A GLOBAL PERSPECTIVE ON THE NEXUS BETWEEN ENERGY AND STOCK MARKETS IN LIGHT OF THE RISE OF RENEWABLE ENERGY

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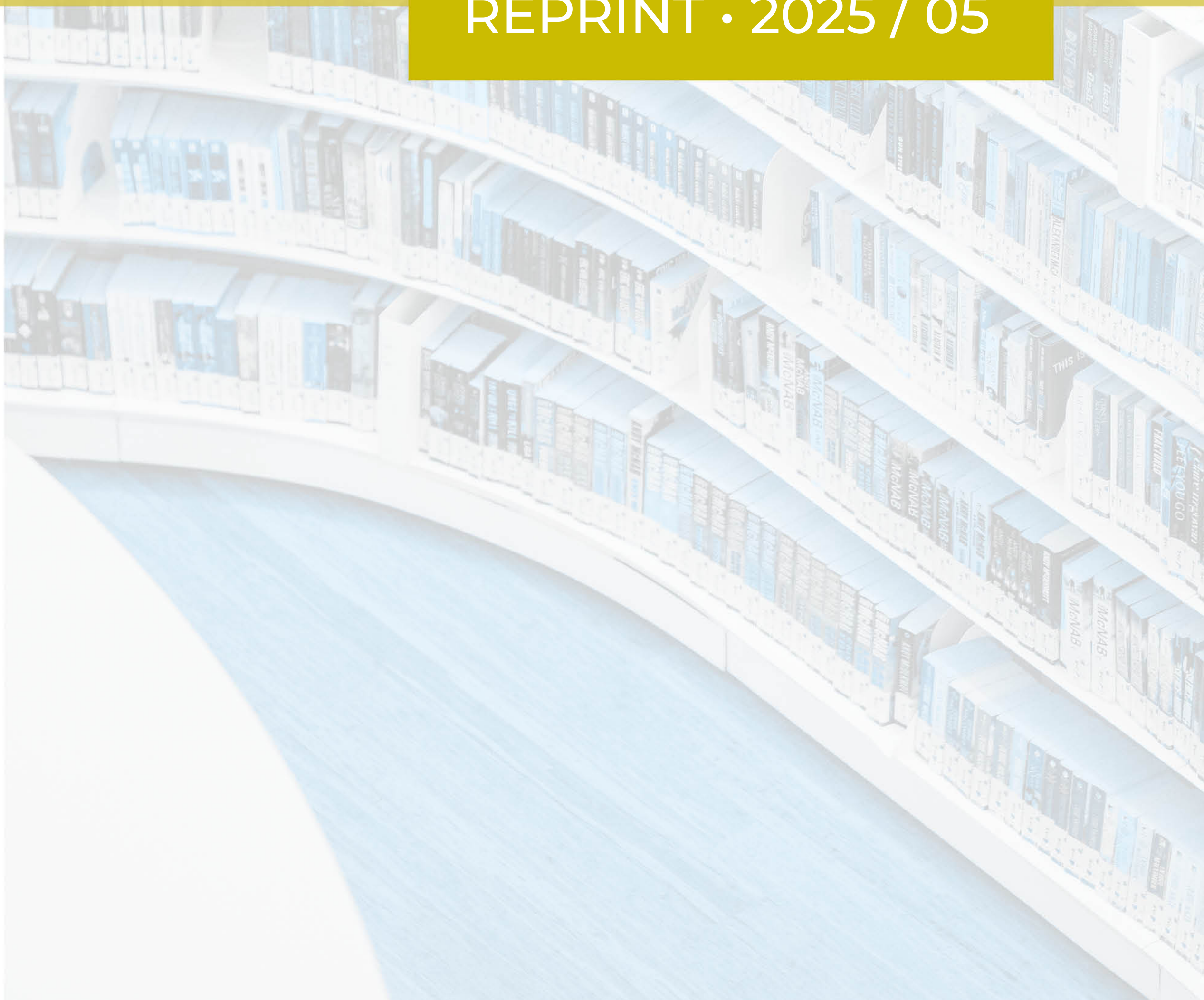

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A Global Perspective on the Nexus Between Energy and Stock Markets in Light of the Rise of Renewable Energy

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Abstract

The rise in renewable energy and the associated divestment initiatives from fossil fuel around the world have become prominent in combating climate change. This paper revisits the relationship between energy and stock markets by accounting for renewable energy through the use of the Divisia index method. The paper contributes to the literature by using three renewable energy tariffs rather than relying on clean energy stocks as a proxy for renewable energy. We retrieve data for both the price and consumption of fossil energy (oil, coal and gas) *and* renewable energy (solar, wind and hydro). We estimate a Vector Autoregressive (VAR) model over the period 2000-2019 across 25 countries globally. Our study identifies a significant time-dependent dynamics between renewable energy and both the energy stock and carbon markets, while fossil energy has no significant influence on those markets. The increasing influence of renewable energy in this nexus signals to policymakers that investors have started to shift their focus of attention from fossil to renewable energy.

JEL Classification: Q1, Q2, Q4, Q5

Keywords: renewable energy prices, fossil energy prices, stock prices

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1 Introduction

Climate change, energy security and growing energy demand have risen to the top of the global political agenda, and all experts henceforth recognize that renewable energy has become prominent in meeting these challenges. Renewable energy has accounted for about 18.1% of the total final consumption in 2017, according to the Renewables 2019 Global Status Report. There is likewise a growing number of countries having more than 20% renewables in their electricity mixes (Xia et al., 2019). The promising rise of the renewable energy sector and the notable divestment from fossil fuel have increased investors' enthusiasm for renewable power and fuel (Liu et al., 2021). Even developing and emerging economies have joined the league. They are becoming major investors in renewable energy. For example, China accounted for 32% of global renewable energy investment in 2018. Total investment in renewable power was almost three times higher than the amount of investment in newly installed gas and coal
generators.

The transition towards renewable energy cannot be segregated from the traditional fossil fuel sector. Fossil fuel prices have a strong influence on the development of renewable energy especially with respect to related investments and returns. For example, developing alternative renewable sources of energy is more costly when the prices of fossil energy are low. Investors have less incentives to boost renewable energy production in these circumstances and it can lead to lower stock prices of renewable energy companies as a consequence. On the contrary, when the price of fossil fuel energy is higher, incentives to further explore renewable energy is stronger, leading to a rise in the stock prices of renewable energy companies. In general, we would expect to see a negative relationship between fossil energy prices and renewable energy stock prices. Empirical studies have examined the relationship between fossil fuel prices such as oil, coal, gas, and their impact on clean energy companies' stock returns. Fewer studies stipulate that energy prices can be influenced by other variables such as carbon returns and technology stock returns (Hammoudeh et al. (2014); Henriques and Sadorsky (2008); Sadorsky (2012); Kumar et al. (2012); Qin (2014); Sun et al. (2019); Xia et al. (2019); Pham (2019), among others).

There is also a much more limited literature on the impact of renewable energy prices on the stock returns of traditional and green energy companies. Practical recommendations for the investment community can still be drawn from this literature. As pointed out by GallegoAlvarez et al. (2015), the transition to low carbon can have a positive effect on financial´ performance because investors can better select the optimal investment portfolio to reduce their risks and get excess returns. For example, abrupt volatility and correlation changes in renewable and fossil energy prices can hit energy intensive companies heavily, and investors have an incentive to identify the better-positioned companies which can quickly adjust their level of energy consumption and adopt innovative technologies (Gong et al., 2021). Given the rise in renewable energy, it is vital to appraise the governing correlation between both renewable and fossil energy prices against stock returns.

Scholars have adopted different models to investigate the correlation between energy and stock market prices. For example, Lin and Li (2015) used a VEC-MGARCH model, Ji et al. (2018) use a VAR model to test the correlation in carbon-energy system whilst Kumar et al. (2012) use a VAR model to study oil prices, carbon prices and clean energy stock prices. Cong et al. (2008) examine the dynamics between oil prices shocks and the stock market using as VAR model as well. Dutta et al. (2018) adopt a VAR-GARCH model to assess the link between carbon price and clean energy stock indices. Zhang and Du (2017) develop a TVP-SV-VAR model to estimate the linkage among stock prices of new energy, high technology and fossil fuel companies.

The existing literature seems to focus mostly on the relationship between renewable (or clean) energy stock returns and fossil fuel energy prices only. However, renewable energy prices may very well impact stock returns. In addition, the existing studies cover a limited number of countries, China and the US being the most investigated ones. In this paper, we take a global perspective, including renewable energy (both prices and consumption) in the analysis for a larger set of 25 countries. Our main research question is to investigate how renewable price changes affect the performance of stocks in general and of energy companies in particular, controlling for all the other types of influences, such as fossil fuel energy prices, carbon market prices as well the correlation with stock market indices and other sectors of activity.

We contribute to the literature in the following ways. First, we consider three types of fossil energy sources (oil, gas and coal) *as well as* three types of renewable energy sources (solar, wind and hydro) in our VAR model. Second, we apply the Divisia index method to renewable energy prices for the first time, extending Sun et al. (2019) which ignore renewable energy.
Third, we cover 25 countries and extend previous studies which mostly considered the US and China.

Our analysis indicates that renewable energy is decoupled from fossil energy and has insignificant relationship with the latter. In spite (or because) of this decoupling, renewable energy is found to pave its own way to financial markets, especially through energy intensive companies. The risk of stranded asset and increasing divestment campaigns coupled with carbon pricing mechanisms incentivise companies to adopt a low carbon transition. The latter significantly influences carbon prices, i.e, increasing investment in renewable energy leads to a decrease in demand and an increase in supply for CO2 permits, further decreasing carbon prices. Interestingly, fossil energy exhibits no significant relationship with any of the variables tested. In an era of low carbon transition, investors conceivably have to commit large sums of financing at long horizons and hence use discounted cash flow models into which they incorporate and smooth the cost of transition away from fossil energy over a long period of time. Our results also show that stock markets are not influenced by renewable energy nor fossil energy but are significantly impacted by technology stocks and carbon prices. Considering a set of 25 countries, we therefore reinforce and generalize the role that technological stocks and carbon prices play in financial markets around the world.

The remainder of this paper is structured as follows. In Section 2, we examine the existing literature on the relationship between energy prices and stock markets, from both theoretical and empirical standpoints. This comprehensive review serves as the foundation for our study and highlights its significance within the broader context. Section 3 explains the methodology and the data. Section 4 specifies and estimates the VAR model based on stock indices, carbon prices, technology stock prices, energy stock prices, the Divisia index of fossil energy as well as the Divisia index of renewable energy. In this section, we also discuss the impulse response, Granger causality, and variance decomposition findings. The last section concludes.

2 Literature review

This section outlines the theoretical framework that governs the connection between stock and energy prices, considering the Natural Capital Theory, the stranded assets issue, and portfolio theory. It also reviews the existing empirical literature and provides rationale for our chosen methodology and selection of outcome and control variables.

2.1 Theoretical foundations

The relationship between renewable energy, fossil energy and stock prices that we explore in our study is governed by the substitutability condition that is conceptualised in the Natural Capital Theory (NCT). The theory explains the paradigm shift from fossil to renewable energy sources (Pearce, 1988; Costanza and Daly, 1992; Barbier, 2019; Khan et al., 2021). NCT suggests that the relationship between renewable and fossil energy is determined by how easily they can be replaced by one another. The theory argues that we can move away from non-renewable resources to renewable ones and still achieve sustainable economic development. This means that companies can use renewable natural resources like wind, solar, or hydropower and at the same time rely less on non-renewable resources like coal, oil, or gas. This is illustrated in Figure 1 by Foster et al. (2017).

It is therefore possible for companies to enhance their environmental protection efforts and promote long-term sustainability by decreasing their dependence on non-renewable resources.

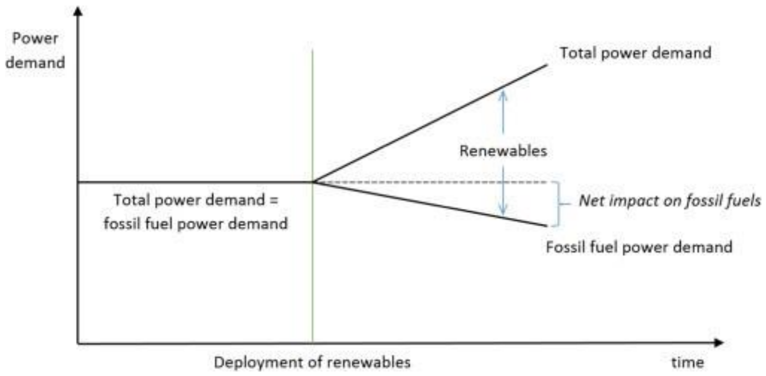

Figure 1: Renewable energy effect on fossil fuels (Source: Foster et al. (2017))

This can help lower their exposure to reputation and systemic risks, and consequently, make their company shares more appealing.

Another theoretical justification behind the relationship between renewable energy, fossil energy and stock prices is given by the existence of stranded assets which lose value or becomes unusable in a sudden or unexpected way. Stranded asset risk can arise through transition risk, i.e., through the implementation of carbon budgets or national and international restrictions on carbon-intensive activities (Chenet et al., 2015). Stranded assets can suffer from devaluation or conversion to liabilities (Caldecott et al., 2014). This poses a risk for investors who have invested in such assets, as they may incur significant losses. It also highlights the need for a smooth and just transition to a low-carbon economy, which involves managing the risk associated with stranded assets and ensuring that affected communities and workers are not left behind. In such an environment, energy price dynamics are clearly related to stock prices as investors are looking for ways to shift investments away from fossil fuel to renewable energy. Conversely, adequate financing mechanisms are also necessary to support the growth of renewable energy, and the stock market is a crucial avenue for funding.

Finally, whilst the just transition and divestment trend is on the rise, the Modern Portfolio Theory (Markowitz, 1968; Roy, 1952; Tobin, 1958) highlights that the constraints related to the substitution of energy sources may leave investors with a less efficient portfolio. Disinvestment would imply lower diversification benefits and more strongly correlated stock returns, leaving investors with lower risk-adjusted returns in fossil-free portfolios in comparison to unconstrained portfolios. For example, Kuang (2021) shows that clean energy stocks generally underperform the overall equity market but outperform dirty stocks. The study also indicates that the efficacy of clean energy portfolio optimization strategies is sensitive to the clean energy stock sub-sectors, which has important implications for investors constructing clean energy portfolios to meet investment objectives.

2.2 Empirical foundations

The fundamental economic principles on which rely the three theoretical frameworks explained in the previous section clearly show that renewable and fossil energy prices are intrinsically connected to company stock prices. In the empirical studies reviewed below, we show that empirical evidence on such a link in the existing literature is essentially documented for fossil energy.

2.2.1 Fossil energy and company stock market prices

Edelstein and Kilian (2009) underline the traditional mechanism through which oil price increases can transmit negative effects on household consumption and aggregate output (through reduced household income and increased production costs), thus resulting in lower stock returns. Kilian (2009) employs a structural VAR model to decompose the oil demand and supply shock on US stock markets. The results show no significant impact of oil supply shock on US stock markets. Apergis and Miller (2009) expand the research to eight countries and find little evidence between oil market and stock markets. Sadorsky (2012) studies the impact of oil in emerging markets and show that oil prices react positively to positive shocks on the emerging stock markets. Similarly, Fang and You (2014) assess the fossil energy impact on stock markets in China, India and Russia and find no significant effect. Chen and Li (2015) find an extreme dependence between oil prices and Chinese stock markets.

Given the increasing adoption of renewable energy, the influence of fossil energy on stock markets must be revisited to account for the impact of renewable energy on stock markets. In our empirical investigation, we put forth the hypothesis that an increase in either fossil or renewable energy prices would adversely affect overall stock prices due to the resulting higher energy costs.

2.2.2 Fossil energy and new energy company stock prices

An increase in fossil energy prices encourages the adoption of alternative energy sources, whereas a decrease tends to deter their use. Fossil energy prices therefore hold a significant influence over the profitability of renewable energy projects and companies.

A series of studies find supporting evidence to the oil-renewable energy company stocks relationship. For example, Henriques and Sadorsky (2008) study the relationship between oil prices and alternative energy company stock prices using a vector regression model (VAR) and conclude that oil prices can Granger cause them. Dutta (2017) find similar results by using a volatility index in the international crude oil markets. Reboredo (2015) uses copula models to measure the dependence between oil prices and renewable energy company stock prices and concludes that oil prices can significantly influence the downside and upside risks of renewable energy company stock returns. Pham (2019) finds heterogeneous relationship between the two variables and also indicates that it differs across sub-sectors. Broadstock et al. (2012) and Wen et al. (2014) document mean and volatility spillover effects between renewable energy and fossil fuel companies in China. However, Ferrer et al. (2018) find no significant influence from crude oil prices to renewable energy company stock prices. Investment risks in renewable energy markets are also higher than in traditional energy industries and they face speculative behaviours (Bohl et al., 2013).

Sun et al. (2019) consider several fossil energy resources and use the Divisia price synthesis method on prices of coal, oil and natural gas to investigate the effect of fossil energy prices on new energy company stock prices. Their results demonstrate that new energy company stock prices are mainly affected by lagged values while the effects of fossil energy prices are weak. Gu et al. (2020) assess the co-movements between steam coal and clean energy company stocks in China using a VAR-DCC-GARCH framework for the period 2008 to 2019 and indicate the presence of significant bi-directional volatility between the variables. Zhang and Du (2017) employ a coal-oil index as an aggregated indicator against stock prices of public companies in China and study its impact on clean energy stocks. The demand and supply of coal directly affect the investment in clean energy sources. Qin (2014) found that new clean energy company stock prices are not impacted by oil and technology company stock prices whilst is positively influenced by coal and carbon prices.

2.2.3 Carbon, fossil energy and new energy company stock prices

Carbon prices are deemed to relate to both economic activity and fossil energy prices (Redmond and Convery, 2006; Ch`eze et al., 2009; Hammoudeh et al., 2014). This relationship can be extrapolated through the fact that the consumption of fossil energy results in carbon emissions. Thus, changes in fossil energy prices affect energy consumption and consequently the demand for carbon emissions (Wu et al., 2020). Dowds et al. (2013) highlight that an increase in carbon price shifts fuel energy consumption from coal to natural gas due to the change in marginal fuel costs for electricity generation. Narayan and Sharma (2015) stipulate that carbon assets, and more specifically carbon futures, are used as a tool for portfolio diversification in order to facilitate risk mitigation and transfer.

Very few studies have assessed the impact of carbon prices on stock indices (Oberndorfer, 2009; Kumar et al., 2012; Luo and Wu, 2016). More directly related to our study, Kumar et al. (2012) study the nexus between carbon prices, clean energy stock prices and oil prices using a VAR model. They conclude that oil prices can affect the stock prices of clean energy firms while carbon prices fail to do so. Jiang et al. (2020) use wavelet methodology to map the time frequency connectedness between coal, new energy stock, and carbon prices in China. The findings show that carbon as well as coal price connectedness occur in both lower and higher frequency while connectedness in new energy stock prices takes place in the middle frequency. This is supported by Marimoutou and Soury (2015); Gronwald et al. (2011); Mansanet-Bataller et al. (2007) who find similar fluctuations between the variables over time. Dutta et al. (2018) highlight through a VAR-GARCH model that EUA carbon prices can boost renewable stock returns. Ji et al. (2018) find that brent crude oil prices can significantly affect carbon prices and risks. Chevallier (2011) find that coal prices can significantly impact on carbon prices. Regarding cap and trade regulations, Bushnell et al. (2013) find that they cause a reduction in stock prices of carbon and electricity intensive companies. Jong et al. (2014) find a negative relationship between equity prices and carbon prices, especially in case of lower carbon intensive holdings. Moreno and da Silva (2016) highlight that the European carbon price negatively impact equity returns in Spain during Phase III. The latter further describes the impact of carbon market as being asymmetric and sector specific. The hypothesis highlights that carbon prices induce the development of clean technology thus positively impacting on renewable energy prices and stock prices but negatively impacts on fossil fuel prices.

2.2.4 Technology company and new energy company stock prices

In this era of technological advancements, innovations in renewable energy sector are essential for the future expansion of renewable energy markets. It is expected that the recent development in technological innovations will support the invention and progress of renewable energy markets (Nasreen et al., 2020). The stock prices of technology companies appear to be highly correlated with those of alternative energy companies and the price of fossil fuel (Henriques and Sadorsky, 2008; Managi and Okimoto, 2013; Kumar et al., 2012; Bondia et al., 2016; Inchauspe et al., 2015). With the rise in oil prices and its growing expense, there is an incentive for economic actors to replace conventional energy with clean alternatives. This, in turn, amplifies the demand for technology, consequently influencing the stock prices of technology firms. This is particularly significant as clean energy enterprises rely substantially on inputs from technology companies (Ahmad, 2017; Managi and Okimoto, 2013).Sadorsky (2012) finds that clean energy stock prices have stronger correlations with technology stock prices rather than with oil prices. Managi and Okimoto (2013) investigate the dynamics between oil prices, interest rates, clean energy and technology stock prices using a structural break in late 2007. Their results show that both oil prices and technology stock prices have positive influence on renewable energy stock prices. These findings are supported by Bondia et al. (2016). Such correlation is fostered through the transition to a low carbon economy, which directs capital investment into innovative technologies. Investors might also view the renewable energy sector as similar to the technology sector given the need for similar resources such as research facilities, prominent engineers, thermoelectric materials and integrated circuits (Zhang and Du, 2017). Exploring the dynamic interconnections and directional influences among oil, renewable energy, and technology firms is of paramount importance for policymakers. This investigation offers insights into the optimal timing and economic policies whether supply-side or demand-side that can effectively promote and bolster investments in clean energy and technology companies (Diebold and Yilmaz, 2012).The hypothesis is that a rise in technological stock prices positively impact on renewable energy prices and stock prices.

2.2.5 Where do we stand?

Table 1 positions our study in the existing literature. Whilst the impact of fossil fuel prices on stock prices as well as on renewable energy sector have been extensively studied, there is scant literature on how renewable energy prices influence stock prices. Similarly, there is a need to assess the relationship between fossil fuel in light of renewable energy.

The gap in literature is further highlighted by Figure 2 which shows that there is increasing interest in fossil energy markets and financial markets but the studies do not involve renewable energy. Further, variables such as carbon prices and innovation have been included in past studies. By studying fossil fuel and renewable energy prices in 25 countries while accounting for their consumption through the Divisia index by Sun et al. (2019), this paper sheds light on the nexus between those energy and stocks in a comprehensive way. Both renewable and fossil energy are considered and special attention is given to technology and energy intensive stocks, as well as carbon allowances.

3 Data and Methodology

3.1 Data

The data set includes six time series, namely renewable energy prices, fossil fuel prices , carbon prices, broad stock index prices, technology company stock prices, and energy company stocks prices. The data set covers the period from 2000 to 2019 at the annual frequency for around 25 countries.

Table 1: Positioning of our study in the literature

Authors (year)	Comparison of variables	Comparison of results
Henriques and Sadorsky (2008)	new energy stock prices, technology stock prices, oil prices and interest rate	Oil prices impact on new energy stock prices is not as effective as technology stock prices
Kumar et al. (2012)	new energy stock prices, technology stock prices, oil prices, oil prices, carbon prices and short term interest rate	technology stock prices influence new energy stock more than oil prices
Sadorsky (2012)	new energy stock prices, technology stock prices and oil prices	There is a higher correlation between technology and energy stock prices than with oil prices
Managi and Okimoto (2013)	clean energy stock prices, technology stock prices and oil prices	There is a positive relationship between oil prices and clean energy prices. A similarity between clean energy stock prices and hightech stock prices is also suggested
Qin (2014)	new energy stock prices, technology stock prices, coal prices, oil prices and carbon prices	new energy stock prices are not impacted by oil and technology stock prices whilst is positively influenced by coal and carbon prices
Zhang and Du (2017)	new energy stock prices, technology stock prices, coal-oil price index	new energy stock prices correlate more highly with technology stock prices than with coal and oil prices
Sun et al. (2019)	new energy stock prices, technology stock prices, carbon prices, Divisia energy price index	the correlation between new energy stock and technology index is more significant than with Divisia fossil energy price index
Nasreen et al. (2020)	clean energy stock prices, technology stock prices, oil prices	technology stocks seem to lead oil prices and clean energy stock returns. Significant relationship noted between oil prices and clean energy stock returns for the period 2006-2009.
This study	Divisia fossil energy price, Divisia Renewable energy price, stock indices, carbon prices, technology stock prices, energy stock prices	renewable energy prices correlated to energy stock prices and carbon prices. Technology stock prices influence carbon prices and stock indices whilst carbon prices impact on stock indices, renewable energy and energy stock prices

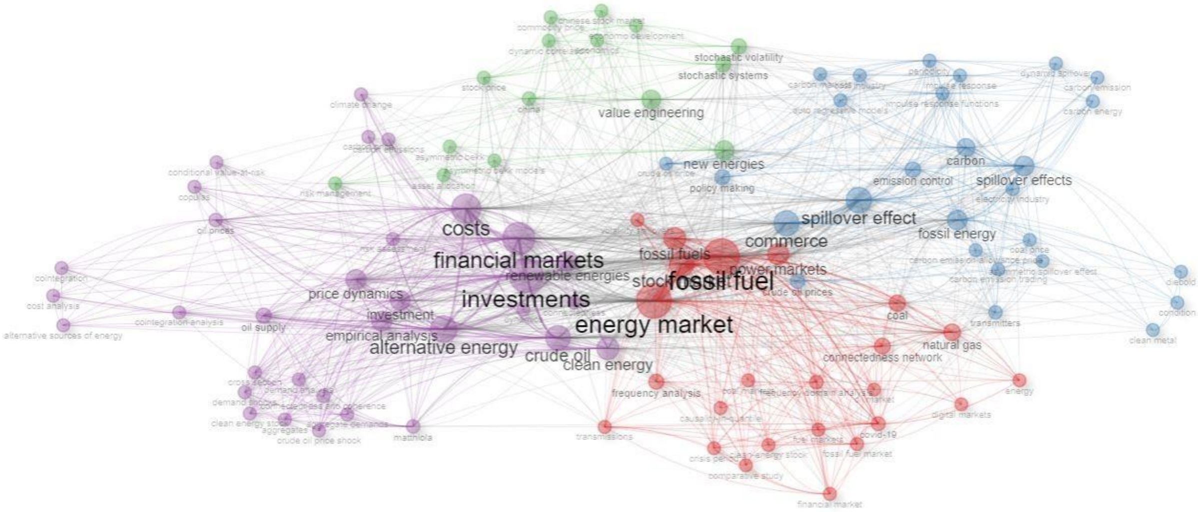

Figure 2: Bibliometric mapping of literature

We had to use annual data since the consumption of renewable and fossil fuel energy is reported on an annual basis. The consumption data has been retrieved from the International Energy Agency (IEA) that reports on energy consumption data. The list of 25 countries in our sample stems from the IEA countries whose data is reported and available publicly. As shown in Table 10 in the Appendix, the list includes both developed and developing countries, although data availability skews the sample towards developed countries.

First, unlike previous studies which use clean energy stocks as a proxy for renewable energy, we directly estimate the renewable energy prices for each country from the renewable energy tariffs reported annually and made publicly available by the OECD.

Second, for fossil fuels (namely oil, coal and natural gas), we extract data from the IndexMundi website. The Brent Crude oil is used as representative for oil prices, South Africa's coal for coal prices, and Henry Hub Natural Gas for natural gas.

Third, daily carbon prices have been downloaded from ICAP and then annualised. Given carbon markets have mushroomed around the world and are nowadays deemed as key financial initiatives to combat climate change, we can use carbon prices based upon the geographical location of each country in our sample, i.e, EU countries have been allocated the EU carbon price, North and South American countries have been attributed the RGGI carbon price and Asian countries have received the Chinese carbon price. However, emission trading systems were only implemented as from 2008.

Finally, we retrieve data on stock prices from Refinitiv. For each country, we use three stock indices: a broad stock index, an energy stock index, and a technology stock index. They are all listed in Table 10 in the Appendix.

Figure 3 shows the trends in price returns for renewable energy, fossil energy, the broad stock market, the technology stock index, the energy stock index, as well as the carbon allowances from different emission trading systems.

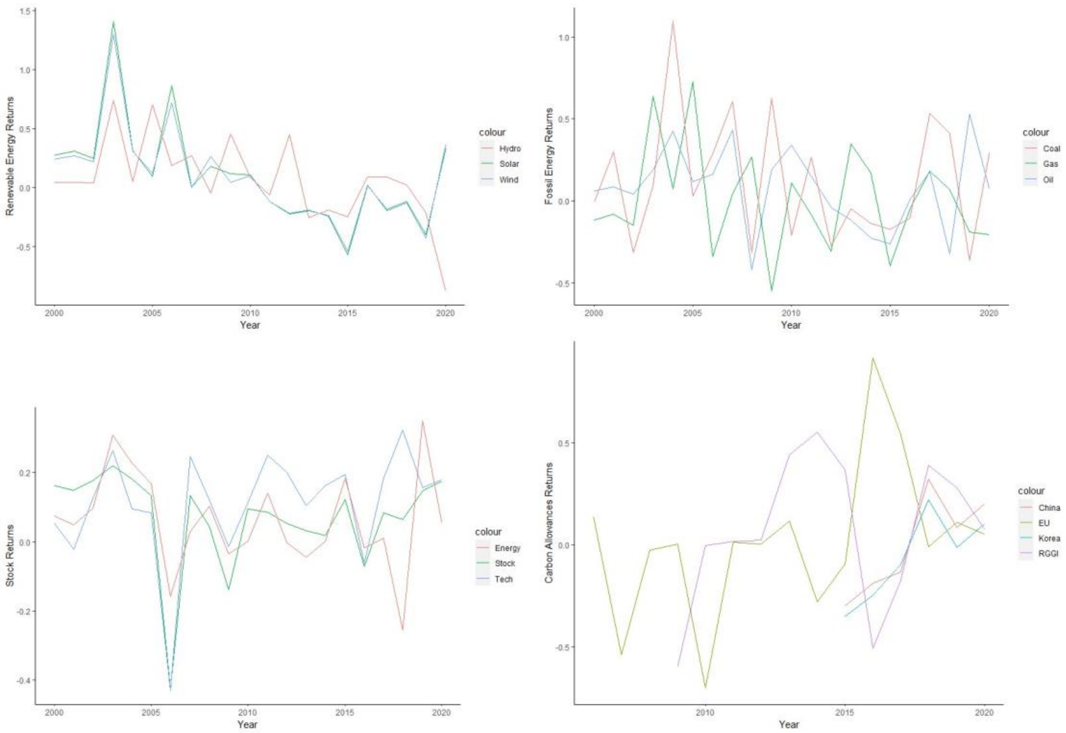

Figure 3: Annual Trend of Variables

3.2 Divisia Index

The Divisia index was first proposed by Boyd et al. (1987) and has been favored in energyrelated studies. Kim et al. (2020) use a decomposed Divisia index to study the factors influencing carbon emission and electricity generation. Similarly, Chapman et al. (2018) adopt the Logarithmic Mean Divisia Index (LDMI) to identify the main contributing changes in carbon emissions in six Northeast Asian countries. Zhou et al. (2017) also assess the drivers of carbon emissions in Chinese regions. While the above studies use the Divisia index to decompose the changes in energy structure, emission factor, energy intensity and renewable energy has never been accounted for. To fill this gap and uncover the relationship between renewable energy prices and stock prices while controlling for the other energy sources, we use the Divisia index synthesis method adopted by Sun et al. (2019) to obtain the Divisia renewable energy price index based on the prices and consumption for renewable energy, namely solar, wind and hydro. We follow the same method to estimate the Divisia fossil energy price index based on fossil energy, namely oil, gas and coal.

For these two Divisia indexes, we calculate the logarithmic percentage, r_t, in the following way:

$$r_t = 100[ln(P_t) - ln(P_{t-1})] = 100[\sum_i 0.5(s_{it} + s_{it-1})(ln(p_{it}) - ln(p_{it-1}))] \tag{3.1}$$

where $s_{it} = \frac{p_{it}x_{it}}{\sum_i p_{it}x_{it}}$, p_{it} represents the unit price of the energy source i in year t, x_{it} indicates the consumption of the energy source i in year t, and P_t represents the Divisia index price in year t. We therefore obtain two time series of log percentages for renewable energies and fossil fuels, respectively the *RR* and *FR* variables.

3.3 Log percentages

For the other four time series, we compute the log percentages, r_t, also called log returns, in the traditional way where $r_t = 100[ln(P_t) - ln(P_{t-1})]$ and P_t is the price at time t.

We therefore obtain the broad stock index log returns (*BSR*), the log percentages of carbon emission prices (*CR*) prevailing on the different carbon markets (EU ETS, California ETS, Quebec ETS, Chinese Pilot ETS and South Korean ETS), the technology stock index log returns (*TSR*), and the energy stock index log returns (*ESR*).

3.4 Descriptive Statistics

In Table 2, it can be inferred that the mean across countries and time are negative for both renewable energy and fossil fuel prices. Fossil fuel prices have a smaller negative return than renewable energy prices. All the three stock indices display positive mean return. As expected, the technology stock index (TSR) performs the best, followed by the broad stock index (BSR) and the energy stock index (ESR). Carbon emission returns also maintain a positive momentum.

Table 2: Descriptive Statistics of Variables

Variable	RR	FR	BSR	CR	TSR	ESR
Mean	-0.1697	-0.0043	0.0608	0.0047	0.0719	0.0215
Median	0	0	0.0912	0	0.0187	0
S.D	4.3935	0.3592	0.2534	0.2968	0.2906	0.8249
Kurtosis	59.0051	277.988	6.7213	6.2635	6.5549	188.24
Skewness	0.7518	-14.8272	-1.1825	0.5829	-0.5889	0.0023
Minimum	-42.5363	-6.7924	-1.0773	-0.8958	-1.4521	-11.946
Maximum	43.0514	1.6046	0.9614	1.0357	1.1983	11.990
Obs	473	473	473	473	473	473

The standard deviation represents the degree to which the sample sequence deviates from the mean of the sample. The smaller the standard deviation, the more concentrated the sample sequence. The volatility in fossil energy prices are more stable than renewable energy prices. Energy stock prices are less volatile than stock prices and technology stock prices.

3.5 Methodology

Various methods have been used in the existing literature on energy to assess the relationship amongst the variables described above. Given the prevalent endogeneity issue, we propose to use a Vector Auto Regression (VAR) model. In a VAR, each variable is treated as endogenous and depends on the lagged values of all the selected variables to correct for the presence of endogeneity (Tseng, 2017). Interestingly, the strengths of using VAR in energy prices have been confirmed by Henriques and Sadorsky (2008); Kumar et al. (2012); Kilian and Murphy (2012); Baumeister and Peersman (2013).

The general specification of our VAR model with lag p order is as follows:

$$Y_t = \phi_t Y_t + ... + \phi_p Y_{t-p} + Hx_t + \xi_t, \tag{3.2}$$

where $t = 1.2,....T$, Y_t stands for the column vector of the k-dimensional endogenous variable, x_t is the column vector of the d-dimensional exogenous variable (including the intercept), p is the lag order, T is the total number of samples, $\phi_1,....\phi_p$ is the dimension of $k * k$ dimension matrix to be evaluated, H is $k * d$ dimensional matrix of estimated coefficients and ξ_t is $k$dimensional random perturbation column vector. Random perturbation can be linked to each other in the same period but is not linked to their own lag value or to the variables on the right side of the equation.

As indicated in the previous sections, we use annual data to investigate the relationship among renewable energy log returns (*RR*), fossil energy log returns (*FR*), carbon log returns (*CR*), broad stock index log returns (*BSR*), energy stock index log returns *(ESR*), and technology stock index log returns (*TSR*). Thus, our VAR model at the country level includes 6 equations and is described as follows:

$$
\begin{pmatrix} BSR \\ RR \\ FR \\ CR \\ TSR \\ ESR \end{pmatrix}_t = A_1 \begin{pmatrix} BSR \\ RR \\ FR \\ CR \\ TSR \\ ESR \end{pmatrix}_{t-1} + A_2 \begin{pmatrix} BSR \\ RR \\ FR \\ CR \\ TSR \\ ESR \end{pmatrix}_{t-2} + ... + C + \xi_t, t = 1, 2, ..., T \qquad (3.3)
$$

where C is a column vector of intercepts and ξ_t is k-dimensional random perturbation column vector.

4 Empirical Findings

We first specify and estimate the VAR model based on the six above-mentioned time series of log percentages. We then explore the relationship using impulse response functions.

4.1 VAR Model Specification

Before applying the VAR model, we must determine the appropriate model specification by identifying the order of integration of each data series, the existence of cointegration among the six variables, and the lag order in the system of equations.

If the variables have a unit root, it is best to take the first difference in order to make the series stationary. In addition, if there is a cointegrating relationship in the system, we should use the vector error correction model rather than the VAR model in the first differences. We therefore conduct the unit root and cointegration tests and summarize the results below.

Prior to estimating the VAR model, we compute the Augmented Dickey-Fuller (ADF) and Kwiatkowski Phillips Schmidt Shin (KPSS) unit root tests in accordance to Henriques and Sadorsky (2008); Sun et al. (2019). The null hypothesis for the ADF test is that the data series has a unit root whereas the null hypothesis for the KPSS test is that the data series is stationary.

Table 3: Unit Root Test

Variables	ADF	KPSS
RR	-8.1945***	0.104
FR	-8.1462***	0.153
BSR	-7.7161***	0.242
CR	-9.7738***	0.047
TSR	-7.1426***	0.786
ESR	-6.4843***	0.153

ADF and KPSS tests have been carried out for all the six variables in the model.[1] There is no evidence of unit roots in the data, so the log percentages are stationary.

The cointegration test has been carried in line with Johansen et al. (1992) in the context of the following k = 6 dimensional vector autoregression model:

$$y_t = \sum_{i-1}^{k} \phi_i y_{t-i} + \mu + \mu_t, \tag{4.1}$$

where y_t are the time series of prices for the six variables, and μ_t is an independently and identically distributed p-dimensional vector with a zero mean and a covariance matrix.

We use both trace and maximum eigenvalue statistics to test for the number of cointegrating vectors. The results in Table 4 show that the null hypothesis that there was no co-integration relationship at the significance level of 5%, is not rejected in both cases. Therefore, there was no long-term equilibrium relationship among the six variables in this model.

Table 4: Unintegrated Cointegration Rank Test

	Eigen Value	Trace Stats	Critical Value	Max Eigen Value	Critical Value
0	0.4213833	673.39	102.14	271.92	40.30
1	0.3208427	401.47	76.07	192.29	34.40
2	0.2401895	209.18	53.12	136.52	28.14
3	0.0672939	72.66	34.91	34.62	22.00
4	0.0444804	38.04	19.96	22.61	15.67
5	0.0305553	15.42	9.24	15.42	9.24

There is a trade-off to determine the lag order in a VAR model. On the one hand, p should be large enough to reflect the dynamics in the model. On the other hand, the greater the lag order,

[1] ***, ** and * denotes statistical significance at 1%, 5% and 10% level respectively.

the more parameters need to be estimated which eventually results in lower degrees of freedom. The lag order can be determined using various methods (Runkle, 1987). When the Akaike information Criterion (AIC), Schwarz's Criterion (SC) or Hannan-Quinn's Criterion (HQ) do not lead to the same lag order, the lag order is usually set by relying on the SC which embodies a stiffer penalty, in line with Tang and Aruga (2021). As shown in Table 5, the lag is set equal to 2. This is also confirmed by the final prediction error (FPE).

Table 5: Lag length selection for VAR model

Lag	AIC	HQ	SC	FPE	LR	LogL
1	-2.723565e+01	-2.708789e+01	-2.686031e+01	1.484956e-12	NA	2415.44
2	-2.764352e+01	-2.736910e+01	**-2.694645e+01**	**9.876703e-13**	0.15	2523.82
3	-2.770590e+01	-2.730482e+01	-2.668710e+01	9.281172e-13	0.21	2563.51
4	-2.787645e+01	-2.734872e+01	-2.653593e+01	7.828660e-13	0.39	2617.96
5	-2.792497e+01	-2.727059e+01	-2.626273e+01	7.462156e-13	0.43	2650.53
6	-2.820827e+01	**-2.742724e+01**	-2.622430e+01	5.625938e-13	0.42	2747.61
7	-2.819146e+01	-2.728378e+01	-2.588578e+01	5.727982e-13	0.39	2768.92
8	-2.813633e+01	-2.710199e+01	-2.550892e+01	6.062055e-13	0.31	2786.57
9	**-2.825184e+01**	-2.709085e+01	-2.530271e+01	5.411488e-13	0.32	2838.57
10	-2.821622e+01	-2.692857e+01	-2.494536e+01	5.621696e-13	0.06	2956.24

The figures in bold represents the lag order selected by the criterion. AIC is the Akaike Information Criterion, HQ represents Hannan-Quinn information criterion, SC is the Schwarz Information Criterion, FPE represents Final prediction error, LR is the Likelihood ratio test and LogL is the Loglikelihood test.

4.2 VAR Model Estimation

As explained in the previous sections, the VAR model reported in Table 6 has been generated with an optimal lag order of 2.[2]

Table 6: VAR Results

Variables	RR	FR	BSR	CR	TSR	ESR
RR(L1)	0.9211***	-2.52e-03	-0.0996	0.0049	-0.3694	2.1219**
FR(L1)	0.1316	0.0340***	-1.5523	1.4701	-4.3291	-1.1609
BSR(L1)	-0.0024	0.0006	-0.1383**	0.1091*	-0.1858***	0.0884
CR(L1)	-0.0056	4.536e-05	0.0534	0.2083***	0.1011**	0.0189
TSR(L1)	-0.0067	-0.0006	0.0641	-0.0098	-0.0163	0.0487

[2] To test the robustness of this pooled VAR model, we have also run the fixed Panel VAR and GMM Panel VAR models. No significant differences were detected.

ESR(L1)	0.0209***	-0.0003	-0.0288	-0.0199	-0.0437*	-0.7601***
RR(L2)	-0.4562***	0.0015	0.0481	-0.9527**	0.0333	-1.5516
FR(L2)	0.0349	-0.0307***	-2.7544	-3.6064	-3.9423	-6.8697
BSR(L2)	-0.0005	0.0010	-0.0320	0.1218**	-0.0568	-0.0990
CR(L2)	-0.0046	-1.060e-05	0.0605	-0.1692***	-0.0185	0.1743
TSR(L2)	-0.0094	-0.0002	0.0857*	0.0251	0.0603	0.1139
ESR(L2)	0.0055	0.0005	0.0124	0.0963*	-0.0121	0.0151
Observations	473	473	473	473	473	473
	0.474	0.1629	0.03849	0.1217	0.06172	0.3662
$AdjustedR$						
	0.4602	0.141	0.01335	0.09871	0.03719	0.3496
F-Stats	34.46***	7.442***	1.531*	5.298***	2.516***	22.1***

***, ** and * denotes statistical significance at 1%, 5% and 10% level respectively.

To the best of our knowledge, this study is the first to identify a bidirectional dynamic link between renewable energy (RR) and energy stocks (ESR). First, renewable energy log returns are positively influenced by past energy stock log returns, as indicated in the first column of Table 6. When the market capitalization of energy companies increases and there is positive momentum in the sector, these companies have more likely to shift towards renewable energy and make it more valuable. Second, renewable energy log returns (RR) positively influence energy stock log returns (ESR), as indicated in the last column of Table 6. This causal relationship can be explained by the greater reliance of energy companies towards cleaner energy sources following the many divestment initiatives from fossil fuel taken globally, especially in the energy sector (Renewable-Energy, 2019). This divestment by energy companies is driven by greater stranded asset risks, i.e, the risk of obsolescence for infrastructures built up around fossil fuels (Curtin et al., 2019). In a low carbon transition regime, impeding danger of stranded assets leads to unburnable carbon, implying that fossil fuel energy sources cannot be burned if the world is to adhere to any given temperature outcome. In these circumstances, the value of fossil energy decreases and fails to have positive return (Caldecott et al., 2014) while it becomes more profitable for energy companies to adopt sources of cleaner energy whose worth therefore tends to rise. Renewable energy is also dynamically related to carbon emission allowances in the VAR model. Increasing renewable energy prices motivate energy companies to increase investment in clean energy. Given that energy-intensive companies rely on emission trading systems extensively, the resulting divestment from fossil fuel leads to a decrease in demand for CO2 allowances, pushing carbon prices down (Akram et al., 2020). Finally, renewable energy displays correlated log returns over time (up to lag 2) and is not relalted to fossil energy log returns (FR), broad (BSR) and tech stock log returns (TSR).

Fossil energy displays weaker interplay in the VAR model than renewable energy. There is no significant relationship between fossil fuel and renewable energy, carbon allowances, or even stock returns. This result is in accordance with Kilian (2009); Inchauspe et al. (2015); Sadorsky (2012); Fang and You (2014) who find little to no evidence of significant impact of fossil energy on stock markets. Existing studies by Ferrer et al. (2018) and Nasreen et al. (2020) find little evidence of connectedness between fossil energy and clean energy stock returns. The insignificant relationship between fossil and renewable energy represents the decoupling of the renewable energy market from the conventional energy market (Umar et al., 2022). Investors in conventional energy may aim to maximise their welfare at a different investment horizon than those who engage in low carbon transition projects. Also, the insignificant influence of fossil fuel on company stock returns might rest on factors such as the investment horizon, the ease of exit, discounted cash flow methods, and ownership of remaining reserves, as put forward by Shimbar (2021). Regarding discounted cash flow models used in corporate finance, they forecast cash flows over many years, typically assuming a smooth market transition thereby decreasing the relationship between fossil fuel shocks and stock market shocks. Also, Heede and Oreskes (2016) find that investor-owned oil, gas, and coal companies hold reserves accounting for only 16% of the remaining carbon budget, meaning that most of the risk of value destruction due to the clean energy transition is faced by countries which hold large state-owned reserves, such as Iran, Iraq, and Saudi Arabia. Therefore, private investors may question the climate commitments from countries due to their high dependence on fossil fuel revenues, anticipating no stringent climate policy to mobilize investor-owned companies and stop them from exploiting their carbon reserves. The stock prices of private companies would therefore be rather immune from changes in fossil fuel prices.

Another finding is the impact that past energy stock returns have on technology stock returns and carbon, with a lag of one and two orders respectively. The level of significance remains rather weak nevertheless, at 10% only. First, our results would suggest that more prosperous energy companies (through higher stock returns) tend to lead to a rise in carbon prices, possibly because they keep expanding without reducing their carbon emissions enough to prevent carbon prices from rising. Second, our analysis points to a negative influence of energy stocks on technology stocks, contrary to Kumar et al. (2012). As explained by Perez (2010), energy intensive companies are motivated to innovate and invest in technology when they face a greater risk of asset impairment. When energy stock returns increase, energy companies prosper and are therefore less exposed to such a risk. In these circumstances, they are less likely to invest in technological innovation, negatively affecting technology stock companies in turn.

The discussion above can also be generalized at the broader stock market level since we identify a positive time-dependent relationship between broad stock index and carbon price changes, in line with Jim´enez-Rodr´ıguez (2019). A bullish trend in stock market prices is typically associated with booming economic activities, thereby increasing carbon emissions and ultimately raising carbon prices.

Finally, looking at time-dependent causal relationships not directly related to energy, our analysis points to a specific price dynamics between technology intensive companies and broad stock index returns. First, when broad stock index prices are lifted by new capital injection, it leads to downward pressure in the prices of tech-intensive companies later. When limited or scarce capital is invested in the broader economy without first prioritizing the tech sector, the tech-intensive company stocks are hurt subsequently due to insufficient new capital injection. Second, when technology-intensive companies become more prosperous in the first place (through higher stock returns), this benefits the whole market later (at a 10% significance level and with a lag order equal to 2). Capital investment in technology is indeed deemed as a risk reduction indicator leading investors to broaden their investment base in the markets. These findings are in accordance with the literature. Similar correlations between technology stocks and developed or energy markets are observed in the literature (Henriques and Sadorsky, 2008; Managi and Okimoto, 2013; Kumar et al., 2012; Bondia et al., 2016).

4.3 Impulse Responses

In order to investigate the dynamic responses of energy from shocks in stocks (and conversely), we use impulse response functions. These functions showcase the effect of adding a standard deviation magnitude on the error term to the current and future values of the endogenous variable. We use a bootstrap of 1000 runs with a 95% confidence interval (in dotted red lines on the following figures).

Impulse Responses of Renewable Energy Prices

Figure 2 depicts the responses of renewable energy prices to changes in fossil energy prices, broad stock index market rices, carbon prices, technology stocks, and energy stock prices over the next 10 periods of time.

The most insightful result is given by the impulse response function of renewable energy prices to energy stock prices. There is a sharp and statistically significant upward trend followed by a reversal move which takes three periods of time to counterbalance the initial shock. This confirms our previous findings. When the market capitalization of energy companies increases, these companies thrive and are more likely to shift towards renewable energy and make it more valuable.

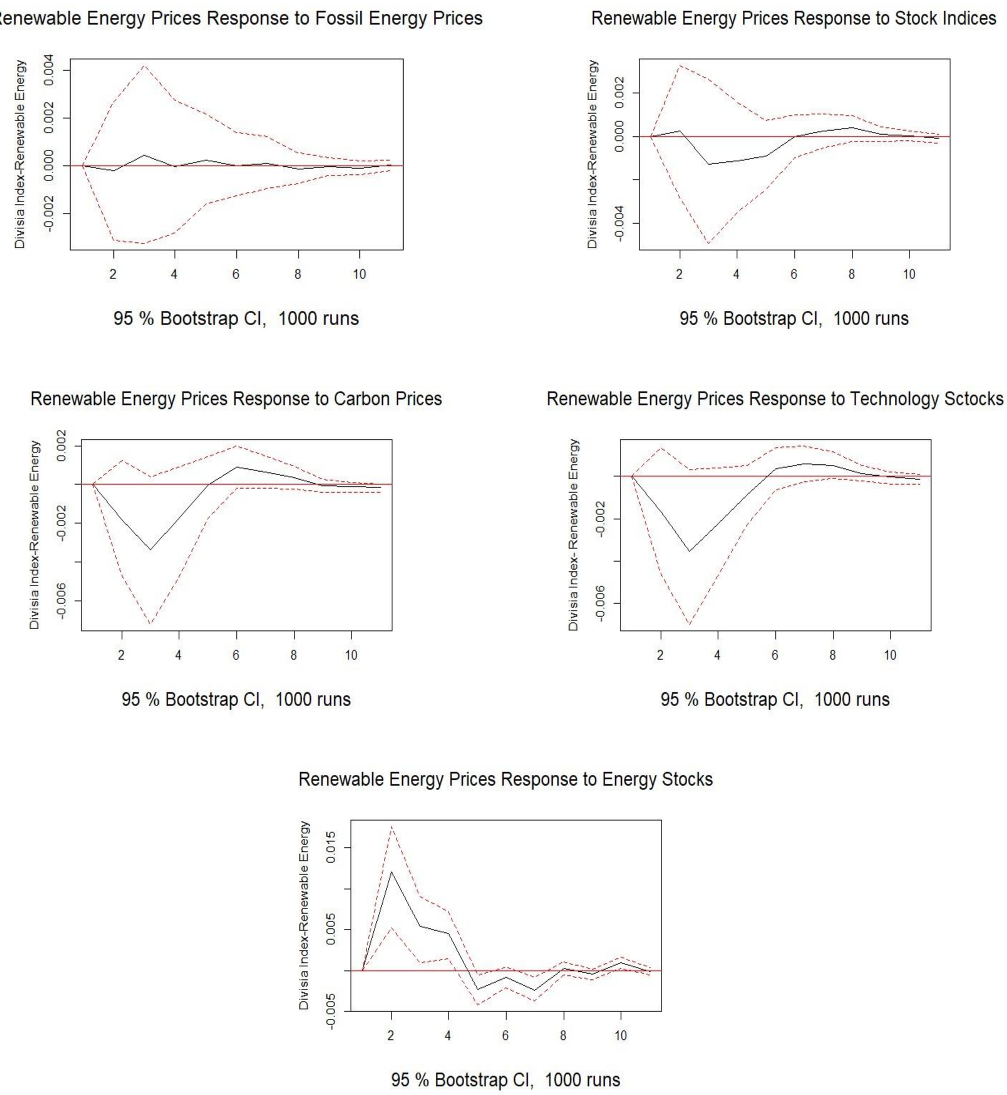

Figure 4: Renewable Energy Impulse Response Functions

Contrary to energy stocks, the influence of fossil energy on renewable energy is very negligible, as indicated in Figure 2. The impulse response exhibits no trend and fluctuates very closely around zero. Contrary to Zhang and Du (2017), we do not find a strong level of interdependence between clean energy and fossil energy. There seems to be no trade-off between fossil and renewable energy prices, their dynamics being weakly interdependent. This would suggest that investments in renewable energy would be structural and not driven by opportunistic arbitrage strategies related to the level of fossil energy prices in the short run.

Shocks in broad stock index prices do not much impact on renewable energy prices over time. A rather short-lived downward trend is observed, but the transition to low carbon energy sources does not seem to be much exposed to market conditions. This probably comes from the lack of market integration related to the feed-in tariffs (FIT) schemes designed by national governments to promote the uptake of renewable and low-carbon electricity generation (Tietjen et al., 2016).

Although a rise in carbon prices may lead to an increase in demand for renewable energy, fuelling price hikes in the short run, we do not observe this chain of events in our impulse response function of renewable energy prices to carbon prices. Overall, the response is shortlived and not statistically significant.

The existing literature on clean energy underlines the important role that technology companies play. Although our results indicates an immediate downward trend, the reversal is quick and the response is never statistically significant.

Impulse Responses of Broad Stock Market Indexes

Figure 5 depicts the responses of the broad stock index prices to changes in renewable and fossil energy prices, carbon prices, technology, and energy stock prices over the next 10 periods.

Stock indices have fluctuating responses to renewable energy prices and these responses remain largely uncertain, with large confidence intervals encompassing the zero response value over time. The same pattern is identified in the case of shocks in energy stock prices. Interestingly, this is not fossil energy but renewable energy which makes the link between higher energy prices, higher energy stocks, and higher broad stock market index prices.

Overall, we cannot reject the null that the responses of stock index prices to shocks in the system are not statistically different from zero, except maybe in the case of shocks in energy stock prices, but still by a very low margin and only in some time periods.

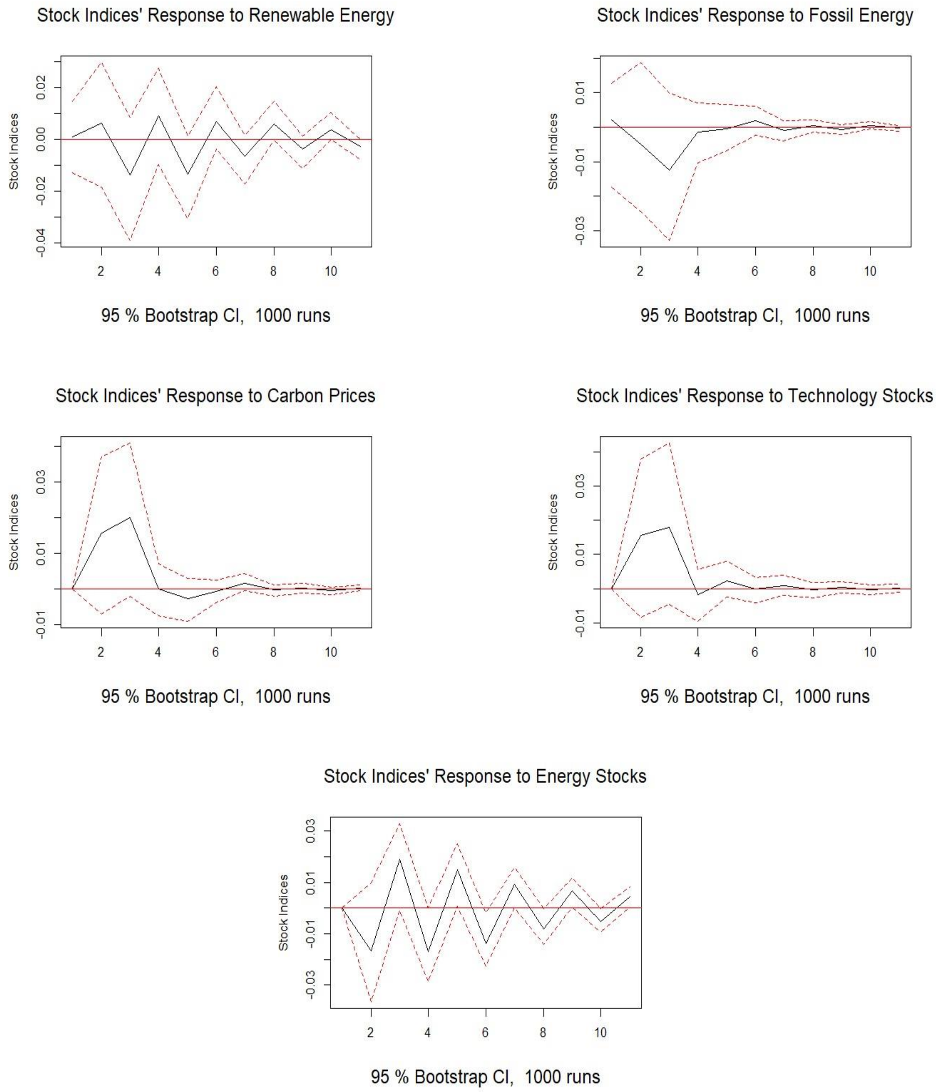

Figure 5: Stock Indices Response

The one standard deviation shock in fossil energy prices has a rather limited immediate effect on stock indices. Similar delayed and short lasting impacts have been found by Apergis and Miller (2009); Kilian (2009); Fang and You (2014). An increase in fossil energy can nevertheless lower gross profit margins and eventually depress stock returns, although such an effect can be mitigated by the pricing power of firms which are then able to move the inflationary pressure on their customers and remain largely unaffected.

Broad stock index prices respond quite strongly to shocks in carbon and technology stock prices over the next two periods of time, with the response fading away afterwards. Regarding carbon price changes, this maybe due to the fact they change the economic incentives of companies, which are then priced in the stock market broadly defined (Moreno and da Silva, 2016; Jim´enez-Rodr´ıguez, 2019). As to one standard deviation positive shocks in technology stock prices, they are also transmitted to the broad stock index prices at least over the next two periods of time into the future.

Impulse Responses of Fossil Energy Prices

The fossil energy prices response to renewable energy price fluctuates over time and takes longer to converge (Figure 4). According to Ueckerdt et al. (2013), the cost of of renewable energy relative to fossil energy matters, but it is controversial to determine how precisely the cost of renewable is accounted for. The use of leverage cost of electricity (LCOE) as a metric for renewable energy might lead to disparity and ambiguity in the measurement of the time dependence between renewable and fossil energies since market prices are instead used for fossil energy.

There is no statistically significant trend in the response of fossil energy prices to shocks in broad stock index prices. Although an increase in fossil energy prices lead to a rise in production costs and eventually reduces the returns (Gomez-Gonzalez et al., 2021), there is no clear evidence of an inverse dynamics from stock indices to fossil energy over time in our results. As in (Demirer et al., 2020; Dutta, 2017), we confirm the traditional view in the literature, that considers fossil fuel prices to be exogenous.

Regarding the shock effect of carbon prices on fossil energy prices, we can conjecture that carbon prices impact the power generation costs and switching costs to marginal low carbon energy. When there is an increase in carbon prices, especially when the marginal conversion cost is lower than the original cost of power generation, the demand for fossil energy from businesses decreases and ultimately the price of fossil energy falls. In our analysis, there is no obvious time varying effect of carbon prices on fossil energy prices at the annual frequency.

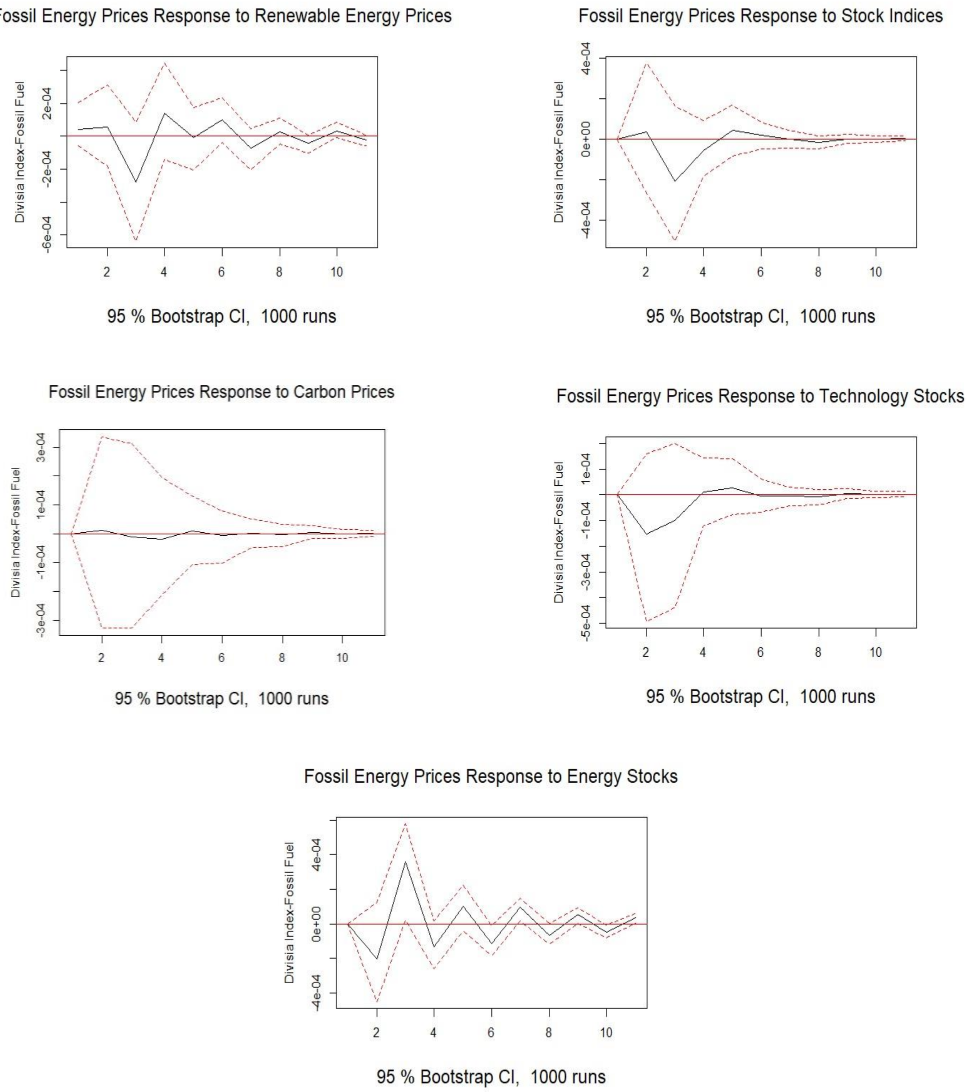

Figure 6: Divisia Fossil Energy Response

Interestingly, Gong et al. (2021) finds that there is a spillover effect of carbon prices on oil and natural gas, but not on coal prices. Since we merge the three sources of energy in the Divisia index, the disconnection between coal and carbon may explain the lack of significance in our results.

Fossil energy prices react negatively to positive increases in technology stock prices, but the variation is not significant and remains limited. This is in line with Kumar et al. (2012) who find that technology stock prices have an insignificant impact on oil prices.

Impulse Response of Energy Stocks

The impulse responses of energy stocks take longer to converge overall, as shown in Figure 6. The responses are also highly fluctuating over the periods.

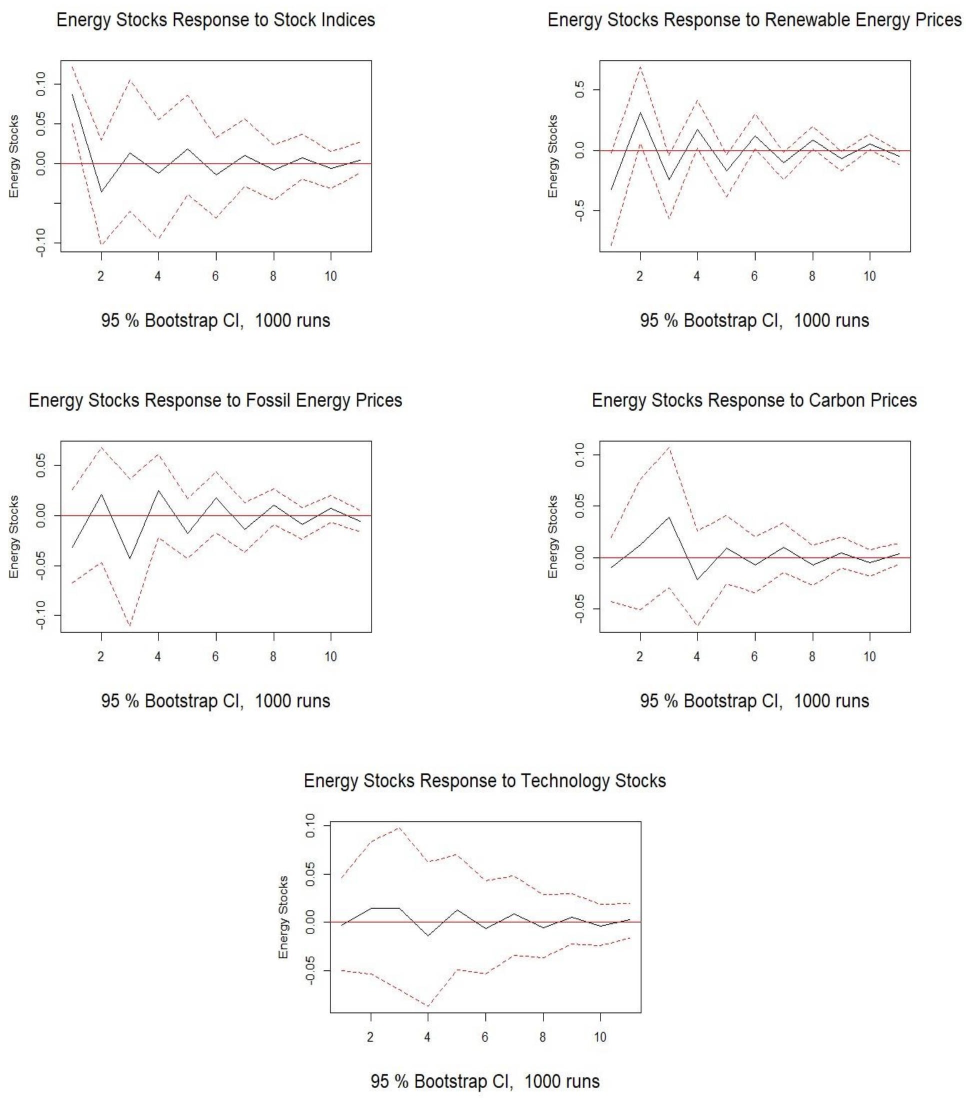

Figure 7: Energy Stock Prices Response

Energy stocks do react to renewable energy prices, with significant variations over time. In an era of international climate agreements and increasing divestment from fossil fuel, energy companies face greater regulatory risks and are increasingly sensitive to variations in renewable energy prices.

Relative to renewable energy, shocks in fossil energy prices does not lead to significant variations in energy company stock prices since the confidence interval always includes the zero value. The degree of convergence is also less obvious. The results are in accordance with Henriques and Sadorsky (2008); Zhang and Du (2017); Sun et al. (2019) who find that the correlation between the price of fossil fuel and energy stock prices is low or insignificant.

Shocks in carbon prices lead to a short-lived positive reaction in energy stock prices, that quickly fades away. The result is similar to Zhang and Du (2017) who find that the responses of energy stocks to carbon prices gradually diminish.

4.4 Granger Causality Test

Granger (1969)'s approach to causality does not imply a cause-effect relationship but is rather based only on the level of 'predictability' or 'forecast ability' over time. It helps detect causal, time-dependent direction between variables. We carry out Granger causality tests in Table 7 to identify the dynamic causal chain considering all the variables in the chain. However, these Granger causality tests can be misleading when applied to more than two variables (Brahmasrene et al., 2014). We therefore run pairwise tests in Table 8. In both cases, the null hypothesis is that there is no Granger causality while the alternative is that there is Granger causality. From the 'global' Granger causality tests, unidirectional causality has been detected from stock markets and energy stocks to other variables. This indicates that returns in fossil energy, renewable energy, and carbon allowances are dependent on the stock markets, as characterized by the broad and energy stock indexes.

Table 7: Granger Causality Test

		Variables	F-stats	p-value	
RR	→−	FR,BSR,CR,TSR,ESR	1.5635	0.1113	No Granger Causality
FR	→−	RR, BSR,CR,TSR,ESR	0.48307	0.902	No Granger Causality
BSR	→−	RR, FR, CR, TSR, ESR	1.9202	0.03824**	Granger Causality
CR	→−	RR, FR, BSR, TSR, ESR	1.2989	0.225	No Granger Causality
TSR	→−	RR, FR, BSR, CR, ESR	0.95344	0.4825	No Granger Causality
ESR	→−	RR, FR, BSR, CR, TSR	7.3285	1.501e-11***	Granger Causality

***, ** and * denotes statistical significance at 1%, 5% and 10% level respectively.

In Table 8, unidirectional causality is only found from renewable energy to carbon prices and from energy stocks to carbon prices. Otherwise, reciprocal causality has been identified between renewable energy prices and energy stocks, stock markets and carbon prices, stock markets and technological stocks, carbon prices and technological stocks. Interestingly, fossil energy prices displays no causality from other variables nor does it Granger causes other variables. Overall, these findings confirms our previous assessment on the increasing role of renewable energy in the nexus of dynamics between energy and stocks.

Table 8: Pairwise Granger Causality Test

		RR	FR	BSR	CR	TSR	ESR
RR	−→	x	0.00317(0.9968)	0.10393(0.9013)	4.5413(0.0109)**	0.40626(0.663)	2.6001(0.00748)**
FR	−→	0.019456(0.9807)	x	0.67214(0.5109)	0.000111(0.9989)	1.5202(0.2192)	0.43353(0.6483)
BSR	−→	0.40554(0.667)	1.0407(0.3536)	x	7.5117(0.0005)***	5.8644(0.0003)***	0.9899(0.373)
CR	−→	1.1779(0.3084)	0.49511(0.6097)	2.6196 (0.07336)*	x	2.9974(0.05141)*	1.8314(0.1608)
TSR	−→	1.9145(0.148)	0.67983(0.507)	2.6496 (0.071)*	4.0611(0.01753)**	x	0.87762(0.4161)
ESR	−→	30.749(1.168e-13)***	0.5713(0.565)	1.0123(0.3638)	4.0428(0.01786)**	2.11(0.1218)	x

The p-values are given in parentheses. ***, ** and * denotes statistical significance at 1%, 5% and 10% level respectively.

4.5 Variance Decomposition

We use variance decomposition in Table 9 to provide information about the relative importance of the random innovations that we depicted in the previous section (Brahmasrene et al., 2014). We use Monte Carlo simulation to predict 10 observation periods. The reported numbers indicate the percentage of the forecast error in each variable that can be attributed to to innovations in each endogenous variable. It also helps assess how shocks reverberate through the nexus and how external shocks matter to each variable.

Table 9: Variance Decomposition (VD) Analysis

Period	VD RR	VD FR	VD BSR	VD CR	VD TSR	VD ESR
			RR Shock			
1	100	0	0.00	0	0	0
2	91.22	0.002	0.003	0.192	0.162	8.421
3	89.18	0.012	0.091	0.756	0.801	9.144
4	87.87	0.012	0.155	0.907	1.045	10.10
5	87.71	0.015	0.195	0.892	1.065	10.12
6	87.84	0.015	0.191	0.918	1.053	9.982
7	87.56	0.015	0.194	0.936	1.065	10.23
8	87.53	0.016	0.201	0.942	1.078	10.23
9	87.53	0.016	0.201	0.940	1.077	10.23
10	87.50	0.016	0.201	0.940	1.077	10.26
			FR Shock			
1	0.000	99.99	0	0	0	0
2	0.014	99.42	0.011	0.001	0.190	0.338
3	0.038	97.49	0.340	0.002	0.257	1.290
4	0.619	97.25	0.353	0.004	0.252	1.394
5	0.742	97.15	0.368	0.005	0.257	1.472
6	0.742	96.99	0.371	0.006	0.257	1.561
7	0.810	96.89	0.370	0.006	0.257	1.625
8	0.850	96.85	0.372	0.006	0.257	1.656
9	0.854	96.81	0.372	0.006	0.257	1.676
10	0.875	99.79	0.372	0.006	0.257	1.694
			BSR Shock			
1	0.001	0.007	99.99	0	0	1.926
2	0.060	0.042	98.79	0.352	0.349	0.399
3	0.324	0.258	96.80	0.907	0.806	0.901
4	0.437	0.260	96.29	0.902	0.806	1.300
5	0.690	0.258	95.72	0.908	0.807	1.601
6	0.753	0.263	95.40	0.906	0.805	1.872

7	0.811	0.263	95.22	0.908	0.805	1.989
8	0.861	0.264	95.08	0.907	0.804	2.076
9	0.880	0.264	95.01	0.905	0.803	2.141
10	0.905	0.264	94.95	0.905	0.803	2.177
			ESR Shock			
1	23.53	0.230	0	1.718	0.020	74.50
2	27.61	0.196	1.210	0.367	0.034	70.91
3	28.13	0.353	0.975	0.371	0.196	70.30
4	27.95	0.372	0.882	0.339	0.218	70.52
5	28.47	0.373	0.848	0.313	0.209	70.03
6	28.42	0.381	0.826	0.297	0.208	70.10
7	28.47	0.386	0.811	0.289	0.208	70.05
8	28.53	0.388	0.801	0.283	0.208	69.99
9	28.53	0.390	0.795	0.278	0.207	70.00
10	28.52	0.391	0.792	0.276	0.207	69.98

Under column (2) in the first period, 100% of the variability in renewable energy price changes is explained by its own innovations. However, it goes down over time to 87.50% after 10 periods of time. Clearly, renewable energy prices are impacted by its own shocks (of course) but then these innovations are essentially transmitted to energy intensive stock prices. After a few periods of time, these innovations in renewable energy prices explain around 10% of the forecast error variance error in energy intensive stock prices.

Fossil energy prices are impacted by their own innovations. The other variables do not have significant influence on them. So fossil energy is exogenous to a certain extent in this system. The same conclusion can be drawn for the broad stock market.

This is obviously the opposite for energy intensive companies, of which innovations in their stock prices are rapidly transmitted to renewable energy prices.

4.6 Policy Implications

Policy design plays a crucial role in the advancement of renewable energy, as supported by scientific literature (see Gatzert and Vogl (2016); Lu¨thi and Wu¨stenhagen (2012)). The findings suggest that renewable energy sources do not affect the stock prices of companies in general but do have an impact on those of energy companies. Consequently, policymakers should focus on implementing regulations and frameworks that promote renewable energy adoption among energy-intensive firms rather than non-energy-intensive ones. This is no easy task since renewable energy projects face social acceptance risk, as discussed by Angelopoulos et al. (2017). This refers to the potential challenges or barriers that a project or initiative may face due to a lack of support or acceptance from the local community, stakeholders, or the public in general. In the context of renewable energy projects, such as onshore wind farms, social acceptance risk can stem from concerns related to visual disturbance, noise, impact on wildlife, or potential effects on property values. These concerns can lead to opposition, delays, or even the cancellation of projects, posing a significant risk for developers and investors involved in renewable energy initiatives.

A growing commitment to renewable energy necessitates additional infrastructure and resources as well, which entail considerable investment expenditures that tend to be shouldered by energy companies rather than end consumers. Market and regulatory risks, often referred to as stranded assets, affect the phasing out of fossil fuels and the increase in renewable energy usage. A stable framework is required to facilitate investments in renewable energy. Improvements are needed in administrative procedures, such as the issuance of renewable energy permits, risk assessments, and the implementation of renewable energy projects.

The stock market, along with energy and environmental policies, lies at the heart of an economy's transition to low carbon. A low cost of capital is vital for incentivizing investments in renewable energy, given the high initial costs involved. Policymakers should prioritize the development of the stock market to stimulate investment in renewable energy. For instance, the introduction of renewable energy funds or socially responsible funds could be considered. Since technology can significantly impact the stock market, policy designs should take into account innovation channels to enhance sustainability.

5 Conclusion

As global climate agreements gain prominence, commitments to shift from fossil fuels to renewable energy sources have become more widespread. While numerous academic studies have explored the time-dependent relationship between energy and stock market prices, the primary focus has been on the impact of fossil energy prices on energy companies, particularly in the United States and China. Although some research has investigated the relationship between clean energy company stock prices and those of other companies, there has been no study explicitly addressing the renewable energy sector. This gap in research is noteworthy, especially given the ongoing transition towards renewable energy worldwide.

Diverging from previous studies that use clean energy stock prices as a proxy for renewable energy prices, our research directly incorporates renewable energy tariffs and consumption to assess the role of renewable energy. We employ the Divisia index method for both fossil and renewable energy prices, offering a more comprehensive understanding of the connection between fossil energy, renewable energy, and stock prices.

Using a sample of annual data from 2000 to 2019 for 25 countries, our study offers a global viewpoint on the interplay between energy and stock markets. We employ a VAR (Vector Autoregression) model to examine the time-dependent dynamics among renewable energy, fossil energy, carbon emissions, and stock markets, zooming in on both energy- and technologyintensive stocks. We also assess the associated impulse response functions, Granger causality tests, and variance decompositions.

This study is the first to identify a bidirectional time-dependent relationship between renewable energy and energy-intensive stocks. When energy stock prices rise, these companies are more prosperous and more likely later to shift towards renewable energy, driving up demand and making it more valuable. Even when renewable energy prices go up, these companies tend to benefit as well, suggesting a virtuous circle. This can be explained by their greater reliance on clean energy following the disinvestment initiatives from fossil energy in the energy sector. Divestment is motivated by greater stranded asset risk, i.e., the risk of obsolescence for infrastructures built up around fossil fuels. Interestingly, renewable energy exhibits no other dynamic link with any of the outcome variables in our model, with the exception of carbon allowances. Increasing renewable energy prices motivate energy companies to increase investment in clean energy. Given that energy-intensive companies rely on emission trading systems extensively, the resulting divestment from fossil fuel leads to a decrease in demand for CO2 allowances, pushing carbon prices down.

Fossil energy displays weaker interplay than renewable energy in our study. There is no significant relationship between fossil fuel and renewable energy, carbon allowances, or stock markets, in line with several previous studies. For example, the insignificant time-dependent relationship between fossil energy and renewable energy is related to the decoupling of the two markets. Investors in conventional energy may aim to maximise their welfare at a different investment horizon than those who engage in low carbon transition projects. Overall, our study points to renewable energy as being more a influential driver compared to fossil energy, signalling a shift in the time-dependent dynamics between stock markets and energy.

Energy-intensive company stocks are also related to technology-intensive stocks. We also find that a bullish trend in stock market prices is typically associated with booming economic activities, thereby increasing carbon emissions and ultimately raising carbon prices. Finally, greater capital injection in tech companies is deemed as a risk reduction signal, leading investors to broaden their investment base in the markets and pushing stock market index prices higher.

The impulse response functions, Granger causality tests, and variance decompositions confirm that renewable energy and energy stocks are significantly interdependent, while fossil energy seems to be rather exogenous to the nexus. In an era of international climate agreements and increasing divestment from fossil fuel, energy companies face greater regulatory risks and are increasingly sensitive to variations in renewable energy prices.

Our findings have key implications for policymakers. We have assessed the dynamics of energy prices and stock markets across different countries, accounting for renewable energy which was an omitted variable in previous studies. The results sheds light on the significant role of renewable energy prices on energy stock markets, suggesting that incentives to invest in renewable energy have made a difference on its interplay with the stock markets.

The research suffers from constraints such as unbalanced representation of developed and emerging economies in the panel. There is a lack of data availability for emerging economies, thus a comparison between the two groups could not be carried out. In addition, the renewable energy prices are reported on an annual basis by OECD. We thus could not work on a higher frequency data in the study.

Several topics have emerged as possible avenues for future research. First, it would be worth using higher frequency data for renewable energy prices and stock markets to further explore their time-dependent dynamics. Likewise, the study can be replicated to account more specifically for the possible regional characteristics influencing the impact of renewable energy on stock markets.

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Appendix

Table 10: List of countries and their stock indices (Part 1)

Countries	Broad Stock Index	Technology Index	Energy Index
Australia	S&P 200	S&P Tech	MSCI Energy
Austria	Austrian Traded Index	MSCI Austria IMI Information Technology Sector Price Index	MSCI Austria Energy Sector Price Index
Canada	Toronto 300	S&P Canadian IT index	S&P/TSX Energy and Clean Tech
China	Shenzhen CSI 300	MSCI International China Tech Index	MSCI International China Energy Index
Czech Republic	PX Prague SE Index	STOXX Europe Technology	EEX EEX Index
Denmark	MSCI Denmark	OMX Copahengen Technology	Nasdaq Denmark Energy Index
Estonia	OMX Tallinn	OMX Baltic Technology Index	MSCI Europe Energy Index
France	CAC440	CAC Tech Index	CAC Energy Index
Germany	DAX	TecDax	Dax Subsector all renewable energy
Greece	Athex Composite Share Price Index	FTSE/Athex Technology Index	AT FTSE Energy Index
India	Nifty Tri Index	MSCI India Tech	Refinitiv India Energy Index
Indonesia	Jakarta SE Composite Index	Indonesia SE Technology Index	Refinitiv Indonesia Energy Index
Italy	FTSE MIB Index	MSCI Italy IMI Information Technology Sector Price Index	FTSE ITALIA ALL-SHARE ENERGY Price Return Index

Table 10: List of countries and their stock indices (Part 2)

Countries	Broad Stock Index	Technology Index	Energy Index
Japan	Nikkei	CNINFO 1000	Refinitiv Japan Energy Index
Korea	Korea SE Kospi 200 Index	MSCI Korea IT Sector	Refinitiv Korea Energy Index

Luxembourg	Luxembourg SE LuxX Index	STOXX Europe Technology	MSCI Europe Energy Index
Netherlands	Refinitiv Netherlands Index	AEX Technology Index	AEX Energy Index
Portugal	Euronext Lisbon PSI 20 Index	PSI Technology Gross Return Index	MSCI Portugal Energy Sector Price Index
Slovakia	SAX Index	STOXX Europe Technology	MSCI Europe Energy Index
South Africa	FTSE/JSE Top 40 companies	FTSE/JSE Tech Index	MSCI International South Africa Energy Sector Index
Spain	Madrid General SE Index	MSCI International Spain Information Technology Price Index	Madrid SE Energy Index
Switzerland	Swiss Market Index	MSCI Switzerland IMI Information Technology Sector Price Index	MSCI International Switzerland Energy industry group Investable Price Index
Turkey	BIST 100 Index	BIST Tech Index	FTSE Energy Index
UK	FTSE	FTSE Tech	MSCI Energy UK
USA	S&P500	Nasdaq 100	Clean Energy Index