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Information Diffusion and Spillover Dynamics in Renewable Energy Markets

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Summary

The aim of this paper is to analyze the connectedness between renewable energy (RE) sectors, the oil & gas sector and other assets using time-scale spillover approach. We find that the RE bioenergy firms are the most connected to oil & gas firms and oil prices. The bond market transmits spillover to the RE sectors, while it receives spillover from the oil & gas sector. Moreover, short-run connectedness drives the dynamic total connectedness. Since changes in bond rates mainly spillover to RE firms and not to oil & gas firms, policy makers should also be aware that changes in interest rates may impact the societal transition to a RE based energy system. Since a shock that increases connectedness in the short run will deter investors from investing in RE assets, it is important for climate policy makers to develop policies that reduce the effect of increased connectedness on RE investments.

Keywords: Renewable Energy, Connectedness, Frequencies, Dynamics, Spillovers

JEL Classification: C1, G15, Q2, Q3, Q43

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Information Diffusion and Spillover Dynamics in Renewable Energy Markets

Abstract

The aim of this paper is to analyze the connectedness between renewable energy (RE) sectors, the oil & gas sector and other assets using time-scale spillover approach. We find that the RE bioenergy firms are the most connected to oil & gas firms and oil prices. The bond market transmits spillover to the RE sectors, while it receives spillover from the oil & gas sector. Moreover, short-run connectedness drives the dynamic total connectedness. Since changes in bond rates mainly spillover to RE firms and not to oil & gas firms, policy makers should also be aware that changes in interest rates may impact the societal transition to a RE based energy system. Since a shock that increases connectedness in the short run will deter investors from investing in RE assets, it is important for climate policy makers to develop policies that reduce the effect of increased connectedness on RE investments.

Keywords: renewable energy; connectedness; frequencies; dynamics; spillovers.

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1. Introduction

The recent geopolitical turbulence and the breakup of the OPEC+ alliance has caused a substantial amount of turmoil in the oil market. Geopolitical turbulence in the form of the Persian Gulf crisis lead to Brent oil futures in London seeing the largest one-day percentage increase since the contract trading began (Bloomberg, 2019). The breakup of the OPEC+ alliance lead to oil prices crashing at a record pace (JPT, 2020). The recent turbulence is evidently impacting oil prices and the volatility of the oil market. The increased risk in the oil market can make investors more hesitant to invest in this market (IEA, 2019a). Alternative energy sources, such as renewable energy (RE), could therefore be more attractive from an investor perspective. The attractiveness of investing in RE is further amplified by the fact that RE is projected to meet 50% of the energy demand in 2040, while oil demand is predicted to flatten by 2030s (IEA, 2019b). Figure 1 presents the investments in RE sub-sectors every year during the time period 2004-2018 in US billion dollars. We can see that the total investments in RE have substantially increased since 2004. Investments in RE have grown by 242,1 billion dollars from 2004 to 2018. We can also note that the investment growth rate in RE has decreased after 2011 and that the investment levels have remained constant with some notable exceptions. Dips in investments occurred during the financial crisis in 2008 and 2009 and the Euro debt crisis around 2011 and 2012.

Insert Figure 1

The low interest rate condition which has prevailed in the recent years has benefited investments in the RE industry more than investments in the oil & gas industry, since debt financing is crucial in the more capital-intensive RE industry (IEA, 2019a). The purpose of this paper is to analyze the connectedness between RE sectors, oil & gas sector and other assets. From the previous literature (see Section 3) there is a lack of studies that consider firm level returns when investigating connectedness between RE sectors, the oil & gas sector and other assets, as previous literature has mostly focused on the usage of RE indices. Another gap in the literature is that there has been no consideration of firm level data when investigating energy market connectedness at different time-frequencies. We expand on previous literature by investigating static and dynamic frequency connectedness between several RE sectors and the oil & gas sector at the firm level and how uncertainties drive this connectedness.
Specifically, we focus on the following main research questions:

I. Is there a difference in connectedness results between using aggregated RE market and RE firm level data? How are RE sectors connected to the oil & gas sector and other assets?

II. Is there any difference in connectedness between frequencies in the dynamic frequency connectedness? Which frequency drives the total connectedness?

To answer our research questions we use weekday daily data, with 2279 observations that span from May 18, 2011 to February 10, 2020. Our sample consists of two RE indices, nine RE firms, nine oil & gas firms and six other assets. The methods we use to measure the connectedness between RE sectors, the oil & gas sector and other assets are the Diebold and Yilmaz (2012; 2014) full sample and rolling window spillover approach and Barunik and Krehlik (2018) dynamic frequency spillover technique. Our first main finding is that the RE bioenergy firms are the most connected to oil & gas firms and oil prices. The second main finding is that the bond market transmits spillover to RE sectors while it receives spillover from the oil & gas sector. The last main finding is that short-run connectedness drives the total dynamic connectedness.

Our results have important policy implications for investors and climate policy makers. Since changes in bond rates mostly spillover to RE and not to oil & gas sector, policy makers should also be aware that changes in interest rates may impact the societal transition to a RE based energy system. Since a shock, which increases connectedness in the short run, will deter investors from investing in RE assets, it is important for climate policy makers to develop policies that reduces the effect of increased connectedness on RE investments.

The paper is organized as follows. Section 2 presents a review of the relevant literature. Data and descriptive statistics are illustrated in Section 3. Section 4 describes the methodology, whereas Section 5 discusses the empirical findings from the connectedness analysis. Section 6 proposes some conclusions and policy implications.

2. Related Literature review

There is a vast literature on the relationship and spillovers between RE assets and other assets. Previous literature can be divided into three research strands: (1) the relationship between RE stock indices and other assets; (2) the market and firm-specific determinants of stock market returns for energy companies; (3) the risk spillover and the connectedness between RE, oil and technology markets.

From these three research strands we conclude that RE returns are affected by global and technology stock prices, oil prices, bond and foreign exchange rates. We can also conclude that firm specific factors, such as size, leverage and value affect energy company returns. For RE companies, oil prices and technology stock prices also have an impact on returns. A summary of the reviewed literature, including methods and results, can be found in the Appendix.

In the first research strand, Henriques and Sadorsky (2008) investigate the relationship between interest rates, oil prices, technology stock prices and alternative energy stock prices. They find that oil prices, interest rates and technology stock prices affect stock prices of alternative energy indices. These results are also supported by Kumar, Managi and Matsuda (2012). Bondia, Ghosh and Kanjilal (2016) find that interest rates, oil prices and technology stock prices affect alternative energy index stock price in the short-run, but not in the long-run. In contrast, Kocaarslan and Soytas (2019) show the existence of both short- and long-term effects. They find that increasing oil prices in the short run lead to increased investments in clean energy stock indices. However, in the long-run, clean energy stock indices are instead negatively affected by increasing oil prices. They also find that interest rates have an impact on clean energy stock indices in the long-run. Reboredo, Rivera-Castro and Ugolini (2017) support the findings of a short- and long-run relationship between oil prices and RE stock indices, both for global RE stock indices and RE sub-sector indices. However, the effects are stronger in the long-run than in the short-run. Non-linear effects of energy prices on returns of clean energy stock prices are investigated by Uddin et. al. (2019). They find that RE returns are impacted by oil prices, but this effect is only found for lower quantiles, i.e. extreme negative market conditions. Exchange rates have a positive impact on RE returns, but only during extreme market conditions.

In the second research strand, Bianconi and Yoshino (2014) find that company size, leverage, market premium, exchange risk and changes in oil prices have an effect on oil & gas company returns. In a similar fashion Mohanty and Nandha (2011) use U.S. gas and oil companies to study the oil and gas sectors stock returns in U.S. The main findings are that changes in oil price and stocks, size, book-to-market value, and market factors determine the stock returns of the gas and oil companies. These findings are supported by Sanusi and Ahmad (2016), who study gas and oil companies in the U.K. Few studies have investigated which factors affect the returns of RE companies. Sadorsky (2012a) investigates the determinants of risk in RE firms. He finds that increasing oil prices have a positive impact on company risk, while company sales growth has a negative impact on company risk. Instead of studying determinants of risk, Gupta (2017) studies the financial performance of alternative energy companies. The results show that stock returns of alternative energy firms are positively affected by increases in technology stock prices, oil prices, company size and price to book value.

In the third research strand, Sadorsky (2012b) analyzes volatility spillovers from oil prices to stock prices of technology indices and clean energy indices. There is no evidence of spillover from oil to technology or clean energy, but long-run negative spillover from technology to clean energy indices is found. He concluded that stock prices of clean energy indices have a higher correlation with technology stock prices than with prices of oil. The strong connection between technology and clean energy is supported by the findings of Ahmad (2017), who shows that the stock of technology companies plays an important role in determining volatility and return spillovers between oil prices and RE stocks. In contrast to Sadorsky (2012b), Ahmad does find strong evidence of volatility spillovers. A result is that the indices of clean energy and technology stocks are the emitters of volatility and return spillovers to the prices of crude oil. Connectedness between technology and clean energy is further found by Reboredo (2015), but only in the short-run. That the volatility spillover can vary over time is demonstrated by Xia et al. (2019), who find that there is a strong and time-varying volatility over time from changes in fossil energy prices to the returns of RE stocks. Volatility and return connectedness between oil prices and RE stocks being time-varying is also demonstrated by Ferrer et al. (2018). They conclude that the volatility and return connectedness is mostly generated in the very short-run (5-day movements) rather than the long-run. The connectedness between oil and RE market has also been studied at a sub-sector level by Pham (2019). The main finding is that there exists a variation in the relationship between the price of oil and clean energy stocks. The least connected stocks to oil price are fuel cells, geothermal and wind stocks and the most connected stocks to oil price are energy management and biofuel stocks.

3. Data description

The data used in this paper is based on 2279 weekday observations from May 18, 2011 to February 10, 2020. We base our sample period on the availability of data. The main variables are the RE stock price indices, RE firm stock prices and oil & gas firm stock prices. We transform these and all other variables to first difference logarithmic form, which gives us the percentual change of the variables. A definition of all the variables used in the empirical analysis is reported in Table 1.

Insert Table 1

3.1 RE and oil & gas firms

Micro level data allow us to explore heterogeneity in connectedness between RE indices and RE firms. The RE firms and oil & gas firms we use are based on the top 25 energy sub-sector honorees appointed by Thomson Reuters (2020a), which are firms regarded as the leaders in each of their sub-sectors. Thomson Reuters (2020b) uses several criteria to choose which energy firms are global leaders in each of their sub-sector. The criteria measure factors such as investor confidence, legal compliance, financial performance, innovation and robustness to shocks. The details of which criteria are used can be found at Thomson Reuters (2020b). Out of the top 25 firms that Thomson Reuters (2020a) include in the RE sector, we choose to include three RE firms from each RE sub-sector. The three sub-sectors are solar, wind and bioenergy. We also choose nine oil & gas firms, which represented the oil & gas sector. The reason for why we choose firms that are leaders in their sub-sectors is that these firms should be the ones leading the societal transition to RE based energy systems. Understanding investments in these firms is therefore of outmost importance.

3.2 Descriptive statistics

Table 2 shows the descriptive statistics for all variables included in the analysis. The mean return per day is negative for the RE indices. Observing the standard deviations, we can see that the risk for the RE indices are well above one percent. The RE industry being riskier is in line with theory and previous literature. All return indices are skewed to the left, which indicates that extreme negative values dominate over extreme positive values. The RE indices show lower skewness and kurtosis than other return indices, which means that extreme market conditions are not as common. So, while the RE industry is riskier in our sample, extreme market conditions are not as frequent.

Looking at the mean daily returns for the RE firms, we note that six RE companies have higher mean returns compared to the RE indices in Table 2. The standard deviations show that the risk is quite similar between companies. Five companies show a positive skewness while four show a negative skewness. The bioenergy sector has the largest amount of positive skewness. The high kurtosis levels indicate that the presence of extreme market conditions is quite common for the wind sector. Most of the oil & gas firms have positive mean returns. The risk in the form of standard deviations shows that the oil & gas firms all have lower risk than the

RE firms. Most of the oil & gas firms show negative skewness. The kurtosis values for the oil & gas firms are not as high as for the RE firms, which indicates that extreme market conditions for oil & gas firms are not as common as for RE firms.

No variable is normally distributed as indicated by the high Jarque-Bera (JB) test values, which is common for stock market returns. The Autoregressive Conditional Heteroskedasticity (ARCH) and Ljung-Box (LB) tests show that there exists heteroskedasticity and autocorrelation in all variables. The existence of heteroskedasticity and autocorrelation is expected in financial data and is not a problem for our estimations. The Augmented Dickey-Fuller (ADF) unit root tests show that all variables are stationary in first differences.

Insert Table 2

In Figure 2 we present the unconditional correlations between our variables. Correlations indicate co-movement and financial interaction, which is why these correlations can give an indication of how spillover effects between the variables look like. In Figure 2 (a) all stock return indices are highly correlated with each other. For both Figure 2 (a) and (b) we observe that the RE indices and firms have low correlations with other assets. The oil & gas firms in Figure 2 (c) and (d) have in general low and positive correlations with each other and with RE firms. The oil & gas firms also have in general low correlations with other assets. In general, oil & gas firms correlate positively with other assets.

Insert Figure 2

From Figure 3 we can observe that the MSCI, ESG, OIL and PSE indices have a large drop around 2019, which can also be observed for the RE indices. We can observe in Figure 4 that MSCI, ESG, OIL, FX, DGS5 and PSE all have high volatility at the beginning of the sample period. MSCI, ESG, OIL and PSE show high volatility in the beginning, middle and the end of the sample period. FX shows a high volatility throughout the entire sample period, while DGS5, on the other hand, has higher volatility during the beginning and the middle of the sample period.

Insert Figure 3

Insert Figure 4

4. Methodological framework

To assess the connectedness among the RE market, oil & gas firms and the other assets, we proceed as follows: (1) we measure the full-sample connectedness by using the variance decompositions framework developed by Diebold and Yilmaz (2012); (2) we use the framework developed by Barunik and Krehlik (2018) that is based on spectral representations of variance decompositions. This allowed us to measure connectedness between our variables in the short-run, medium-run and long-run; (3) we combine the spectral representations with the rolling estimation window framework developed by Diebold and Yilmaz (2012; 2014), which allows us to measure time-varying connectedness.

We start estimating RE indices with other assets and then move to estimating RE firms with other assets. By doing this we are able to see if heterogeneity between RE indices and RE firms exist. Next, we estimate RE firms with oil & gas firms and finally we include other assets with RE firms and oil & gas firms. The last two steps allow us to see whether the inclusion of other assets impact the connectedness between RE firms and oil & gas firms.

4.1 Variance decomposition

Variance decompositions are helpful when a researcher wants to investigate how shocks in variable *j* affect future uncertainty of variable *i*, and how much of this uncertainty in variable *i* is originating from variable *j*. Diebold and Yilmaz (2012) show that, through variance decompositions in a Vector AutoRegression (VAR) model, system connectedness could be distinguished. By including variance decompositions for several variables, it is possible for us to investigate the interconnectedness of an entire system.

The variance decomposition matrix of a VAR is the basis of our measure of connectedness. This measure can be obtained by estimating a VAR of lag-length *p* that is a covariance stationary process with N variables, as

$$x_t = \Phi_1 x_{t-1} + \Phi_2 x_{t-2} + \ldots + \Phi_p x_{t-p} + \epsilon_t \,, \qquad (1)$$

where $x_t, \ldots, x_{t-p}$ are Nx1 vectors of variables, $\Phi_1, \ldots, \Phi_p$ stand for the corresponding coefficient matrices and ϵ_t stands for the white noise covariance matrix. Every variable in the system is not only lagged on its own *p* lags, but also regressed on the *p* lags of the other variables included in the same system. We estimate four VAR models, the first formed by the RE indices and other assets (N = 8), the second including the RE firm stocks and other assets (N = 15), the third composed by the oil &gas firm stocks and the RE firm stocks (N = 18), the fourth made by RE firm stocks, oil & gas firm stocks and other assets (N = 24). Each VAR model had four lags (p = 4), based on previous VAR residual autocorrelation analysis and in the line with the results by Diebold and Yilmaz (2012).

In order to identify the shocks when estimating variance decompositions, it is necessary to orthogonalize the shocks. This is important since shocks to a specific variable do not appear alone, which makes it necessary to distinguish between the different kinds of shocks. To orthogonalize the shocks we use generalized variance decompositions. According to Pesaran and Shin (1998), this procedure is unaffected by the ordering of the variables in the system. The generalized variance decomposition can be presented as

$$(\theta_H)_{j,k} = \frac{\sigma_{kk}^{-1} \Sigma_{h=0}^{H} ((\Psi_h \Sigma)_{j,k})^2}{\Sigma_{h=0}^{H} (\Psi_h \Sigma \Psi_h')_{j,j}}, \quad (2)$$

where $\sigma_{kk} = (\Sigma)_{k,k}$, $\Psi_h$at lag h is a (N × N) matrix of moving average coefficients and where the contribution of the kth variable to the variance of the forecast error of element j at horizon h is represented by $(\theta_H)_{j,k}$. The matrix of the variance decomposition θ_H and its rows do not necessarily sum up to one, which means that every entry can be normalized by the sum of the rows

$$(\underline{\theta}_H)_{j,k} = (\theta_H)_{j,k} \,/\, \sum_{k=1}^{N} \, (\theta_H)_{j,k}, \quad (3)$$

where the summation of all the components in $\underline{\theta}_H$ becomes equal to N and where $\Sigma_{j=1}^{N} (\underline{\theta}_H)_{j,k} \; = 1$. The pairwise connectedness at horizon H from j to i is measured by $(\underline{\theta}_H)_{j,k}$. By aggregating this information, it becomes possible to quantify the total connectedness in the system.

The measure of connectedness can then be described as a part of the forecasts variance that is contributed from errors besides the own errors or the sum of the off-diagonal components ratio to the sum of the whole matrix. This can be presented as

$$C_H = 100 \cdot \frac{\Sigma_{j \neq} (\underline{\theta}_H)_{j,k}}{\Sigma \underline{\theta}_H} = 100 \cdot (1 - \frac{Tr\{\underline{\theta}_H\}}{\Sigma \underline{\theta}_H}), \quad (4)$$

where the denominator denotes the $\underline{\theta}_H$ matrix and the sum of all its components and where the trace operator is represented by Tr $\{\cdot\}$. This shows that the contribution of the connectedness from the variables in the system to the forecast variances is relative.

4.2 Spectral representation

Barunik and Krehlik (2018) argue that the size of shocks related to economic activity and its effects on other variables differ across frequencies. The different frequencies represent different types of connectedness that create systemic risk in the short-run, medium-run and long-run. Therefore, it is suggested that when investigating the fundamental systemic risk it is important to study the connectedness and linkages throughout different frequencies. The authors further argue that the difference in connectedness across frequencies arises due to the different investment horizons of investors, these different investment horizons are in turn formed by investor preferences.

We use the spectral representation of variance decomposition that was developed by Barunik and Krehlik (2018). In the spectral framework, a Fourier transform of the coefficients Ψ_h with $i = \sqrt{-1}$ is used to obtain the frequency response function, $\Psi(e^{-i\omega}) = \Sigma_h e^{-i\omega h}\Psi_h$. A Fourier transform of MA(∞) can be used to define at frequency ω the spectral density of x_t such as a filtered series

$$\boldsymbol{S_x(\omega)} = \sum_{h=-\infty}^{\infty} \boldsymbol{E}(x_t \boldsymbol{x'_{t-h}})e^{-\boldsymbol{i\omega h}} = \boldsymbol{\Psi}(e^{-i\omega})\boldsymbol{\Sigma}\boldsymbol{\Psi'}(e^{+i\omega}), \quad (5)$$

where $S_x(\omega)$ shows how the variance of x_t is allocated over the frequency elements ω and is the most relevant quantitative measure to understand the frequency dynamics. By using covariance spectral representation such as, $E(x_t x'_{t-h}) = \int_{-\pi}^{\pi} S_x(\omega)e^{i\omega h}d\omega$, it is possible to proceed to define components of the frequency variance decomposition. Over the frequencies $\omega \in (-\pi, \pi)$ the generalized causation spectrum can be defined

$$(f(\omega))_{j,k} \equiv \frac{\sigma_{kk}^{-1}|(\Psi(e^{-i\omega})\Sigma)_{j,k}|^2}{(\Psi(e^{-i\omega})\Sigma\Psi'(e^{+i\omega}))_{j,j}}, \quad (6)$$

where the Fourier transformed impulse response Ψ_h is represented by $\Psi(e^{-i\omega}) = \Sigma_h e^{-i\omega h}\Psi_h$, and where the spectrum of the *j*th variable because of shocks in the *k*th variable at a specific frequency is represented by, $(f(\omega))_{j,k}$. Since the spectrum of the *j*th variable at a specific frequency ω is held by the denominator, i.e. by the on-diagonal component of the cross-spectral density of x_t, it becomes possible to interpret this quantity as within-frequency causation. Proceeding with weighting $(f(\omega))_{j,k}$ with the frequency share of the variance of the jth variable, we can obtain a natural decomposition of variance decompositions to frequencies. This weighting function can be presented as

$$\Gamma_j(\omega) = \frac{(\Psi(e^{-i\omega})\Sigma\Psi'(e^{+i\omega}))_{j,j}}{\frac{1}{2\pi}\int_{-\pi}^{\pi} (\Psi(e^{-i\lambda})\Sigma\Psi'(e^{+i\lambda}))_{j,j} d\lambda}, \tag{7}$$

which shows at a given frequency the effect of the jth variable, and sums through frequencies to a constant value of 2π.

Assuming that x_t is wide-sense stationary with the properties of, $\sigma_{kk}^{-1}\Sigma_{h=0}^{\infty}|(\Psi_h\Sigma)_{j,k}| < +\infty, \forall j, k$, then

$$(\theta_\infty)_{j,k} = \frac{1}{2\pi}\int_{-\pi}^{\pi} \Gamma_j(\omega)\,(f(\omega))_{j,k}\,d\omega, \tag{8}$$

which is the effect of the relationship, weighted by the strength of the series, on a given frequency, since $(\theta_H)_{j,k}$ at $H \rightarrow \infty$ can be interpreted as the average weighted generalized causation spectrum $(f(\omega))_{j,k}$. The theoretical value of the original $(\theta_H)_{j,k}$becomes rebuilt by the integral over allowed frequencies. It is rather the aggregated information through frequencies than the heterogenous frequency responses that is regarded as measuring the connectedness in the time domain given that $(\theta_H)_{j,k}$ at $H \rightarrow \infty$. Further, $(\theta_H)_{j,k}$ also becomes influenced by the effects the whole range of frequencies.

In the next step, bands of frequencies are estimated, which can be determined as the quantity of forecast error variance created on a collection of frequencies that are convex. By integrating over the demanded frequencies $\omega \in (a, b)$ it becomes possible to obtain the quantity. The frequency band can be defined as $d = (a, b): a, b \in (-\pi, \pi), a < b$ and the generalized variance decomposition on the frequency band d can be presented

$$(\theta_d)_{j,k} = \frac{1}{2\pi}\int_{d} \Gamma_j(\omega)\,(f(\omega))_{j,k}\,d\omega, \tag{9}$$

where the original variance decomposition becomes recovered through the summation of the disjoint intervals that cover the range $(-\pi, \pi)$.

By presenting the scaled generalized variance on the frequency band, $d = (a, b): a, b \in (-\pi, \pi), a < b$,

$$(\underline{\theta}_d)_{j,k} = (\theta_d)_{j,k} \ / \ \sum_k \ (\theta_\infty)_{j,k}, \tag{10}$$

then the frequency connectedness on the frequency band d can be defined

$$C_d^F = 100 \cdot \left(\frac{\Sigma(\underline{\theta}_d)}{\Sigma(\underline{\theta}_\infty)} - \frac{Tr\{\underline{\theta}_d\}}{\Sigma\underline{\theta}_\infty}\right), \tag{11}$$

where the sum of all the components of the $\underline{\theta}_d$ matrix is represented by $\Sigma\underline{\theta}_d$ and the trace operator is represented by $Tr\{\cdot\}$. The frequency connectedness divides the original connectedness measure into different parts by decomposing the overall connectedness.

The frequency bands that we include in our estimations are 1 to 2 days, 2 to 5 days, 5 to 21 days and 21 to 252 days. Through these frequency bands we get daily, daily to weekly, weekly to monthly and monthly to yearly connectedness in our spillover estimations. The short-run is represented by 1 to 2 days and 2 to 5 days, the medium-run is defined by 5 to 21 days and the long-run is defined as 21 to 252 days.

4.3 Rolling window estimation

Diebold and Yilmaz (2012; 2014) use a rolling estimation window as a framework to measure dynamic connectedness, which allows for time-varying parameters in the approximating model. The estimation is based on a uniform one-sided window with a width that in each period sweeps through the whole sample by using solely the recent periods to calculate measures of connectedness and to estimate the approximating model. This rolling estimation window can be represented as

$$\hat{C}_t = (x, H, M_{t-w:t}(\hat{\theta})), \tag{12}$$

and shows that the sample connectedness $\hat{C}_t$ is dependent on the set of variables x, the predictive horizon H and the time-varying parameters in the approximating model $M_{t-w:t}(\hat{\theta})$. By using VARs with $p = 4$, we conduct a rolling estimation window of 756 days, with a forecast horizon of 252 days. This corresponds to three years of trading days and one year of trading days, respectively. We have approximately nine years of trading day data, which can be considered as a long-time horizon and allow us to choose a window of appropriate length for our analysis.

5. Connectedness and spillover between energy markets

Connectedness values describe the amount of spillover, or how much of the share of error variance in one variable can be explained by shocks in other variables. All connectedness estimations in this section are based on cross-sectional correlations, since Barunik and Krehlik (2018) have shown that not considering cross-sectional correlation may bias connectedness measures.

5.1 Full-sample total connectedness

Table 3 shows the full sample connectedness between the RE return indices and the other assets. The total connectedness is 57,73% which means that 57,73% of the total variance in RE returns can be explained by shocks in these variables. The highest connectedness values are seen in the diagonal of the matrix which consist of the variables own connectedness, i.e. how much of the error variance in one period can explain the error variance in the subsequent period. When observing the "TO" and "FROM" row and column, we see that unsurprisingly, the global stock indices MSCI and ESG both transmit and receive the highest amount of spillover. The RE indices, together with the PSE technology index, all transmit and receive a similar share of spillover. OIL and FX transmit and receive low amounts of spillover. Investigating net spillover row, we can see that SPGCE, OIL, FX and DGS5 are net receivers of spillover, where OIL is the asset that is the largest net receiver of spillover. ECO, MSCI, ESG and PSE are net emitters of spillover.

Looking at individual connectedness we can see that OIL receives more spillover from the RE indices than it transmits to the RE indices. The finding is in line with Ahmad (2017). We also observe that shocks in the RE indices spill over to a large degree to PSE at 14,46% and 9,89%. The impact of technology shocks also affect the RE indices to a large degree. The connectedness between RE and technology is stronger than the connectedness between RE and crude oil prices, which is in line with Sadorsky (2012b).

Insert Table 3

Table 4 shows the full sample connectedness between the RE firms and the other assets. The total connectedness is 38,88%, which means that 38,88% of the total error variance in returns can be explained by shocks in our variables. The total connectedness is 19% lower than in the sample with the RE indices, which is not surprising since indices consist of an aggregate of several companies which enables higher connectedness. We can see that there is a higher self-connectedness compared to the Table 4. Observing the "TO" and "FROM" row and column we can see that the spillovers are low in general, they are quite much lower compared to Table 4. Again, MSCI and ESG show the highest amount of spillover received and transmitted. The RE sub-sectors receive and transmit spillover quite similarly. In a similar fashion to Table 4, MSCI, ESG and technology transmit the highest amount of spillover. Looking at the net spillovers we see that every RE firm and OIL, FX and DGS5 are net receivers of spillover. The global stock indices MSCI and ESG, and the technology index PSE are net transmitters of spillover.

Looking at individual connectedness of the RE sub sectors, we observe that the bioenergy sub sector seems to have the highest connectedness with the oil prices, which confirms the findings of Pham (2019). The net pairwise connectedness shows that two solar and two bioenergy companies receive more spillover from OIL than they transmit to OIL. Two wind energy companies transmit more spillover to OIL than they receive from OIL. A conclusion is that crude oil prices transmit more spillover than they receive from RE firms. This is in contrast with the findings of Reboredo, Rivera-Castro and Ugolini (2017) and Table 4 where OIL received more spillover from RE indices than it transmitted to them. Since wind energy companies transmit more spillover than they receive from crude oil markets, it could be that this sub sector is driving the spillover results in Table 4 for the renewable indices. Technology stocks transmit more spillover to RE firms than they receive from them. Compared to the RE indices in Table 4, the firms do not transmit as much spillover to the technology sector.

Insert Table 4

Table 5 shows the full-sample total connectedness between oil & gas firms and RE firms. The total connectedness is 43,50%, which is a higher total connectedness compared to the total connectedness between RE firms and the other assets. This can be argued to be a reasonable result since both type of firms is in the energy sector and because RE is a substitute to fossil fuel, which should yield a high connectedness. The "TO" and "FROM" row and column show us that the spillovers for each firm is low. The oil & gas firms transmit more and receive less spillover compared to the RE firms. The net pairwise connectedness tells us that oil & gas firms transmit more spillover to bioenergy firms than to wind and solar energy firms. We observe that RE firms transmit spillover mostly to other RE firms. The net spillover row indicates that all RE firms are net receivers of spillover while most oil & gas firms are net transmitters. One explanation for this directional spillover could be that oil & gas sector is a competitor to RE sector. The returns of oil & gas firms, who dominate the energy market, should affect the returns of the competing RE companies. Another explanation could be that several oil & gas companies are trying to transition to integrated energy companies by investing in RE. According to Lu, Guo and Zhang (2019) acquisitions and investments in RE technology are two types of investments that are common. Returns for oil & gas firms, which could affect their investments in RE, could in turn affect the return for RE firms.

Insert Table 5

Table 6 shows the full-sample total connectedness between oil & gas firms and RE firms, but several other assets are now also included. As expected, the total connectedness is higher with other assets included, as the connectedness is 55,30%, which is around twelve percent higher than in Table 6 without other assets. The spillover patterns between RE firms and oil & gas firms are similar to Table 6. Looking at the pairwise connectedness we see that RE and oil & gas firms seem to be equally connected with FX. Wind energy, bioenergy and oil & gas sector seem to be more connected with bond market, compared with solar energy. Solar energy, bioenergy and oil & gas sector are more connected with technology market, compared to wind energy. Looking at net pairwise connectedness, we observe that RE and oil & gas sectors receive more spillover from technology than they emit. We also observe that RE sectors receive more spillover from bond market than it emits, while the oil & gas sector emits more spillover to the bond market than it receives. RE being affected by interest rates confirms previous literature (Henriques & Sadorsky, 2008; Kumar, Managi & Matsuda, 2012; Bondia, Ghosh and Kanjilal, 2016; Kocaarslan & Soytas, 2019) and oil & gas firms not being affected by interest rates confirms the findings of Mohanty and Nandha (2011).

Insert Table 6

5.2 Dynamic connectedness - total and frequencies

In Figure 5 (a) we observe the dynamic total connectedness when the RE indices are included. The total connectedness starts at a very high level, between 66 and 70 percent at 2014 and then drops down to 50% in the end of 2015. From around 2016 to 2017 the connectedness increases slightly and lies on a constant level until around 2018 where it after that year slightly decreases. Barunik and Krehlik (2018) argue that financial crises through its uncertainty transmission channel increases total connectedness. By this reasoning, the explanation for the sudden drop in total connectedness in the period around 2014 and 2015 could be due to the end of the European debt crisis. The oil price plunge of 2014-2016 did not seem to increase the total connectedness during this time period. The slight increase from 2016 to 2017 coincides with the American presidential election and the Brexit referendum in 2016, and the U.S withdrawal from the Paris climate agreement in 2017.

In Figure 5 (b) we present the frequency connectedness, where the sum of each frequency band is equal to the total connectedness in Figure 5 (a). We can observe that it is the short-term connectedness in the form of 1 to 2 days and 2 to 5 days that is mainly driving the total connectedness. The finding of short-term connectedness driving total connectedness supports the findings of Ferrer et al. (2018). The medium-term connectedness between 5 and 21 days is also substantial, but the long-term connectedness from 21 to 252 days is almost zero. The implication of short-term connectedness dominating is that the market processes information quickly, i.e. that shocks diminish after a few days and that investors expect that shocks to uncertainty have a short-term impact. Thus, investors expected the uncertainty between 2016 and 2017 that stemmed from the American presidential election, the Brexit referendum and U.S withdrawal from the Paris climate agreement to have a short-term impact on the RE market. The low connectedness in the long run implies that investors have a belief of long-term stability in RE investments. Furthermore, this belief of a long-term stability could stem from the belief that RE is a market that will receive constant growth due to society wanting to transition from fossil fuel to RE dependence. Shocks not having an impact in the long run could also be due to RE being regarded by investors as ethically, socially and environmentally beneficial to invest in regardless of financial shocks.

The 1 to 2 days connectedness move similar to the 2 to 5 days connectedness, with the exception that the former seems to be increasing between 2016 and 2018 while the latter is constant. This tells us that during this time period, investors increasingly believed that shocks in uncertainty would have a short-term daily impact on the RE market. We can also note some asymmetry between the two frequency bands at peaks and drops. For example, between 2014 and 2015 there is one small dip in the first mentioned band while there is a peak in the latter mentioned band. Between 2015 and 2016 the 1 to 2 day band has a slight peak and sudden drop, while the 2 to 5 day band has a slight decrease and sudden peak. This asymmetry is also evident between 2018 and 2019. So, when connectedness in the 1 to 2 day band peaks (drops), the connectedness in the 2 to 5 day band drops (peaks), hence peaks and drops seem to transmit between the two frequencies. The interpretation of the asymmetry is that investors beliefs are impacted by shocks in such a way that they believe that the impact of a uncertainty shock today will transmit to the rest of the week, if the 1 to 2 day connectedness is declining and the 2 to 5 day connectedness is rising. The reverse is true if the 1 to 2 day connectedness is rising while the 2 to 5 day connectedness is declining. However, the asymmetrical peaks and drops are not seen in the end of the time period from 2019 to 2020, the 1 to 2 day band is relatively constant while the 2 to 5 day band drops quite significantly.

Insert Figure 5

In Figure 6 (a) we can observe the dynamic total connectedness when RE firms are included instead of RE indices. The level of total connectedness for RE firms is lower than the RE indices, which is not strange since the aggregated market for RE should lie in a higher level of total connectedness than separate firms. Even here we can observe that the total connectedness starts at a high level at 2014, and then suddenly drops down around the end of 2015. However, the difference is that the connectedness starts to increase at a much higher rate, from 36 percent around the end of 2015 to return to the initial total connectedness between 44 and 48 percent around 2017. The connectedness drops more sharply by 2019 in this firm sample than in the indices sample.

A reason for the sharp increases and decreases for the RE firm sample connectedness could be that uncertainty in market specific factors affect individual RE firms more than the aggregated RE market. When the market uncertainty and connectedness increased between 2016 and 2017 due to the U.S presidential election, the Brexit referendum and the U.S withdrawal from the Paris climate agreement, this could have increased connectedness more for individual RE firms. Another reason could be that firm specific uncertainty increases the upward and downward swings. For example, when the market uncertainty and connectedness increased between 2016 and 2017, uncertainties in renewable firm specific factors, such as leverage and revenues, could have been impacted at the same time, which increases the connectedness even more.

In Figure 6 (b) we present the frequency connectedness. In the figure we can again observe that it is the short-term connectedness in the form of 1 to 2 days and 2 to 5 days connectedness that is mainly driving the total connectedness. The medium-term connectedness between 5 and 21 days is relatively higher here than in the figure 4 plot (b) for the renewable indices. The long-term connectedness from 21 to 252 days is again almost zero. Focusing on the 1 to 2 days and 2 to 5 days connectedness again we can see that there exists a higher heterogeneity of movements in this sample. Some asymmetrical patterns for peaks and drop exist but only from 2015 to 2016. The 1 to 2 day and the 2 to 5 day connectedness have more sharp drops compared to the previous sample. The 2 to 5 day connectedness drops significantly two times in the end of the sample. In contrast, at the end of the sample, the 1 to 2 day band only drops once.

From our results we can conclude that there exists heterogeneity in total dynamic connectedness when one uses RE indices and when one on the other hand uses firm level returns. The heterogeneity is showcased by that there are sharper swings in total connectedness between RE firms and other assets. We conclude that there is a justification in taking returns at the firm level into consideration when measuring connectedness, which is why we proceed with measuring dynamic connectedness between RE firms and oil & gas firms.

Insert Figure 6

In Figure 7 (a) we can observe the dynamic total connectedness between RE firms and oil & gas firms. The level of total connectedness is, throughout the sample, somewhat higher here compared to the total connectedness between RE firms and other assets in figure 6 (a). This higher connectedness is in line with our result for full-sample connectedness in table 6. The total connectedness starts at almost the same high level, 48 percent in 2014, and then suddenly drops down to around 39 percent around 2015. This is similar to figure 5 (a), except that the drop was not interrupted during a short time period in 2015. A contrasting result is that the connectedness between RE and oil & gas firms starts to rise again in 2015 while a new period of connectedness downturn starts in figure 6 (a). The connectedness rises in 2015 is short lived, connectedness starts to drop just like the connectedness in figure 6 (a). Between the end of 2015 and 2017 connectedness increases sharply and then lies at a constant level to then drop after 2018. This is in line with the dynamic of figure 6 (a). The main difference between connectedness dynamics between RE firms and oil & gas firms, and the connectedness dynamics between RE firms and other assets, is the time period from 2015 to 2016. The increase in connectedness for the former and decrease in connectedness for the latter, indicates that an uncertainty is increasing the connectedness for one but not for the other. The explanation for the increase could be that the oil price plunge in 2014-2016, which increased crude oil price uncertainty, was overshadowed by the decreased uncertainty from the end of the Euro debt crisis in 2015. When the Euro debt crisis ended and the oil plunge was still ongoing, the total uncertainty increased which increased the connectedness during the first half of 2015. The oil price plunge starts to ebb away at the latter half of 2015 which decreases uncertainty and the connectedness until 2016. The connectedness between RE firms and other assets should not have been impacted as much by the oil price plunge which is why the uncertainty and connectedness did not increase during 2015 in figure 6 (a).

In Figure 7 (b) the frequency connectedness is shown. We again observe that it is the short-term connectedness in the form of 1 to 2 days and 2 to 5 days connectedness that is mainly driving the total connectedness. The 2 to 5 days connectedness was the frequency that was mainly impacted by the decreased uncertainty from the end of the Euro debt crisis. We also note that the decrease in connectedness from 2014 to 2020 was also driven by the 2 to 5 day connectedness, in fact the 1 to 2 day connectedness increased slightly during this time period.

We conclude that the dynamics of total connectedness between RE firms and assets, and RE firms and oil & gas firms is similar. The main difference is that it seems that the latter was impacted by an uncertainty that did not impact the former. This could mean that oil & gas firms are the reason to why connectedness increased during 2015. The oil price plunge of 2014-2016 is a possible source of uncertainty.

Insert Figure 7

In Figure 8(a) we can observe the dynamic total connectedness between RE firms and oil & gas firms, but this time with other assets included. An almost identical pattern to Figure 7 (a) appears. The only difference is that the level of connectedness is higher in this figure. Figure 8 (b) which shows the frequency connectedness is also almost identical to its counterpart in Figure 7 (b). These results indicate that the inclusion of other assets does not affect the dynamic pattern of connectedness between RE firms and oil & gas firms that was observed in Figure 7 (a), which is in line with our findings in the full-sample connectedness, see Table 7. In other words, market factors do not seem to have a large impact on the dynamic connectedness between RE and oil & gas firms, but they have an impact on the level of connectedness.

Insert Figure 8

7. Conclusions & policy implications

Applying the full-sample and rolling-window framework developed by Diebold and Yilmaz (2012, 2014) and dynamic frequency connectedness framework developed by Barunik and Krehlik (2018), we investigate the connectedness and spillover between RE sectors, the oil & gas sector and other assets.

The answers to our research questions are: **(I)** there is a difference in connectedness results between using aggregated RE market and RE firm level data. We also find that RE firms are net receivers of spillover from oil & gas firms. The bioenergy sector seems to be the most connected to oil & gas firms and oil prices. Bioenergy, solar and oil & gas energy sector are the most connected sectors to technology. Wind, bio and oil & gas sector are more connected to bond market, compared to solar sector. RE receives spillover from the bond market while oil & gas firms emit spillover to the bond market; **(II)** there is a clear difference in connectedness between frequencies in our dynamic frequency connectedness results. The total dynamic connectedness is driven by short term connectedness, i.e. high frequency connectedness.

Our results have several policy implications. Since changes in bond rates mainly spillover to RE sectors and not to the oil & gas sector, policy makers should also be aware that changes in interest rates may impact the societal transition to a RE based energy system. Short term connectedness driving the total connectedness provides a greater understanding for climate policy makers regarding designing the optimal climate policies to reduce environmental degradation. The benefits of diversifying the portfolio through RE assets will not be available in the short run, since a shock that affects oil & gas firms would likely affect RE assets too. Climate policy makers can prioritize policies that reduce the effect of increased connectedness in the short run, since the high short run connectedness can deter investors from investing in RE assets.

The main findings of our investigation could be unique for the specific firms that are included in our estimations, and hence there could be firm specific characteristics that affect the result. It would also be interesting to include more firms in other RE sub-sectors and to include firms that are chosen by other criteria than the ones mentioned by Thomson Reuters (2020b). Lastly, it would be interesting to measure asymmetric connectedness since it will enable investigation of spillovers due to negative and positive returns and hence tell if the information transmission is symmetric or not.

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Table 1. Variables, definitions and sources.

Variable	Definition	Source
RE indices		
ECO	WilderHill Clean Energy price index	Thomson Reuters Datastream
SPGCE	S&P Global Clean Energy price index	Thomson Reuters Datastream
Solar energy firms		
CASO	Canadian Solar stock price	Thomson Reuters Datastream
RIEN	Risen Energy stock price	Thomson Reuters Datastream
MOTE	Motech Industries stock price	Thomson Reuters Datastream
Wind energy firms		
SGRE	Siemens Gamesa RE stock price	Thomson Reuters Datastream
SUZN	Suzlon Energy stock price	Thomson Reuters Datastream
VEST	Vestas Windsystems stock price	Thomson Reuters Datastream
Bioenergy firms		
CREN	CropEnergies stock price	Thomson Reuters Datastream
GREP	Green Plains stock price	Thomson Reuters Datastream
PATH	Pacific Ethanol stock price	Thomson Reuters Datastream
Oil & gas firms		
BHAR	Bharat Petroleum stock price	Thomson Reuters Datastream
BP	British Petroleum stock price	Thomson Reuters Datastream
CHEV	Chevron Corporation stock price	Thomson Reuters Datastream
CONO	ConocoPhilips stock price	Thomson Reuters Datastream
EXMO	ExxonMobil stock price	Thomson Reuters Datastream
GAZP	Gazprom stock price	Thomson Reuters Datastream
INOIL	Indian Oil stock price	Thomson Reuters Datastream
RDS	Royal Dutch Shell stock price	Thomson Reuters Datastream
EQUI	Equinor stock price	Thomson Reuters Datastream
Other assets		
MSCI	MSCI World price index	Thomson Reuters Datastream
ESG	MSCI World ESG Leaders price index	Thomson Reuters Datastream
OIL	NYMEX Light Crude Oil futures settle price	Thomson Reuters Datastream
FX	Euro to US Exchange rate	Thomson Reuters Datastream
DGS5	5-Year Treasury Constant Maturity Rate (bond)	Federal Reserve Bank of S.T Louis
PSE	NYSE Arca Technology 100 price index	Thomson Reuters Datastream

Notes: All 2279 observations of the data are daily over the period 2011-05-18 to 2020-02-10.

Table 2. Summary Statistics

	Mean (%)	Max	Min	Std. dev (%)	Skewness	Kurtosis	JB	ARCH (10)	LB (10)	ADF (c)	ADF (ct)
Indices											
ECO	−0.008	0.082	−0.102	1.618	−0.292	2.589	670.656***	367.190***	816.307***	-21.827[4]***	-21.937[4]***
SPGCE	−0.013	0.071	−0.081	1.200	−0.410	3.888	1510.888***	399.170***	912.773***	-17.232[6]***	-17.376[6]***
Solar energy firms											
CASO	0.037	0.288	−0.203	4.017	0.149	4.824	2223.764***	44.163***	57.421***	-32.604[1]***	-32.597[1]***
RIEN	0.002	0.095	−0.114	3.008	−0.161	2.768	740.025***	264.060***	598.363***	-33.528[1]***	-33.540[1]***
MOTE	−0.108	0.095	−0.105	2.634	0.037	2.411	554.652***	103.020***	139.633***	-31.085[1]***	-31.080[1]***
Wind energy firms											
SGRE	0.038	0.181	−0.194	2.696	−0.079	5.952	3374.293***	32.248***	41.611***	-33.313[1]***	-33.308[1]***
SUZN	−0.134	0.256	−0.415	3.741	0.033	12.109	13948.970***	150.970***	188.035***	-30.937[1]***	-30.932[1]***
VEST	0.065	0.212	−0.278	2.893	−0.391	11.111	11802.830***	39.647***	52.808***	-28.484[2]***	-28.494[2]***
Bioenergy firms											
CREN	0.027	0.133	−0.153	2.372	−0.299	4.959	2374.763***	48.659***	53.773***	-15.757[7]***	-15.781[7]***
GREP	0.006	0.248	−0.146	2.940	0.164	4.577	2005.212***	38.803***	48.169***	-31.789[1]***	-31.798[1]***
PATH	−0.188	0.503	−0.415	5.414	0.856	10.240	10254.443***	59.739***	81.085***	-33.529[1]***	-33.526[1]***
Oil & gas firms											
BHAR	0.068	0.110	−0.222	2.082	−0.582	7.734	5819.576***	245.270***	332.360***	-33.900[1]***	-33.894[1]***
BP	0.002	0.069	−0.091	1.403	−0.093	2.784	741.574***	337.180***	590.955***	-16.183[8]***	-16.180[8]***
CHEV	0.003	0.061	−0.078	1.317	−0.187	2.806	763.373***	471.850***	998.190***	-23.303[4]***	-23.302[4]***
CONO	0.002	0.093	−0.097	1.706	−0.074	3.436	1126.341***	494.310***	940.092***	-33.819[1]***	-33.812[1]***
EXMO	−0.014	0.054	−0.064	1.166	−0.185	3.033	889.124***	554.400***	1246.866***	-23.559[4]***	-23.603[4]***
GAZP	0.005	0.152	−0.150	1.602	0.224	8.634	7111.756***	473.690***	428.395***	-32.360[1]***	-32.407[1]***
INOIL	0.016	0.101	−0.173	1.928	−0.276	5.032	2438.749***	171.560***	215.025***	-34.838[1]***	-34.832[1]***
RDS	−0.002	0.065	−0.080	1.296	−0.247	3.786	1387.902***	384.240***	731.794***	-24.701[3]***	-24.701[3]***
EQUI	0.003	0.087	−0.076	1.555	0.141	2.602	652.417***	340.380***	621.271***	-36.063[1]***	-36.056[1]***
Other assets											
MSCI	0.024	0.041	−0.053	0.789	−0.649	5.166	2672.364***	356.700***	857.777***	-23.494[4]***	-23.492[4]***
ESG	0.026	0.039	−0.050	0.776	−0.635	4.980	2549.469***	347.450***	847.247***	-23.594[4]***	-23.594[4]***
OIL	−0.030	0.137	−0.108	2.055	0.104	3.758	1360.192***	214.990***	454.467***	-34.942[1]***	-34.935[1]***
FX	0.012	0.023	−0.026	0.521	−0.012	2.138	441.353***	134.300***	227.848***	-34.177[1]***	-34.177[1]***
DGS5	−0.013	0.147	−0.199	3.154	−0.074	2.833	769.742***	151.170***	295.213***	-19.996[5]***	-19.991[5]***
PSE	0.060	0.059	−0.059	1.055	−0.409	3.466	1224.942***	302.23***	742.627***	-23.598[4]***	-23.615[4]***

Notes: All variables contain 2278 daily observations over the period 2011-05-19 to 2020-02-10. All the variables are represented in first differences and all the variables are log transformed. JB is the Jarque-Bera. ARCH(10) is the Autoregressive Conditional Heteroskedasticity test with 10 lags. LB (10) is the Ljung-Box test for the squared residuals with 10 lags. ADF (c) and ADf (ct) is the Augmented Dickey-Fuller unit root test with a constant and with a constant and trend respectively and includes the optimal lag length in the brackets that minimizes the AIC. The notations *, ** and *** indicates significance at 10%, 5% and 1%.

Table 3. Full-sample total connectedness - RE indices and other assets

	ECO	SPGCE	MSCI	ESG	OIL	FX	DGS5	PSE	**FROM**
ECO	**29.759**	17.190	15.880	15.582	3.709	0.524	2.516	14.835	8.780
SPGCE	18.303	**30.685**	16.676	16.553	3.326	2.022	1.793	10.637	8.664
MSCI	12.977	12.884	**23.956**	23.783	3.830	2.178	3.150	17.237	9.505
ESG	12.855	12.911	24.017	**24.187**	3.738	2.271	3.031	16.986	9.476
OIL	7.419	6.217	9.327	9.042	**59.053**	1.106	3.128	4.705	5.118
FX	1.350	5.235	6.940	7.170	1.519	**76.680**	0.448	0.653	2.914
DGS5	5.508	3.932	8.380	7.986	3.378	0.164	**64.723**	5.926	4.409
PSE	14.468	9.890	20.878	20.357	2.301	0.323	2.708	**29.071**	8.866
TO	9.110	8.532	12.762	12.559	2.725	1.073	2.097	8.872	**57.735**
NET	0.330	−0.131	3.257	3.083	−2.392	−1.841	−2.312	0.006	

Notes: The full-sample unconditional connectedness predictive horizon is 252 days. The ij-th entry of the upper-left 8×8 sub-matrix sector represents the ij-th directional pairwise connectedness. The net pairwise connectedness is calculated as $C_{i \to j} - C_{j \to i}$. The FROM column produces directional total connectedness from one sector to another and is defined by the sum of the row, i.e. from all others to i. The TO row receives the directional total connectedness to one sector from another and is defined by the sum of the column, i.e. to all others from j. The NET row represents the difference between the TO row and the FROM column in the directional total connectedness. The bottom-right cell is representing the total connectedness.

Table 4. Full-sample total connectedness - RE firms and other assets

	CASO	RIEN	MOTE	SGRE	SUZN	VEST	CREN	GREP	PATH	MSCI	ESG	OIL	FX	DGS5	PSE	**FROM**
CASO	**55.609**	0.443	1.043	2.501	0.264	1.945	0.759	4.473	1.525	9.508	9.315	3.040	0.353	1.366	7.849	2.959
RIEN	1.258	**90.046**	0.474	0.544	0.552	0.273	0.327	0.846	0.225	1.505	1.507	0.550	0.115	0.605	1.166	0.663
MOTE	2.428	0.685	**77.863**	1.614	0.682	0.863	0.468	1.327	0.721	4.325	4.351	1.035	0.251	0.626	2.754	1.475
SGRE	2.352	0.263	0.473	**50.705**	0.352	14.229	0.581	1.872	0.669	9.806	9.823	1.097	0.233	2.411	5.129	3.286
SUZN	0.744	0.387	0.267	0.739	**90.775**	0.416	0.277	0.523	0.085	1.820	1.798	0.863	0.211	0.375	0.711	0.614
VEST	1.875	0.084	0.334	16.402	0.301	**58.272**	0.588	2.125	0.275	6.755	6.829	0.741	0.356	1.807	3.247	2.781
CREN	1.498	0.258	0.330	0.940	0.239	0.756	**83.844**	0.547	0.214	3.369	3.373	1.417	0.110	0.634	2.464	1.077
GREP	4.280	0.252	0.266	1.964	0.206	1.511	0.276	**52.891**	5.042	8.912	8.655	6.072	0.209	1.961	7.496	3.140
PATH	2.171	0.180	0.186	0.826	0.061	0.358	0.153	7.113	**72.922**	3.989	3.831	3.269	0.272	1.318	3.343	1.805
MSCI	4.364	0.253	0.569	4.925	0.370	2.851	0.941	4.281	1.296	**25.830**	25.647	4.199	2.421	3.477	18.570	4.944
ESG	4.313	0.252	0.575	4.963	0.375	2.905	0.933	4.180	1.240	25.902	**26.083**	4.097	2.517	3.357	18.301	4.927
OIL	3.148	0.251	0.135	1.465	0.428	0.857	0.422	6.434	2.353	9.223	8.946	**57.505**	1.058	3.012	4.757	2.832
FX	0.565	0.204	0.368	0.350	0.104	0.641	0.031	0.278	0.107	7.440	7.662	1.547	**79.499**	0.454	0.742	1.366
DGS5	1.533	0.152	0.176	2.940	0.277	1.989	0.687	2.333	1.103	8.393	8.027	3.277	0.162	**63.015**	5.927	2.465
PSE	4.400	0.188	0.565	3.178	0.225	1.699	0.769	4.397	1.443	22.902	22.329	2.620	0.376	3.033	**31.869**	4.542
TO	2.328	0.257	0.384	2.890	0.296	2.086	0.481	2.715	1.087	8.256	8.140	2.255	0.576	1.629	5.497	**38.884**
NET	−0.630	−0.406	−1.091	−0.395	−0.318	−0.695	−0.595	−0.424	−0.718	3.312	3.212	−0.577	−0.789	−0.836	0.955	

Notes: The full-sample unconditional connectedness predictive horizon is 252 days. The ij-th entry of the upper-left 15×15 sub-matrix sector represents the ij-th directional pairwise connectedness. The net pairwise connectedness is calculated as $C_{i \to j} - C_{j \to i}$. The FROM column produces directional total connectedness from one sector to another and is defined by the sum of the row, i.e. from all others to i. The TO row receives the directional total connectedness to one sector from another and is defined by the sum of the column, i.e. to all others from j. The NET row represents the difference of the TO row and the FROM olumn in the directional total connectedness. The bottom-right cell is representing the total connectedness.

Table 5. Full-sample total connectedness - Oil & gas firms and RE firms

	BHAR	BP	CHEV	CONO	EXMO	GAZP	INOIL	RDS	EQUI	CASO	RIEN	MOTE	SGRE	SUZN	VEST	CREN	GREP	PATH	**FROM**
BHAR	**64.859**	0.418	0.167	0.143	0.138	0.243	28.910	0.536	0.336	0.115	0.015	0.414	0.260	2.571	0.165	0.287	0.211	0.212	1.952
BP	0.180	**32.058**	8.870	8.111	8.015	3.327	0.072	16.960	12.470	1.425	0.108	0.195	2.315	0.257	1.354	0.508	2.855	0.921	3.775
CHEV	0.033	7.278	**30.217**	16.049	18.775	1.836	0.028	7.658	6.045	2.639	0.114	0.232	1.470	0.075	0.797	0.549	4.888	1.318	3.877
CONO	0.037	7.226	17.180	**32.318**	14.977	1.739	0.029	7.404	6.239	2.682	0.099	0.148	1.241	0.161	0.736	0.539	5.871	1.375	3.760
EXMO	0.012	6.804	19.430	14.504	**31.225**	2.290	0.032	7.069	6.136	2.540	0.117	0.299	1.785	0.109	1.143	0.311	4.719	1.475	3.821
GAZP	0.261	6.146	4.319	4.018	4.856	**59.260**	0.314	5.062	5.740	1.228	0.249	0.259	2.657	0.567	1.769	0.850	1.610	0.836	2.263
INOIL	28.836	0.317	0.143	0.169	0.062	0.290	**64.717**	0.384	0.304	0.185	0.047	0.264	0.436	2.908	0.290	0.322	0.198	0.130	1.960
RDS	0.183	16.775	9.528	8.478	8.490	2.616	0.161	**31.399**	13.141	1.427	0.159	0.258	1.949	0.193	1.035	0.637	2.748	0.823	3.811
EQUI	0.092	13.480	8.773	8.587	8.030	3.245	0.050	14.414	**33.434**	1.609	0.178	0.145	2.157	0.149	1.427	0.395	2.767	1.069	3.698
CASO	0.118	2.415	5.314	5.257	5.042	1.239	0.281	2.305	2.930	**61.292**	0.454	1.191	2.567	0.302	2.123	0.862	4.771	1.539	2.150
RIEN	0.499	0.429	1.062	0.633	0.795	0.368	0.457	0.634	0.683	1.120	**90.179**	0.439	0.513	0.552	0.243	0.302	0.912	0.177	0.546
MOTE	0.495	1.523	3.106	2.152	2.692	0.555	0.187	1.585	0.720	2.593	0.647	**78.143**	1.628	0.681	0.816	0.397	1.350	0.729	1.214
SGRE	0.184	4.017	2.747	2.102	3.010	2.500	0.390	3.471	3.611	2.466	0.283	0.500	**55.547**	0.364	15.526	0.593	2.028	0.660	2.470
SUZN	3.338	0.916	0.625	0.587	0.709	0.645	3.830	0.809	0.491	0.769	0.388	0.289	0.675	**84.703**	0.382	0.301	0.465	0.078	0.850
VEST	0.070	2.604	1.681	1.560	2.331	1.711	0.161	2.037	2.541	1.999	0.077	0.283	17.416	0.309	**62.080**	0.592	2.271	0.277	2.107
CREN	0.368	1.354	1.726	1.719	1.265	1.287	0.584	1.616	1.201	1.507	0.247	0.321	0.872	0.260	0.706	**84.190**	0.539	0.238	0.878
GREP	0.256	3.982	8.091	8.978	7.396	1.369	0.122	3.627	3.188	3.882	0.258	0.260	1.836	0.192	1.448	0.262	**49.894**	4.960	2.784
PATH	0.190	2.149	3.527	3.245	3.800	0.850	0.303	1.686	1.958	1.974	0.197	0.196	0.721	0.047	0.334	0.190	7.274	**71.359**	1.591
TO	1.953	4.324	5.349	4.794	5.021	1.451	1.995	4.292	3.763	1.676	0.202	0.316	2.250	0.539	1.683	0.439	2.527	0.934	**43.507**
NET	0.001	0.549	1.473	1.034	1.200	−0.813	0.035	0.481	0.065	−0.475	−0.344	−0.898	−0.220	−0.311	−0.424	−0.440	−0.257	−0.657	

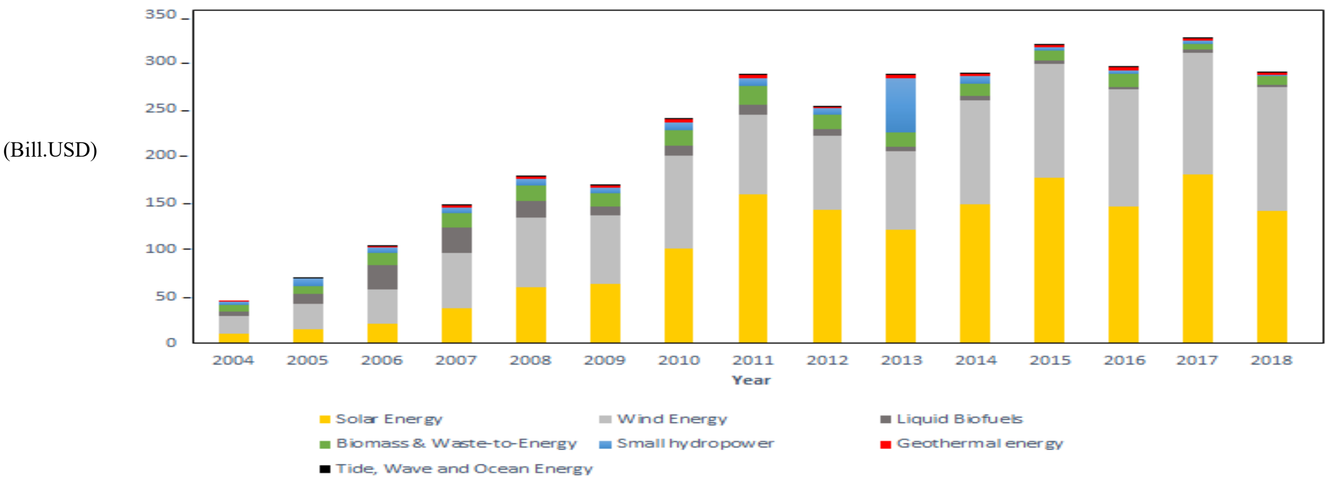
Notes: The full-sample unconditional connectedness predictive horizon is 252 days. The ij-th entry of the upper-left 18×18 sub-matrix sector represents the ij-th directional pairwise connectedness. The net pairwise connectedness is calculated as $C_{i\to j} - C_{j\to i}$. The FROM column produces directional total connectedness from one sector to another and is defined by the sum of the row, i.e. from all others to i. The TO row receives the directional total connectedness to one sector from another and is defined by the sum of the column, i.e. to all others from j. The NET row represents the difference of the TO row and the FROM column in the directional total connectedness. The bottom-right cell is representing the total connectedness.

Table 6. Full-sample total connectedness - Oil & gas firms, RE firms and other assets

	BHAR	BP	CHEV	CONO	EXMO	GAZP	INOIL	RDS	EQUI	CASO	RIEN	MOTE	SGRE	SUZN	VEST	CREN	GREP	PATH	MSCI	ESG	OIL	FX	DGS5	PSE	**FROM**
BHAR	**63.517**	0.394	0.182	0.148	0.143	0.208	28.079	0.513	0.342	0.111	0.016	0.365	0.258	2.452	0.163	0.269	0.182	0.209	0.640	0.647	0.551	0.037	0.154	0.421	1.520
BP	0.128	**24.697**	6.940	6.326	6.296	2.558	0.055	12.979	9.706	1.165	0.072	0.144	1.771	0.208	1.042	0.365	2.191	0.691	6.455	6.208	5.259	0.055	1.326	3.364	3.138
CHEV	0.020	5.008	**20.510**	10.928	12.765	1.216	0.020	5.261	4.140	1.858	0.083	0.158	1.011	0.046	0.556	0.397	3.317	0.919	8.880	8.591	6.059	0.431	1.486	6.341	3.312
CONO	0.028	5.082	12.069	**22.625**	10.539	1.174	0.020	5.237	4.430	1.898	0.074	0.110	0.852	0.107	0.509	0.366	4.086	0.949	7.328	7.151	8.425	0.206	1.668	5.066	3.224
EXMO	0.008	4.623	12.968	9.711	**20.807**	1.509	0.024	4.777	4.111	1.733	0.078	0.206	1.214	0.068	0.780	0.218	3.171	1.016	9.376	9.059	5.436	0.351	1.885	6.870	3.300
GAZP	0.173	4.801	3.306	3.050	3.781	**46.310**	0.223	3.934	4.424	0.977	0.206	0.199	2.084	0.424	1.429	0.629	1.243	0.658	7.105	7.042	2.434	0.646	1.485	3.436	2.237
INOIL	28.178	0.300	0.142	0.170	0.056	0.260	**63.756**	0.353	0.274	0.190	0.040	0.268	0.444	2.857	0.307	0.303	0.195	0.116	0.457	0.451	0.223	0.176	0.094	0.391	1.510
RDS	0.131	12.852	7.451	6.632	6.649	1.993	0.124	**24.207**	10.203	1.151	0.105	0.191	1.492	0.159	0.806	0.466	2.140	0.632	6.341	6.105	5.434	0.202	1.154	3.380	3.158
EQUI	0.077	10.553	6.884	6.751	6.295	2.483	0.043	11.267	**25.924**	1.280	0.136	0.114	1.754	0.103	1.180	0.291	2.209	0.855	5.765	5.547	6.081	0.225	1.300	2.883	3.087
CASO	0.087	1.881	4.064	3.923	3.810	0.943	0.206	1.807	2.213	**45.234**	0.391	0.886	1.947	0.211	1.554	0.610	3.559	1.114	7.756	7.585	2.424	0.338	1.152	6.307	2.282
RIEN	0.509	0.363	1.027	0.619	0.732	0.370	0.437	0.520	0.645	1.178	**85.454**	0.436	0.486	0.536	0.246	0.304	0.902	0.175	1.366	1.361	0.574	0.113	0.575	1.070	0.606
MOTE	0.393	1.365	2.676	1.902	2.403	0.477	0.163	1.392	0.712	2.326	0.581	**68.977**	1.409	0.626	0.693	0.386	1.160	0.632	3.744	3.761	0.979	0.195	0.524	2.522	1.293
SGRE	0.137	3.053	2.132	1.587	2.351	1.920	0.307	2.613	2.894	1.922	0.220	0.375	**42.525**	0.298	11.840	0.436	1.572	0.523	8.031	8.053	0.873	0.189	1.975	4.173	2.395
SUZN	3.067	0.942	0.604	0.533	0.708	0.572	3.589	0.837	0.464	0.664	0.381	0.261	0.661	**80.102**	0.401	0.262	0.445	0.059	1.724	1.715	0.766	0.198	0.367	0.678	0.829
VEST	0.066	2.138	1.434	1.287	1.977	1.466	0.140	1.693	2.247	1.650	0.071	0.243	14.342	0.295	**51.330**	0.488	1.882	0.231	5.826	5.896	0.657	0.309	1.542	2.790	2.028
CREN	0.326	1.161	1.677	1.573	1.210	1.100	0.519	1.458	1.007	1.312	0.239	0.287	0.765	0.231	0.640	**75.716**	0.475	0.195	2.986	2.991	1.323	0.110	0.533	2.166	1.012
GREP	0.192	2.990	6.123	6.764	5.653	1.028	0.088	2.759	2.495	2.965	0.215	0.182	1.390	0.134	1.089	0.188	**37.798**	3.648	6.563	6.377	4.284	0.179	1.411	5.486	2.592
PATH	0.161	1.824	3.165	2.812	3.441	0.748	0.275	1.439	1.766	1.672	0.173	0.159	0.659	0.049	0.296	0.151	6.090	**61.491**	3.360	3.233	2.768	0.248	1.203	2.818	1.605
MSCI	0.161	4.123	7.365	5.556	7.629	2.491	0.133	3.981	3.472	2.868	0.162	0.337	3.125	0.248	1.809	0.586	2.873	0.824	**16.835**	16.715	2.735	1.574	2.242	12.155	3.465
ESG	0.164	4.017	7.252	5.514	7.504	2.509	0.137	3.872	3.391	2.856	0.161	0.342	3.180	0.255	1.861	0.585	2.832	0.795	17.029	**17.147**	2.697	1.651	2.180	12.072	3.452
OIL	0.041	6.098	8.810	11.089	7.781	1.437	0.051	6.337	6.114	1.608	0.143	0.066	0.744	0.227	0.454	0.207	3.308	1.226	4.817	4.680	**30.119**	0.572	1.559	2.510	2.912
FX	0.121	0.137	1.461	0.676	1.200	1.022	0.109	0.576	0.400	0.612	0.175	0.357	0.321	0.109	0.593	0.034	0.322	0.100	6.978	7.189	1.493	**74.881**	0.442	0.691	1.047
DGS5	0.051	2.444	3.689	3.846	4.497	1.621	0.149	2.154	2.451	1.258	0.115	0.135	2.283	0.248	1.540	0.521	1.867	0.903	6.580	6.282	2.582	0.119	**49.937**	4.726	2.086
PSE	0.089	2.614	6.987	5.081	7.449	1.598	0.111	2.453	2.192	3.104	0.134	0.373	2.191	0.160	1.168	0.519	3.216	1.005	16.434	16.007	1.890	0.269	2.180	**22.778**	3.218
TO	1.430	3.282	4.517	4.020	4.370	1.279	1.458	3.259	2.920	1.515	0.165	0.258	1.849	0.419	1.290	0.358	2.052	0.728	6.064	5.943	2.748	0.350	1.185	3.847	**55.305**
NET	−0.091	0.144	1.205	0.796	1.070	−0.958	−0.052	0.101	−0.166	−0.767	−0.441	−1.035	−0.545	−0.410	−0.738	−0.654	−0.540	−0.876	2.599	2.491	−0.164	−0.697	−0.901	0.629	

Note: The full-sample unconditional connectedness predictive horizon is 252 days. The ij-th entry of the upper-left 24×24 sub-matrix sector represents the ij-th directional pairwise connectedness. The net pairwise connectedness is calculated as $C_{i\to j} - C_{j\to i}$. The FROM column produces directional total connectedness from one sector to another and is defined by the sum of the row, i.e. from all others to i. The TO row receives the directional total connectedness to one sector from another and is defined by the sum of the column, i.e. to all others from j. The NET row represents the difference of the TO row and the FROM column in the directional total connectedness. The bottom-right cell is representing the total connectedness.

Figure 1. Global investment in RE

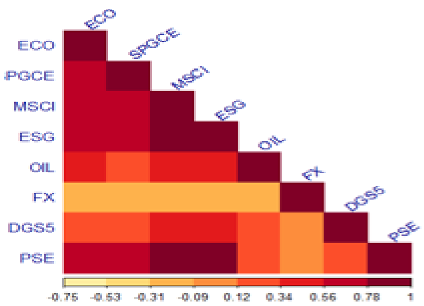


Notes: Data source: IRENA, 2019. Global trend in RE investment 2019.

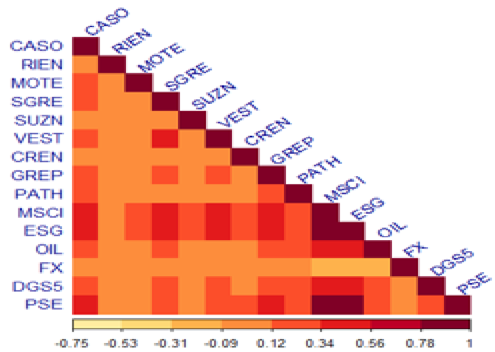
Figure 2. Correlation heat maps

Year

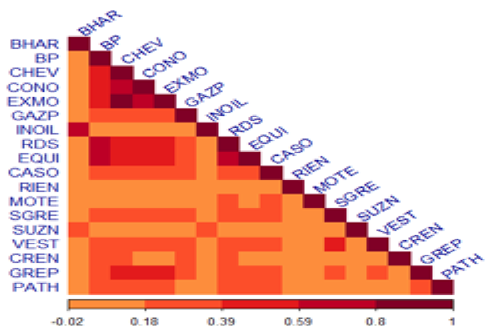
(a) RE indices, other assets and uncertainties



(b) RE firms, other assets and uncertainties

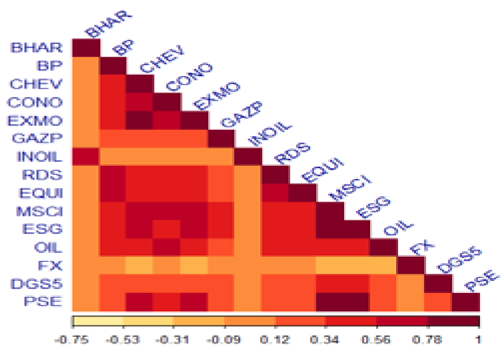


(c) Oil & gas firms and RE firms



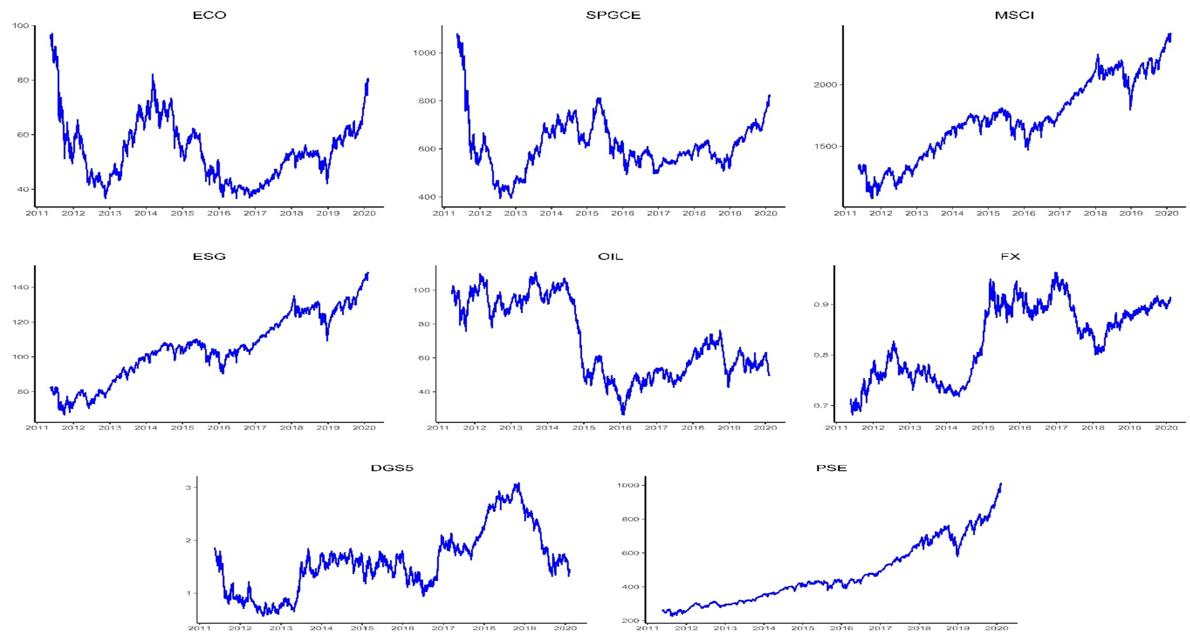
(d) Oil & gas firms, other

assets and uncertainties



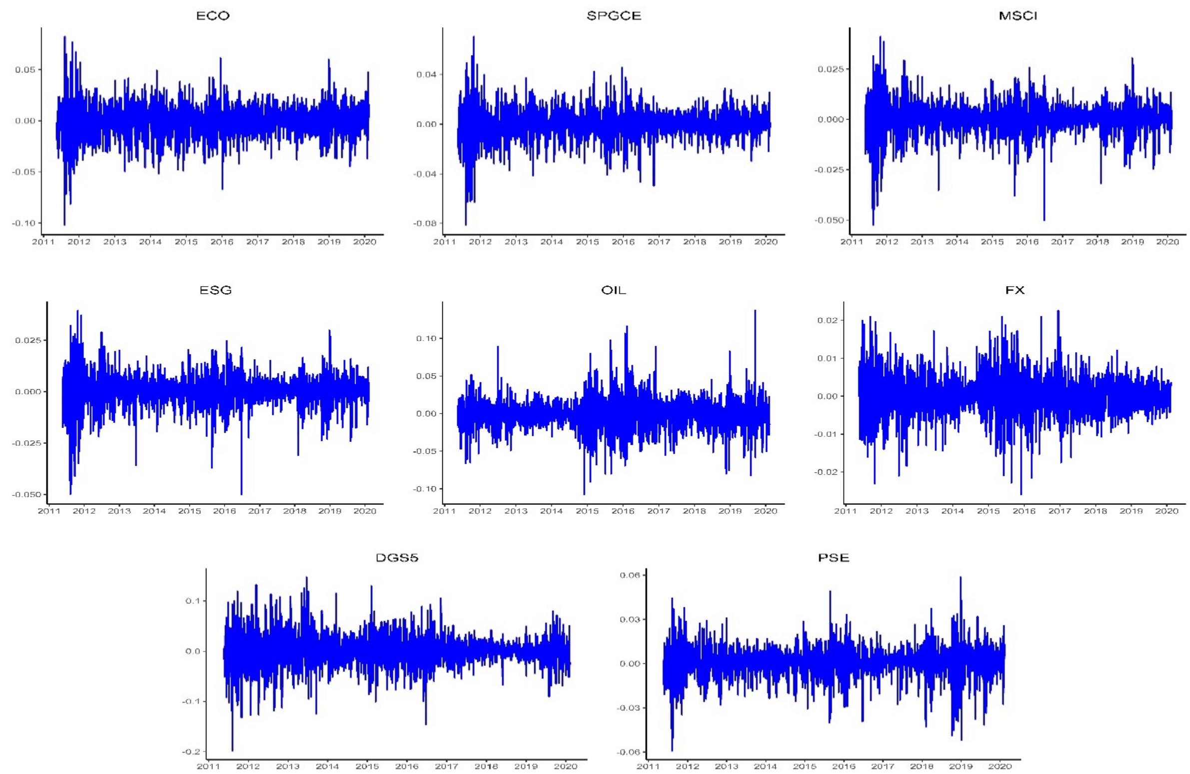
Notes: All variables contain 2278 daily observations over the period 2011-05-19 to 2020-02-10. All the variables are represented in first differences and all the variables are log transformed.

Figure 3. Historical prices (level)



Notes: All variables contain 2279 daily observations over the period 2011-05-18 to 2020-02-10. Index values are presented on the vertical axis and time period is indicated on the horizontal axis.

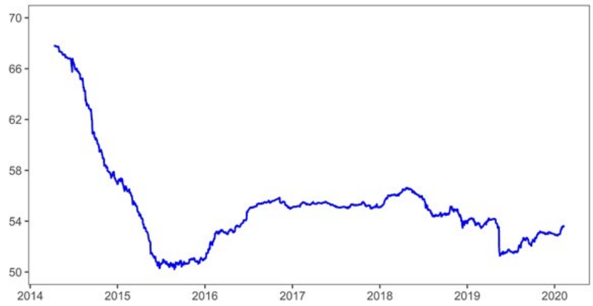
Figure 4. Logarithmic returns



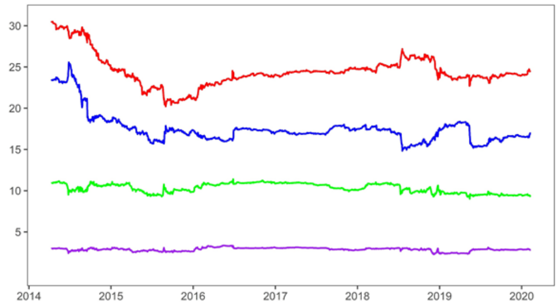
Notes: All variables contain 2278 daily observations over the period 2011-05-19 to 2020-02-10. All the variables are represented in first differences and all the variables are log transformed. Index values are presented on the vertical axis and time period is indicated on the horizontal axis.

Figure 5. Dynamic connectedness - RE indices and other assets

(a) Total connectedness



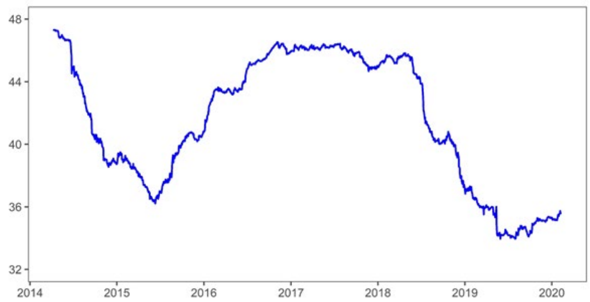
(b) Frequency connectedness



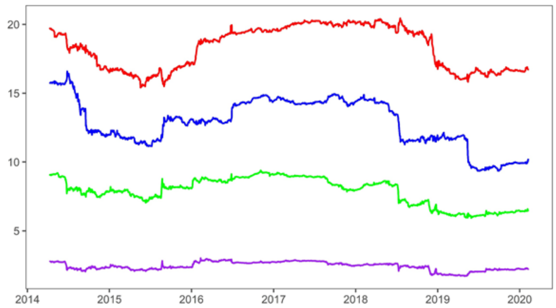
Notes: The vertical axis shows percentual connectedness and the horizontal axis shows years. Plot (a) shows total connectedness over time, represented by the blue line. Plot (b) shows frequency connectedness, where the red line represents daily connectedness (1 to 2 days), the blue line represents daily to weekly connectedness (2 to 5 days), the green line represents weekly to monthly connectedness (5 to 21 days) and the purple line represents monthly to yearly connectedness (21 to 252 days). The rolling window is 756 days while the rolling sample of the predictive horizon for the variance decomposition is 252 days.

Figure 6. Dynamic connectedness - RE firms and other assets

(a) Total connectedness



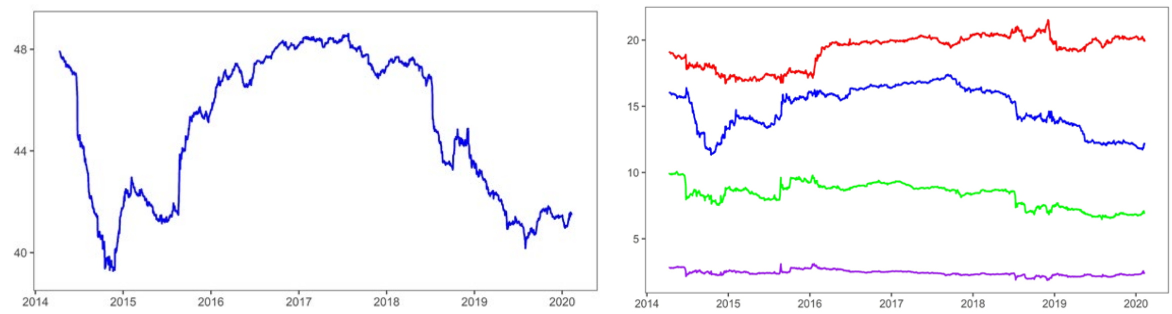
(b) Frequency connectedness



Notes: The vertical axis shows percentual connectedness and the horizontal axis shows years. Plot (a) shows total connectedness over time, represented by the blue line. Plot (b) shows frequency connectedness, where the red line represents daily connectedness (1 to 2 days), the blue line represents daily to weekly connectedness (2 to 5 days), the green line represents weekly to monthly connectedness (5 to 21 days) and the purple line represents monthly to yearly connectedness (21 to 252 days). The rolling window is 756 days while the rolling sample of the predictive horizon for the variance decomposition is 252 days.

Figure 7. Dynamic connectedness - RE firms and oil & gas firms

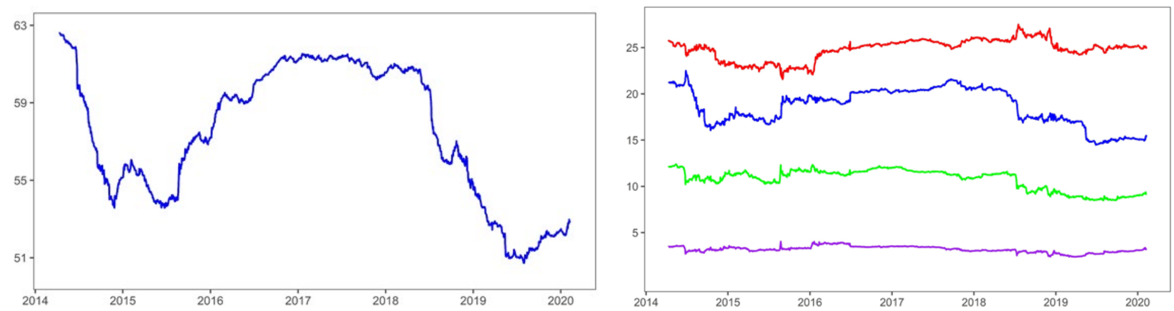
(a) Total connectedness (b) Frequency connectedness



Notes: The vertical axis shows percentual connectedness and the horizontal axis shows years. Plot (a) shows total connectedness over time, represented by the blue line. Plot (b) shows frequency connectedness, where the red line represents daily connectedness (1 to 2 days), the blue line represents daily to weekly connectedness (2 to 5 days), the green line represents weekly to monthly connectedness (5 to 21 days) and the purple line represents monthly to yearly connectedness (21 to 252 days). The rolling window is 756 days while the rolling sample of the predictive horizon for the variance decomposition is 252 days.

Figure 8. Dynamic connectedness - RE firms, oil & gas firms and other assets

(a) Total connectedness (b) Frequency connectedness



Note: The vertical axis shows percentual connectedness and the horizontal axis shows years. Plot (a) shows total connectedness over time, represented by the blue line. Plot (b) shows frequency connectedness, where the red line represents daily connectedness (1 to 2 days), the blue line represents daily to weekly connectedness (2 to 5 days), the green line represents weekly to monthly connectedness (5 to 21 days) and the purple line represents monthly to yearly connectedness (21 to 252 days). The rolling window is 756 days while the rolling sample of the predictive horizon for the variance decomposition is 252 days.

APPENDIX

Table A1. *Summary of literature review*

Article (year)	Period	Method	Variables	Directionality / Key findings
Henriques and Sadorsky (2008)	2001-2007 (weekly)	VAR, Generalized impulse responses	Energy stock prices (ECO index), technology stock prices (PSE index), oil prices (future contract trades NYMEX) and interest rates	Technology & oil prices affects alternative energy prices. Shocks to technology prices has larger impact on alternative energy prices than shock in oil prices.
Mohanty and Nandha (2011)	1992-2008 (monthly)	Fama-French-Carhart's four-factor asset pricing model augmented with oil price and interest rate	Firm-specific variables for oil and gas firms, West Texas Intermediate (WTI), yield on 10-year Treasury bond	Market, book-to-market, size factors, momentum characteristics of firms and changes in oil price affects the returns for oil and gas firms. Oil price risk exposure for the oil and gas firms are significant, positive and varies over time, across firms and industry subsectors.
Kumar et al. (2012)	2005-2008 (weekly)	VAR	Stock index of clean energy (NEX, ECO & SPGCE), Technology stock index (PSE), Oil prices, carbon allowance price (European emission trading) and short-term interest rates	Oil prices and technology stock prices separately affect the stock prices of clean energy firms. No significant relationship between carbon prices and the stock prices of the firms.
Sadorsky (2012a)	2002-2007 (annual)	Variable Beta Model	Company stock returns, firm size (annual total assets), firm leverage (debt to equity ratio), R&D expenditure relative to firm sale, company sale growth. Market returns (U.S Stock market index, oil price returns(WTI))	Company sales growth has a negative impact on company risk while oil price increases have a positive impact on company risk. When oil price returns are positive and moderate, increases in sales growth offset the impact of oil price returns and this leads to lower systematic risk.
Sadorsky (2012b)	2001-2010 (daily)	VAR, Multivariate GARCH models	Clean Energy Index (ECO), Technology Index (PSE), Crude oil futures contract	Stock prices of clean energy companies correlate more highly with technology stock prices than with oil prices.
Bianconi and Yoshino (2014)	2003-2012 (daily)	Multivariate GARCH, dynamic conditional correlation and VaR	Firm-sepcific variables for oil and gas firms, market premium, VIX, exchange rates (FX), West Texas Intermediate (WTI)	Specific risk factors, such as leverage and company size, explain returns of the firms, Common risk factors, such as market excess return, VIX, WTI and FX, also explain returns of the firms.
Reboredo (2015)	2005-2013 (daily)	CoVaR	Oil priced for Brent oil, Three global clean energyindices (ECO,SPGCE,ERIX), three sectoral clean energy indices (WIND, SOLAR, TECH)	Oil price dynamics significantly contributes around 30% to downside and upside risk of renewable energy companies.
Bondia et al. (2016)	2003-2015 (weekly)	Cointegration, Structural breaks, Granger causality	WilderHill New Energy Global Innovation Index (ECO), New York Stock Exchange Arca Tech 100 Index (PSE), closing spot prices of West Texas Intermediate (WTI), 10-Year Treasury Constant Maturity Rate	Presence of cointegration among the variables with two endogenous structural breaks. Ignoring the presence of structural breaks in a long time series data can produce misleading results. The stock prices of alternative energy companies are impacted by technology stock prices, oil prices and interest rates in the short run. There is no causality running towards prices of alternative energy stock prices in the long run.
Sanusi and Ahmad (2016)	2004-2015 (daily)	Four factor Fama-French-Carhart model augmented with lagged returns of Brent crude oil price	Returns of oil and gas firms, FTSE All Share index, Brent crude oil price, risk free rate	Market risk, oil price risk, size and book-to-market determines asset returns of oil and gas firms. Oil price shocks have no strong effect on oil and gas firms stock returns.
Ahmad (2017)	2005-2015 (daily)	Diebold & Yilmaz (2009, 2012) directional spillover/spillover index, Multivariate GARCH model (DCC-GARCH)	WilderHill Clean Energy Index (ECO), NYSE Arca Technology Index (PSE), futures contracts (nearest contract to maturity) of West Texas Intermediate (WTI)	Technology and clean energy indices are the dominant emitters of return and volatility spillovers to the crude oil prices. The time and event-dependent movements are well captured by the directional spillover approach.
Gupta (2017)	1987-2014 (daily)	Cross-country analysis	Firm-level data, country-specific market returns, NYMEX one month future oil price, country specific risk-free rate, NYSE Arca Tech index (PSE), cultural dimension scores	Alternative energy firms are rewarded by the market when country-level innovation and technology are well developed. Cross-country differences in financial performance of alternative energy firms can be explained by cultural dimensions.
Reboredo et al. (2017)	2006-2015 (daily)	Continuous and discrete wavelets, Wavelet	Oil spot prices for West Texas Intermediate (WTI), Wilder Hill Clean Energy Index (ECO), S&P	Dependence between oil and renewable energy returns in the short run is weak but gradually strengthened towards the long run. Causality tests provide evidence against linear causality at

		coherence, Granger linear and non-linear causality	Global Clean Energy Index (SPGCE), European Renewable Energy index, NYSE Bloomberg Global Wind Energy Index, NYSE Bloomberg Global Solar Energy Index, NYSE Bloomberg Global Energy Smart Technologies Index	higher frequencies and in favour of unidirectional and bidirectional linear causality at lower frequencies. Finds evidence of non linear causality running from renewable energy indices to oil prices at different time horizons and mixed evidence of causality running from oil to renewable energy prices.
Ferrer et al. (2018)	2003-2017 (daily)	Return and volatility connectedness time-frequency approach by Barunik & Krehlik (2018), The dynamic interactions in time and frequency, extension of spillover index approach by Diebold & Yilmaz (2012)	Closing prices of U.S renewable energy stocks, high technology stocks, conventional energy stocks, crude oil futures contracts, U.S. 10-year Treasury bond yields, the default spread and the volatility of the U.S. stock and Treasury bond markets (VIX and TYVIX.).	Return and volatility connectedness is generated in the very short-term, the long-term plays a minor role. Higher degree of interconnectedness across crude oil and financial markets since the onset of the U.S. subprime mortgage crisis in summer of 2007 Crude oil prices not a key driver of the stock market performance of renewable energy companies in the short-term or the long-term. Crude oil prices are net receiver of financial shocks. A significant pairwise connectedness is found, mainly in the shortterm between clean energy and technology stock prices.
Pham (2019)	2010-2018 (daily)	Diebold & Yilmaz (2012, 2014) directional spillovers, forecast error variance decomposition from generalized VAR, multivariate GARCH (DCC, ADCC, GO-GARCH)	NASDAQ OMX Green Economy Index Family, NYMEX continuous oil future contracts nearest to maturity, spot WTI and the Brent crude oil prices.	The relationship between oil price and clean energy stock varies largely across clean energy stock sub-sectors. Biofuel and energy management stocks most connected to oil price, while wind, geothermal, fuel cell stocks are least connected to oil price.
Uddin et al. (2019)	2003-2017 (daily)	Cross-quantilogram	S&P Global Renewable Energy Index, S&P Composite index, oil futures, gold futures, USD/EUR exchange rate	The relationship between RE stock returns,changes in oil prices and aggregate stock returns is not symmetric across quantiles, where asymmetry is higher in longer lags. The positive effect of exchange rates and gold returns on RE stock returns is observed only during extreme market conditions.
Xia et al. (2019)	2008-2019 (daily)	VaR, connectedness network, ARMA-GARCH	ERIX, Oil, Natural gas, Electricity, Carbon, Coal	The fossil energy-renewable energy network system shows high interdependence. connectedness network. Dynamic results from fossil energy price changes to renewable energy returns have strong time-varying pattern with high volatility over time. Total connectedness in the positive returns network is stronger than in the negative returns network for the sample period.

Note: VAR: Vector autoregressive; GARCH: Generalized autoregressive conditional heteroskedasticity; CoVaR: Conditional value at risk; DCC-GARCH: Dynamic conditional correlation generalized autoregressive conditional heteroskedasticity; GVAR: Global vector autoregressive; NARDL: Non-linear autoregressive distributed lag; VaR: Value at risk; ARMA-GARCH: Autoregressive moving average generalized autoregressive conditional heteroskedasticity

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