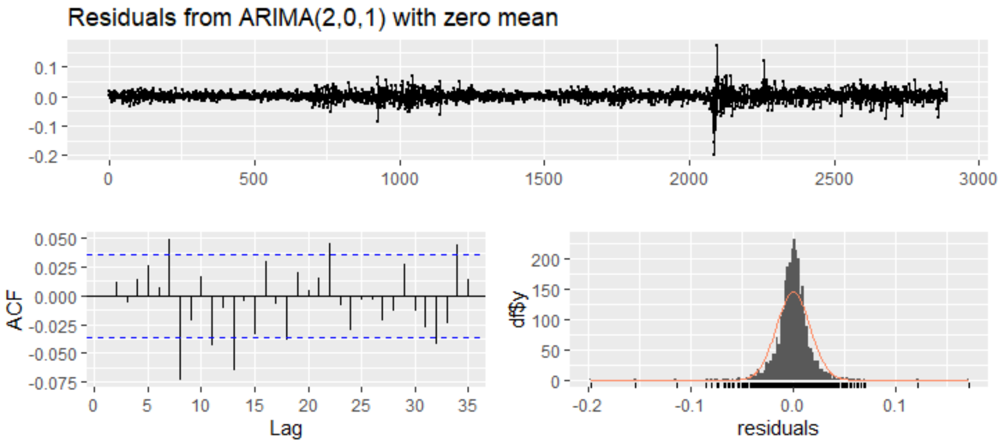
Appendix C PACF and ACF plots squared residuals of mean model.

Figure 7: ERIX mean model



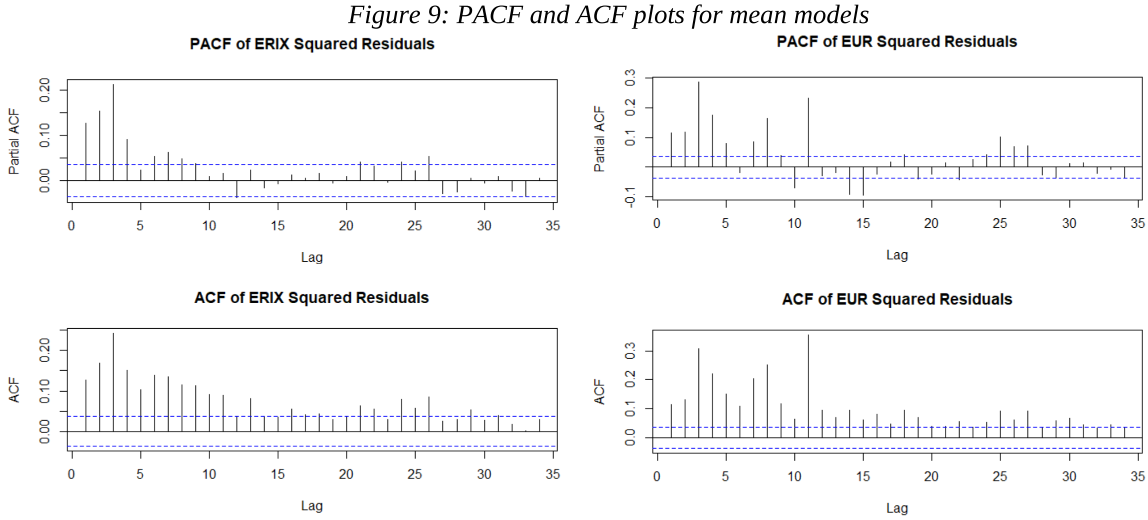
Note: Fitted on residuals obtained from the mean model ARMA(5,3).

Figure 8: EUR mean model



Note: Fitted on residuals obtained from the mean model ARMA(5,3).

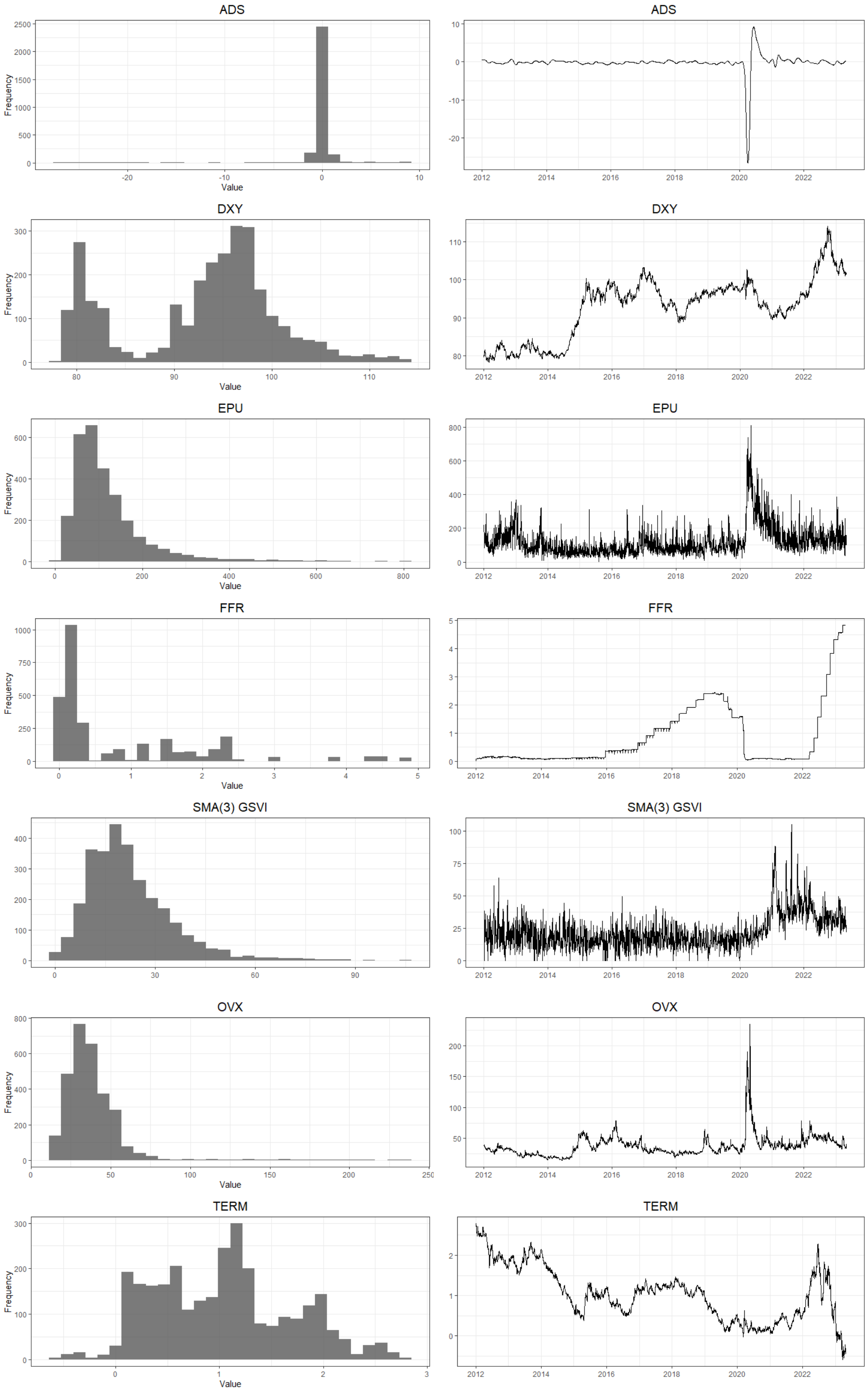
Figure 9: PACF and ACF plots for mean models

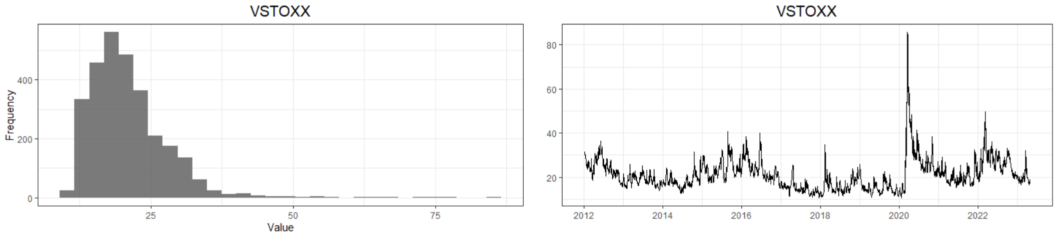


Note: Obtained from the squared residuals of the mean models of ARMA order (5,3) and (2,1) for respectively the ERIX and EUR series.

Appendix D Distribution of explanatory variable series

Figure 10: Distribution of explanatory variables





Note: *European stock market uncertainty (VSTOXX). Economic policy uncertainty (EPU). Oil market uncertainty (OVX). Aruba Diebold and Scotti business cycle measure (ADS). Federal Fund Rate (FFR). Difference between 3-month treasury bond yield and 10-year treasury bond yield (TERM). 3-day SMA Google Search Volume Index (SMA(3) GSVI)*

Table 8: Descriptive statistics transformed explanatory variables

	mean	**sd**	**median**	**min**	**max**
VSTOXX	20.99	6.98	19.79	10.68	85.62
EPU	118.67	86.23	94.65	3.32	807.66
OVX	37.75	18.17	34.67	14.67	234.66
diffADS	0.00	0.19	0.00	-3.35	4.95
diffFFR	0.00	0.04	0.00	-0.85	0.75
diffTERM	0.00	0.05	0.00	-0.31	0.22
diffDXY	0.01	0.41	0.00	-2.37	2.29
GSVI	22.31	12.87	19.67	0.00	105.00
DCC_{t-1}	0.25	0.10	0.25	-0.04	0.58

Note: European stock market uncertainty (VSTOXX). Economic policy uncertainty (EPU). Oil market uncertainty (OVX). First order difference Aruba Diebold and Scotti business cycle measure (diffADS). First order difference Federal Fund Rate (diffFFR). First order difference between 3-month treasury bond yield and 10-year treasury bond yield (diffTERM). First order difference US dollar index (diffDXY). 3-day SMA Google Search Volume Index (GSVI). First day lag DCC (DCC_{t-1}).

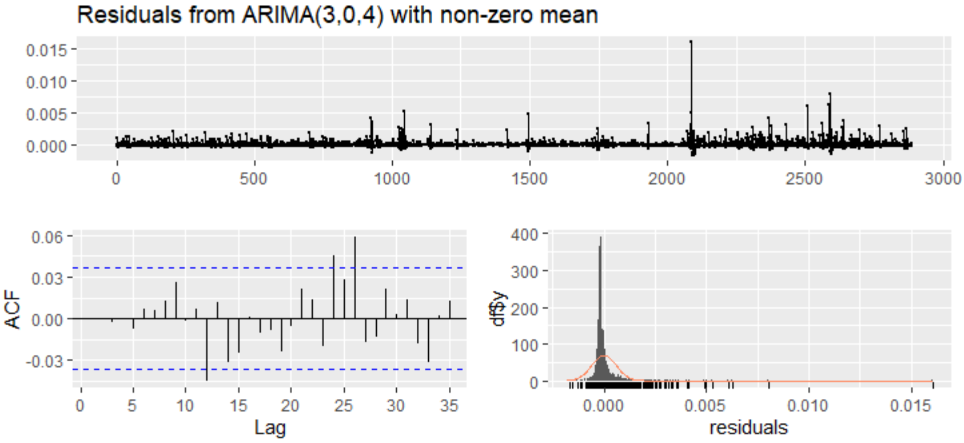
Table 9: Correlation matrix transformed explanatory variables

	EPU	**OVX**	**diffADS**	**diffFFR**	**diffTERM**	**diffDXY**	**GSVI**
VSTOXX	0.44***	0.71***	-0.15***	-0.05***	0	0.05**	0.13***
EPU		0.54***	0.12***	-0.03*	-0.02	-0.02	0.14***
OVX			0.06***	-0.02	0.01	0.01	0.1***
diffADS				0.13***	-0.02	0	-0.02
diffFFR					0	0.06***	0.03*
diffTERM						0.01	0.01
diffDXY							0

*Note: Conditional Pearson correlation with corresponding significance. Highest correlation among VSTOXX and OVX of 0.71. European stock market uncertainty (VSTOXX). Economic policy uncertainty (EPU). Oil market uncertainty (OVX). First order difference Aruba Diebold and Scotti business cycle measure (diffADS). First order difference Federal Fund Rate (diffFFR). First order difference between 3-month treasury bond yield and 10-year treasury bond yield (diffTERM). First order difference US dollar index (diffDXY). 3-day SMA Google Search Volume Index (GSVI). *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.*

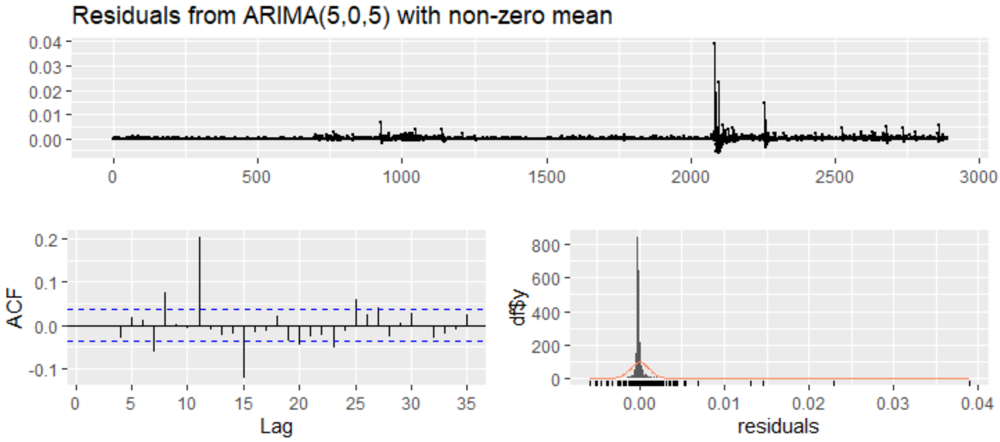
Appendix E DCC-GARCH model fitting

Figure 11: ERIX variance model



Note: Fitted on residuals obtained from the mean model ARMA(5,3). Ljung-Box test on the residuals of the fitted ARMA(3,4) variance model indicates no presence of autocorrelation (p-value of 0.9976 is greater than 0.05) and so the null hypothesis that no autocorrelation exists is not rejected.

Figure 12: EUR variance model



Note: Fitted on residuals obtained from the mean model ARMA(2,1). Ljung-Box test on the residuals of the fitted ARMA(5,5) model indicates no presence of autocorrelation (p-value of 0.8874 is greater than 0.05) and so the null hypothesis that no autocorrelation exists is not rejected.

Table 10: Estimated mean and variance models and test statistics indices and individual stocks

Stock	Jarque-Bera	Shapiro	ADF	ARCH	Ljung-Box	Mean.model	Variance.model	Univariate.Garch p-value
ERIX	0	2.2e-16	0.01	0	0	ARMA(5,3)	ARMA(3,4)	0.708
EUR	0	2.2e-16	0.01	0	0	ARMA(2,1)	ARMA(5,5)	0.359
EDPR	0	1.2e-28	0.01	0	0	ARMA(0,0)	ARMA(5,1)	0.283
MBTN	0	4.1e-38	0.01	0	0	ARMA(0,1)	ARMA(3,3)	0.258
SCATC	0	1.5e-25	0.01	0	0	ARMA(0,0)	ARMA(1,1)	0.160
S92	0	8.4e-38	0.01	0	0.26	ARMA(4,4)	ARMA(1,2)	0.811
SLR	0	1.0e-43	0.01	0	0	ARMA(0,0)	ARMA(1,3)	0.071
VBK	0	4.4e-35	0.01	0	0	ARMA(1,0)	ARMA(2,1)	0.764
VER	0	1.2e-35	0.01	0	0	ARMA(0,0)	ARMA(1,1)	0.529
ORSTED	0	2.8e-23	0.01	0	0	ARMA(0,0)	ARMA(4,2)	0.529
VWS	0	1.4e-34	0.01	0	0	ARMA(3,0)	ARMA(4,0)	0.952

Note: Table reports p-values of test statistics at individual stock level and fitted mean and variance models which are input for the DCC-GARCH(1,1) model fitting. All test results are significant at the 1% level except for the Ljung-Box test, column 6, for S92 indicating no presence of serial autocorrelation in the squared residuals of the mean model indicating no ARCH effect. However the LM test indicates presence of ARCH effects and hence the volatility is modelled. Column 9 displays Ljung-Box test results for the univariate GARCH model corresponding to the individual stock. All show no presence of serial autocorrelation in residuals indicating an adequate model fit. ADF test with lag length of 14. ARCH test with 12 df. Ljung-Box test with 10 df. Jarque-Bera test with 2 df.

Table 11: Dynamic conditional correlation summary statistics

	Dynamic Conditional Correlation between individual stock and EUR									**ERIX-EUR**
	EDPR	**MBTN**	**SCATC**	**S92**	**SLR**	**VBK**	**VER**	**ORSTED**	**VWS**	
n	2888	2888	2187	2888	2888	2888	2888	1760	2888	2888
mean	0.26	0.23	0.26	0.23	0.20	0.17	0.27	0.12	0.25	0.38
median	0.25	0.23	0.25	0.23	0.21	0.16	0.26	0.11	0.25	0.40
sd	0.14	0.02	0.08	0.05	0.06	0.09	0.09	0.06	0.10	0.15
min	-0.13	0.16	0.07	-0.33	-0.11	-0.08	-0.13	-0.11	-0.04	-0.02
max	0.61	0.30	0.63	0.56	0.51	0.48	0.68	0.46	0.58	0.75
DCCa	0.026**	0.003	0.02**	0.041**	0.022**	0.015***	0.046***	0.029*	0.027	0.024***
DCCb	0.963***	0.988***	0.947***	0.584***	0.915***	0.972***	0.862***	0.834***	0.943***	0.968***

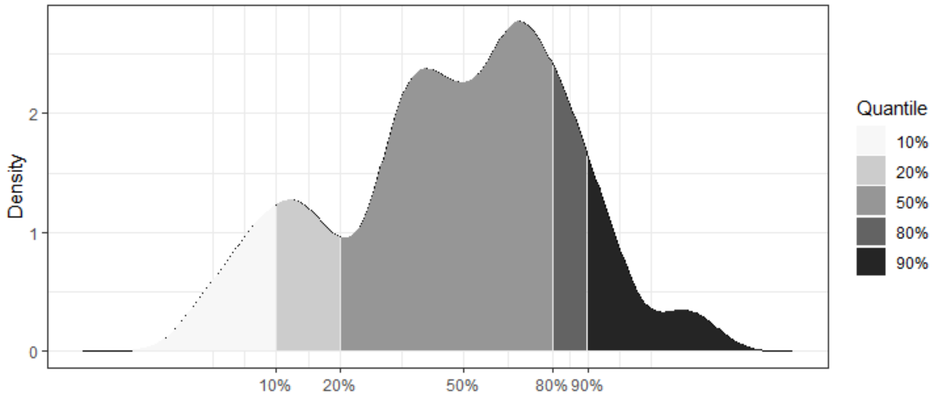
*Note: Results in Columns 2-10 indicate DCC between one of the stocks included in the ERIX index and the overall European fossil fuel market index EUR. European Renewable Energy index (ERIX). Column 12 DCC on index level. MSCI Europe Energy index (EUR). Meyer burger technology ag (MBTN). Solaria energia y medio ambiente (SLR). Sma solar technology ag (S92). Verbio vereinigte bioenergy (VBK). Verbund ag (VER). Orsted a/s (ORSTED). Edp renovaveis sa (EDPR). Vestas wind systems a/s (VWS). Scatec asa (SCATC). DCCa and DCCb correspond to the property of $a + b < 1$. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.*

Appendix F Quantile regression Indices

Figure 13: DCC ERIX-EUR with quantile lines

Note: Quantile lines at 0.1, 0.2, 0.5, 0.8 and 0.9 of the DCC distribution in red.

Figure 14: DCC ERIX-EUR density quantile areas



Note: Quantile regressions estimated on each quantile.

Table 12: Quantile regressions DCC ERIX-EUR, no correction for serial autocorrelation in residuals

Coefficient	$\tau = 0.1$	$\tau = 0.2$	$\tau = 0.5$	$\tau = 0.8$	$\tau = 0.9$
Intercept	0.142***	0.159***	0.226***	0.282***	0.298***
VSTOXX	0.002***	0.003***	0.004***	0.005***	0.007***
EPU	0***	0**	0*	0**	0
OVX	0.001***	0.001***	0.001***	0	0*
diffADS	0.045	0.033	0.019	0.016***	0.018
diffFFR	0.024	-0.035	-0.092	-0.023	-0.039
diffTERM	-0.076	-0.019	-0.038	-0.095*	-0.095
diffDXY	-0.001	0.005	0	-0.012**	-0.008
GSVI	-0.002***	-0.003***	-0.003***	-0.003***	-0.002***
R^1	0.25	0.27	0.19	0.14	0.15
Ljung-Box test	0	0	0	0	0
Obs.	2888	2888	2888	2888	2888

*Note: Ljung-Box test results indicate the presence of first order serial autocorrelation in residuals of the estimated quantile regressions at each level of the distribution (reported p-value). European stock market uncertainty (VSTOXX). Economic policy uncertainty (EPU). Oil market uncertainty (OVX). First order difference Aruba Diebold and Scotti business cycle measure (diffADS). First order difference Federal Fund Rate (diffFFR). First order difference between 3-month treasury bond yield and 10-year treasury bond yield (diffTERM). First order difference US dollar index (diffDXY). 3-day SMA Google Search Volume Index (GSVI). R^1 goodness of fit. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.*

Appendix G Quantile regression individual stocks

Table 13: Static Pearson correlation fossil fuel stocks

	ENI	EQNR	NESTE	REP	SHEL	TTE
BP	0.66***	0.61***	0.31***	0.64***	0.75***	0.7***
ENI		0.66***	0.35***	0.76***	0.77***	0.81***
EQNR			0.32***	0.64***	0.71***	0.68***
NESTE				0.35***	0.33***	0.39***
REP					0.73***	0.76***
SHEL						0.82***

*Conditional Pearson correlation with corresponding p-values among individual stocks that make up the EUR index that have a weight higher than 3%. BP (BP). ENI (ENI). Equinor (EQNR). Neste corporation (NESTE). Repsol (REP). Shell (SHEL). TotalEnergies (TTE). *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.*

Table 14: Static Pearson correlation clean energy stocks

	MBTN	SCATC	S92	SLR	VBK	VER	VWS	ORSTED
EDPR	0.21***	0.43***	0.29***	0.38***	0.25***	0.41***	0.48***	0.58***
MBTN		0.21***	0.28***	0.24***	0.17***	0.11***	0.26***	0.16***
SCATC			0.26***	0.34***	0.26***	0.27***	0.40***	0.40***
S92				0.28***	0.27***	0.19***	0.37***	0.26***
SLR					0.17***	0.26***	0.31***	0.33***
VBK						0.17***	0.29***	0.22***
VER							0.30***	0.38***
VWS								0.51***

*Note: Conditional Pearson correlation with corresponding p-values among individual stocks that make up the ERIX index. SCATC and ORSTED closing price data is available from 2014 and 2016 respectively. Correlation coefficients for SCATC and ORSTED with the other stocks are constructed on a subset of the data depending on the data availability. MSCI Europe Energy index (EUR). Meyer burger technology ag (MBTN). Solaria energia y medio ambiente (SLR). Sma solar technology ag (S92). Verbio vereinigte bioenergy (VBK). Verbund ag (VER). Orsted a/s (ORSTED). Edp renovaveis sa (EDPR). Vestas wind systems a/s (VWS). Scatec asa (SCATC). *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.*

Table 15: Quantile regression DCC EDPR-EUR

	$\boldsymbol{\tau = 0.1}$	$\boldsymbol{\tau = 0.2}$	$\boldsymbol{\tau = 0.5}$	$\boldsymbol{\tau = 0.8}$	$\boldsymbol{\tau = 0.9}$
(Intercept)	-0.0253***	-0.0091***	0.0018***	0.0107***	0.0227***
VSTOXX	0.0004*	0.0001	0.0001***	0.0007***	0.0013***
EPU	0	0	0	0***	0**
OVX	0	0	0	-0.0001**	-0.0002***
diffADS	0.0013	-0.0006	0.0004	0.0036	0.0036
diffFFR	0.0055	0.0004	-0.0063***	-0.011**	-0.004
diffTERM	-0.0012	-0.0064	0.0037	0.0094	0.0057
diffDXY	-0.003	-0.0013	-0.0001	0.0003	0.002
GSVI	0	0	0	-0.0001***	-0.0002***
DCC_{t-1}	1.0017***	0.9969***	0.9874***	0.9666***	0.944***
R^1	0.81	0.86	0.89	0.86	0.83
Ljung-Box test	0.213	0.137	0.101	0.35	0.08
Obs.	2888	2888	2888	2888	2888

Note: Edp renovaveis sa (EDPR). European stock market uncertainty (VSTOXX). Economic policy uncertainty (EPU). Oil market uncertainty (OVX). First order difference Aruba Diebold and Scotti business cycle measure (diffADS). First order difference Federal Fund Rate (diffFFR). First order difference between 3-month treasury bond yield and 10-year treasury bond yield (diffTERM). First order difference US dollar index (diffDXY). 3-day SMA Google Search Volume Index (GSVI). First day lag DCC (DCC_{t-1}). R^1 goodness of fit. Ljung-Box test shows no signs of first order autocorrelation in error terms (reported p-value). **** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.*

Table 16: Quantile regression DCC MBTN-EUR

	$\boldsymbol{\tau = 0.1}$	$\boldsymbol{\tau = 0.2}$	$\boldsymbol{\tau = 0.5}$	$\boldsymbol{\tau = 0.8}$	$\boldsymbol{\tau = 0.9}$
(Intercept)	-0.0002	0.0011*	0.0019***	0.0038***	0.0052***
VSTOXX	0	0	0***	0.0001***	0.0001***
EPU	0	0	0*	0**	0
OVX	0	0	0*	0	0
diffADS	0.0006	0.0003	0	0.0002	0.0001
diffFFR	-0.0013	-0.0021	0.0004*	-0.001	-0.0023
diffTERM	0.0003	-0.0004	-0.0001	-0.0003	0.0004
diffDXY	-0.0003	-0.0001	0	0	0.0002
GSVI	0	0	0	0	0***
DCC_{t-1}	0.9911***	0.9915***	0.9909***	0.9828***	0.9792***
R^1	0.88	0.90	0.91	0.89	0.87
Ljung-Box test	0.531	0.586	0.561	0.346	0.773
Obs.	2888	2888	2888	2888	2888

Note: Meyer burger technology ag (MBTN). European stock market uncertainty (VSTOXX). Economic policy uncertainty (EPU). Oil market uncertainty (OVX). First order difference Aruba Diebold and Scotti business cycle measure (diffADS). First order difference Federal Fund Rate (diffFFR). First order difference between 3-month treasury bond yield and 10-year treasury bond yield (diffTERM). First order difference US dollar index (diffDXY). 3-day SMA Google Search Volume Index (GSVI). First day lag DCC (DCC_{t-1}). R^1 goodness of fit. Ljung-Box test shows no signs of first order autocorrelation in error terms (reported p-value). **** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.*

Table 17: Quantile regression DCC SCATC-EUR

	$\tau = 0.1$	$\tau = 0.2$	$\tau = 0.5$	$\tau = 0.8$	$\tau = 0.9$
(Intercept)	-0.0124***	-0.0013	0.0073***	0.0142***	0.0208***
VSTOXX	0	0	0.0001***	0.0005***	0.0009***
EPU	0	0	0	0***	0**
OVX	0	0	0	0	0
diffADS	-0.0002	-0.0012	-0.0001	0.0014	-0.0018
diffFFR	-0.0066	0.0033	-0.0026	-0.0044	-0.0044
diffTERM	-0.0006	0.0011	-0.0024	-0.0028	0.0031
diffDXY	0.003*	0.0019*	0.0002	-0.0001	-0.0023
GSVI	0	0	0	0	-0.0001**
DCC_{t-1}	0.9816***	0.9701***	0.9649***	0.9447***	0.9267***
R^1	0.73	0.78	0.82	0.80	0.79
Ljung-Box test	0.264	0.203	0.129	0.2	0.1
Obs.	2187	2187	2187	2187	2187

Note: Scatec asa (SCATC). European stock market uncertainty (VSTOXX). Economic policy uncertainty (EPU). Oil market uncertainty (OVX). First order difference Aruba Diebold and Scotti business cycle measure (diffADS). First order difference Federal Fund Rate (diffFFR). First order difference between 3-month treasury bond yield and 10-year treasury bond yield (diffTERM). First order difference US dollar index (diffDXY). 3-day SMA Google Search Volume Index (GSVI). First day lag DCC (DCC_{t-1}). R^1 goodness of fit. Ljung-Box test shows no signs of first order autocorrelation in error terms (reported p-value). **** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.*

Table 18: Quantile regression DCC S92-EUR

	$\tau = 0.1$	$\tau = 0.2$	$\tau = 0.5$	$\tau = 0.8$	$\tau = 0.9$
(Intercept)	0.0538***	0.0758***	0.0846***	0.0927***	0.101***
VSTOXX	-0.0004	-0.0001	0.0002***	0.0012***	0.0017***
EPU	0	0	0	0**	0
OVX	0.0001	0	0	-0.0001***	-0.0002
diffADS	0.0031	0.0049	-0.0006	0.0008	0.0078
diffFFR	-0.0009	-0.0213	-0.0037	-0.0117	-0.0313
diffTERM	-0.0004	0.0198	0.003	-0.0008	0.0529
diffDXY	-0.0037	-0.0013	0.0002	0.002	-0.0003
GSVI	-0.0002	-0.0001	0**	-0.0001*	-0.0001
DCC_{t-1}	0.684***	0.639***	0.6309***	0.5941***	0.5963***
R^1	0.25	0.29	0.34	0.30	0.27
Ljung-Box test	0.265	0.323	0.38	0.001	0
Obs.	2888	2888	2888	2888	2888

Note: Sma solar technology ag (S92). European stock market uncertainty (VSTOXX). Economic policy uncertainty (EPU). Oil market uncertainty (OVX). First order difference Aruba Diebold and Scotti business cycle measure (diffADS). First order difference Federal Fund Rate (diffFFR). First order difference between 3-month treasury bond yield and 10-year treasury bond yield (diffTERM). First order difference US dollar index (diffDXY). 3-day SMA Google Search Volume Index (GSVI). First day lag DCC (DCC_{t-1}). R^1 goodness of fit. Ljung-Box test shows no signs of first order autocorrelation in error terms for τ equal to 0.1, 0.2, 0.5 (reported p-value). **** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.*

Table 19: Quantile regression DCC SLR-EUR

	$\tau = 0.1$	$\tau = 0.2$	$\tau = 0.5$	$\tau = 0.8$	$\tau = 0.9$
(Intercept)	-0.0051*	0.0065***	0.0117***	0.0181***	0.0248***
VSTOXX	0.0001	0	0.0001**	0.0006***	0.001***
EPU	0	0	0	0	0
OVX	0	0	0	-0.0001**	-0.0002**
diffADS	-0.002	-0.0037	-0.0018**	0.0026	0.0023
diffFFR	0.0024	-0.0027	-0.001	-0.0081***	-0.0172**
diffTERM	-0.0209*	0.0056	0.0042	0.0044	0.0166
diffDXY	-0.0034***	-0.001	0.0003	0.0018*	0.0032**
GSVI	-0.0001*	-0.0001*	0	-0.0001**	-0.0001
DCC_{t-1}	0.9547***	0.9422***	0.9381***	0.9207***	0.9067***
R^1	0.68	0.72	0.75	0.72	0.68
Ljung-Box test	0.415	0.815	0.763	0.882	0.178
Obs.	2888	2888	2888	2888	2888

Note: Solaria energia y medio ambiente (SLR). European stock market uncertainty (VSTOXX). Economic policy uncertainty (EPU). Oil market uncertainty (OVX). First order difference Aruba Diebold and Scotti business cycle measure (diffADS). First order difference Federal Fund Rate (diffFFR). First order difference between 3-month treasury bond yield and 10-year treasury bond yield (diffTERM). First order difference US dollar index (diffDXY). 3-day SMA Google Search Volume Index (GSVI). First day lag DCC (DCC_{t-1}). R^1 goodness of fit. Ljung-Box test shows no signs of first order autocorrelation in error terms (reported p-value). **** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.*

Table 20: Quantile regression DCC VBK-EUR

	$\tau = 0.1$	$\tau = 0.2$	$\tau = 0.5$	$\tau = 0.8$	$\tau = 0.9$
(Intercept)	-0.0092***	-0.004***	0.0017***	0.004***	0.0039**
VSTOXX	0	0.0001*	0**	0.0003***	0.0008***
EPU	0	0	0	0*	0***
OVX	0.0001**	0	0	0*	-0.0001**
diffADS	-0.0008	0.0005	-0.0001	0.0014	0.0007
diffFFR	-0.0066	-0.0041	-0.0026	-0.0001	-0.0053
diffTERM	-0.0023	-0.0115*	-0.0011	0.002	0.0186
diffDXY	-0.0005	0.0004	0.0003*	0.0007	0.0011
GSVI	-0.0001**	0	0	0	0
DCC_{t-1}	0.9815***	0.9791***	0.9848***	0.9768***	0.9675***
R^1	0.83	0.86	0.89	0.86	0.85
Ljung-Box test	0.519	0.403	0.407	0.481	0.104
Obs.	2888	2888	2888	2888	2888

*Note: Verbio vereinigte bioenergi (VBK). European stock market uncertainty (VSTOXX). Economic policy uncertainty (EPU). Oil market uncertainty (OVX). First order difference Aruba Diebold and Scotti business cycle measure (diffADS). First order difference Federal Fund Rate (diffFFR). First order difference between 3-month treasury bond yield and 10-year treasury bond yield (diffTERM). First order difference US dollar index (diffDXY). 3-day SMA Google Search Volume Index (GSVI). First day lag DCC (DCC_{t-1}). R^1 goodness of fit. Ljung-Box test shows no signs of first order autocorrelation in error terms (reported p-value). *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.*

Table 21: Quantile regression DCC VER-EUR

	$\tau = 0.1$	$\tau = 0.2$	$\tau = 0.5$	$\tau = 0.8$	$\tau = 0.9$
(Intercept)	-0.0137**	0.0104***	0.0223***	0.0384***	0.0527***
VSTOXX	-0.0001	0	0.0002***	0.0009***	0.0017***
EPU	0	0	0	0	0
OVX	0.0001	0	0	0	-0.0001
diffADS	0.0044	-0.0003	-0.0005	0.0042	0
diffFFR	-0.0052	0.0046	-0.0061	-0.0203	-0.0327
diffTERM	-0.007	0.0134	-0.0003	0.0205	0.0589
diffDXY	-0.0039	-0.0022	-0.0002	0.0017	0.0036
GSVI	-0.0003**	-0.0003***	0*	-0.0001**	-0.0003*
DCC_{t-1}	0.9379***	0.909***	0.9022***	0.8728***	0.8484***
R^1	0.59	0.63	0.68	0.64	0.59
Ljung-Box test	0.581	0.789	0.529	0.273	0
Obs.	2888	2888	2888	2888	2888

*Note: Verbund ag (VER). European stock market uncertainty (VSTOXX). Economic policy uncertainty (EPU). Oil market uncertainty (OVX). First order difference Aruba Diebold and Scotti business cycle measure (diffADS). First order difference Federal Fund Rate (diffFFR). First order difference between 3-month treasury bond yield and 10-year treasury bond yield (diffTERM). First order difference US dollar index (diffDXY). 3-day SMA Google Search Volume Index (GSVI). First day lag DCC (DCC_{t-1}). R^1 goodness of fit. Ljung-Box test shows no signs of first order autocorrelation in error terms for τ equal to 0.1, 0.2, 0.5, 0.8 (reported p-value). *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.*

Table 22: Quantile regression DCC ORSTED-EUR

	$\tau = 0.1$	$\tau = 0.2$	$\tau = 0.5$	$\tau = 0.8$	$\tau = 0.9$
(Intercept)	-0.0112**	0.0032	0.0141***	0.0185***	0.0198***
VSTOXX	-0.0002	0.0001	0.0002***	0.001***	0.0019***
EPU	0	0	0	0**	0*
OVX	0.0001	0	0	-0.0001	-0.0002
diffADS	-0.0016	0.0028	-0.001	0.0007	0.0001
diffFFR	-0.0171	-0.0061	-0.0011	-0.0147	-0.0118
diffTERM	-0.007	0.001	-0.0054	0.0026	-0.0011
diffDXY	-0.0057*	-0.0043***	-0.0007	-0.0004	0.0059**
GSVI	-0.0001	-0.0001**	0	-0.0001	-0.0001*
DCC_{t-1}	0.8932***	0.8864***	0.8637***	0.8442***	0.8416***
R^1	0.53	0.58	0.64	0.61	0.57
Ljung-Box test	0.655	0.618	0.743	0.508	0.009
Obs.	1760	1760	1760	1760	1760

*Note: Orsted a/s (ORSTED). European stock market uncertainty (VSTOXX). Economic policy uncertainty (EPU). Oil market uncertainty (OVX). First order difference Aruba Diebold and Scotti business cycle measure (diffADS). First order difference Federal Fund Rate (diffFFR). First order difference between 3-month treasury bond yield and 10-year treasury bond yield (diffTERM). First order difference US dollar index (diffDXY). 3-day SMA Google Search Volume Index (GSVI). First day lag DCC (DCC_{t-1}). Ljung-Box test shows no signs of first order autocorrelation in error terms for τ equal to 0.1, 0.2, 0.5, 0.8 (reported p-value). R^1 goodness of fit. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.*

Table 23: Quantile regression DCC VWS-EUR

	$\tau = 0.1$	$\tau = 0.2$	$\tau = 0.5$	$\tau = 0.8$	$\tau = 0.9$
(Intercept)	-0.008*	-0.0013	0.007***	0.0119***	0.0239***
VSTOXX	0.0002	0.0001	0.0001***	0.0008***	0.0013***
EPU	0	0	0	0*	0
OVX	0	0	0	-0.0001**	-0.0002**
diffADS	0.0065	0.0032	0.0015*	0.0042	0.0045
diffFFR	0.0012	0.0006	-0.0032	-0.0139	-0.0114
diffTERM	-0.0074	-0.0085	0.0006	0.0225*	0.0235
diffDXY	-0.0026	-0.0019	0.0002	0.0012	-0.0006
GSVI	-0.0002***	-0.0001**	0**	-0.0001	-0.0002**
DCC_{t-1}	0.9745***	0.9721***	0.9677***	0.9511***	0.9317***
R^1	0.74	0.78	0.83	0.79	0.75
Ljung-Box test	0.618	0.911	0.992	0.304	0.001
Obs.	2887	2887	2887	2887	2887

*Note: Vestas wind systems a/s (VWS). European stock market uncertainty (VSTOXX). Economic policy uncertainty (EPU). Oil market uncertainty (OVX). First order difference Aruba Diebold and Scotti business cycle measure (diffADS). First order difference Federal Fund Rate (diffFFR). First order difference between 3-month treasury bond yield and 10-year treasury bond yield (diffTERM). First order difference US dollar index (diffDXY). 3-day SMA Google Search Volume Index (GSVI). First day lag DCC (DCC_{t-1}). R^1 goodness of fit. Ljung-Box test shows no signs of first order autocorrelation in error terms for τ equal to 0.1, 0.2, 0.5, 0.8 (reported p-value). *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.*

Appendix H Quantile regression subsample periods

Table 24: Quantile regression January 2012 to March 2016

	$\boldsymbol{\tau = 0.1}$	$\boldsymbol{\tau = 0.2}$	$\boldsymbol{\tau = 0.5}$	$\boldsymbol{\tau = 0.8}$	$\boldsymbol{\tau = 0.9}$
Intercept	-0.0015	-0.0021	0.0062***	0.0082	0.0236*
VSTOXX	-0.0002	0.0002	0.0002***	0.0009***	0.0017***
EPU	0	0	0	0	0
OVX	0.0001	0	0*	-0.0002**	-0.0005***
diffADS	0.011	0.0051	-0.0023	0.0186	0.0016
diffFFR	0.0059	0.0129	-0.0226*	-0.0017	0.0069
diffTERM	-0.0176	-0.0042	0.004	0.0502**	0.032
diffDXY	-0.0046	-0.0028*	0.0006	0.0021	0.0031
GSVI	-0.0001	0	0	0	0.0001
DCC_{t-1}	0.9602***	0.9621***	0.967***	0.9582***	0.9247***
R^1	0.71	0.77	0.81	0.76	0.70
Ljung-Box test	0.700	0.916	0.940	0.802	0.007
Obs.	1077	1077	1077	1077	1077

*Note: Sample period comprises of 1078 datapoints. European stock market uncertainty (VSTOXX). Economic policy uncertainty (EPU). Oil market uncertainty (OVX). First order difference Aruba Diebold and Scotti business cycle measure (diffADS). First order difference Federal Fund Rate (diffFFR). First order difference between 3-month treasury bond yield and 10-year treasury bond yield (diffTERM). First order difference US dollar index (diffDXY). 3-day SMA Google Search Volume Index (GSVI). First day lag DCC (DCC_{t-1}). R^1 goodness of fit. Ljung-Box test shows no signs of first order autocorrelation in error terms for τ equal to 0.1, 0.2, 0.5, 0.8 (reported p-value). *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.*

Table 25: Quantile regression April 2016 to October 2019

	$\boldsymbol{\tau = 0.1}$	$\boldsymbol{\tau = 0.2}$	$\boldsymbol{\tau = 0.5}$	$\boldsymbol{\tau = 0.8}$	$\boldsymbol{\tau = 0.9}$
Intercept	-0.0271***	-0.0096**	0.0066***	0.0081*	0.011
VSTOXX	0.0001	0.0003	0.0002**	0.0014***	0.001***
EPU	0	0	0	0	0**
OVX	0.0003	0.0002*	0	-0.0001	0
diffADS	-0.0883	-0.042	0.0076	0.0679	0.12**
diffFFR	-0.0267	-0.0313*	-0.0109***	-0.0255***	-0.037*
diffTERM	-0.0076	0.0083	0.0053	0.0456**	0.056
diffDXY	-0.0008	0.0024	-0.0003	0.0009	0.002
GSVI	0	0	0	-0.0001	0*
DCC_{t-1}	1.0028***	0.9655***	0.9609***	0.9309***	0.907***
R^1	0.69	0.76	0.81	0.77	0.74
Ljung-Box test	0.971	0.868	0.962	0.081	0.061
Obs.	918	918	918	918	918

*Note: Sample period comprises of 918 datapoints. European stock market uncertainty (VSTOXX). Economic policy uncertainty (EPU). Oil market uncertainty (OVX). First order difference Aruba Diebold and Scotti business cycle measure (diffADS). First order difference Federal Fund Rate (diffFFR). First order difference between 3-month treasury bond yield and 10-year treasury bond yield (diffTERM). First order difference US dollar index (diffDXY). 3-day SMA Google Search Volume Index (GSVI). First day lag DCC (DCC_{t-1}). R^1 goodness of fit. Ljung-Box test shows no signs of first order autocorrelation in error terms (reported p-value). *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.*

Table 26: Quantile regression November 2019 to April 2023

	$\tau = 0.1$	$\tau = 0.2$	$\tau = 0.5$	$\tau = 0.8$	$\tau = 0.9$
Intercept	-0.0306***	-0.0084	0.0061***	0.0106***	0.0235***
VSTOXX	0.0001	0	0.0001	0.0006***	0.0012***
EPU	0	0	0	0*	0
OVX	0.0001	0.0001	0	0	-0.0001
diffADS	0.0054	0.0019	0.0006	0.0002	-0.0018
diffFFR	0.008	0.0009	-0.0015	0.0055	-0.0073
diffTERM	-0.005	-0.0129	-0.0039	-0.0014	-0.0055
diffDXY	-0.0045	-0.0011	0.0004	0.0005	-0.003
GSVI	-0.0001	-0.0001	0	-0.0001	-0.0002**
DCC_{t-1}	0.9835***	0.9784***	0.9691***	0.9515***	0.9244***
R^1	0.74	0.79	0.83	0.82	0.79
Ljung-Box test	0.771	0.886	0.983	0.554	0.19
Obs.	892	892	892	892	892

*Note: Sample period comprises of 892 datapoints. European stock market uncertainty (VSTOXX). Economic policy uncertainty (EPU). Oil market uncertainty (OVX). First order difference Aruba Diebold and Scotti business cycle measure (diffADS). First order difference Federal Fund Rate (diffFFR). First order difference between 3-month treasury bond yield and 10-year treasury bond yield (diffTERM). First order difference US dollar index (diffDXY). 3-day SMA Google Search Volume Index (GSVI). First day lag DCC (DCC_{t-1}). R^1 goodness of fit. Ljung-Box test shows no signs of first order autocorrelation in error terms (reported p-value). *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.*