Maastricht University

UNITED NATIONS UNIVERSITY

UNU-MERIT

Working Paper Series

#2022-027

Dynamic dependence between clean investments and economic policy uncertainty

Christian Urom, Hela Mzoughi, Gideon Ndubuisi and Khaled Guesmi

Published 15 August 2022

Maastricht Economic and social Research institute on Innovation and Technology (UNU-MERIT)
email: info@merit.unu.edu | website: http://www.merit.unu.edu

Boschstraat 24, 6211 AX Maastricht, The Netherlands
Tel: (31) (43) 388 44 00

Dynamic dependence between clean investments and economic policy uncertainty

Christian Urom[†], Hela Mzoughi*, Gideon Ndubuisi[†,♣,♠1] and Khaled Guesmi[†]
[†]Paris School of Business, Paris, France
*University of Tunis Carthage, Tunisia
[†]Delft University of Technology, the Netherlands
♣German Institute for Development and Sustainability (IDOS), Germany
♠UNU-MERIT, the Netherlands

Abstract

This paper examines how clean investments across different sectors respond to economic policy uncertainty (EPU) using the NASDAQ OMX Green Economy sectoral Indexes. We rely on Wavelets and the Cross-quantilogram techniques to examine the dependence and directional predictability from EPU to each sector's clean energy stock prices. Our results highlight evidence in support of strong heterogeneous dependence and directional predictability of sectoral clean energy returns from EPU across different market conditions and investment horizons. Second, we employ the Time-Varying Parameter-VAR (TVP-VAR) model with stochastic volatility to characterize the level of integration between clean energy sectors and EPU under different investment horizons. We find that the level of connectedness is weak in the short-term but becomes stronger in the medium- and long-term. Nonetheless, we distill some important heterogeneities in the predictive power of EPU for the different sectors across different investment horizons. Taken together, our results demonstrate that the direction and magnitude of the response of clean energy stock prices to EPU vary across sectors and depend on market conditions and horizons. This offers diversification benefits to investors and portfolio managers that may be interested in clean energy stocks across sectors, market conditions, and horizons.

Keywords: Economic-policy uncertainty; Clean-energy equities; Sectoral analysis; Time-frequency domains; Spillover; Directional predictability
JEL Classification: G10; Q42; R11

[1] Corresponding author: G.O.N.Ndubuisi@tudelft.nl

1 Introduction

The importance of energy to the functioning of daily socioeconomic activities across the globe cannot be overemphasized. While fossil fuels are considered dirty energy sources, they constitute an essential component of the global energy source, providing economic actors the means to meet their energy needs such as lighting up homes, streets, and schools, commuting to work and moving goods, capital, and labor both within and across the border. Over the past decade, however, the continuous global pressures to transition to alternative energy sources due to energy security and climate-related issues that are associated with fossil fuels, have intensified investments in clean energy sources such as solar, wind, and hydro-power (Eyraud *et al.,* 2011; Akhmat *et al.* 2014; Auffhammer & Mansur, 2014; Elie *et al.,* 2019; Zhao, 2020). For instance, the Finance, Bloomberg New Energy (2018) reports that between 2004 and 2017, new investment in clean energy increased from U.S$62 billion to U.S$280 billion globally.

Amid this rise in the importance of clean energy sources, empirical analysis of the stock market performance of clean energy firms has proliferated for at least two reasons. First, investing in clean energy requires well-developed funding mechanisms, which stock markets provide (Kocaarslan & Soytas, 2019). Second, investors and energy policy analysts need more information on the dynamics of clean energy stocks to determine whether they are good investment opportunities, make sound portfolio allocation decisions, and determine hedging strategies. To date, studies on the stock market performance of clean energy firms have largely focused on the role of oil price changes or oil market uncertainty. In this paper, we focus on the role of economic policy uncertainty, paying particular attention to the heterogeneous response of different clean energy sectors across time scales and investment horizons.

Economic policy uncertainty refers to uncertainties regarding fiscal, monetary, and regulatory policies (Brogaard & Detzel, 2015; Baker *et al.,* 2016). It escalates risk premium and causes delays in individual and business spending until it is resolved (Brogaard & Detzel, 2015). Clean energy sources compared to fossil fuels are nascent and, therefore, highly supported by the government through financial subsidies, investment tax credits, accelerated depreciation, transfer payments, and preferential tax policies (Zhao, 2020). Hence, it is presumed that clean energy stocks would be more vulnerable to economic policy uncertainty. Despite this obvious connection between economic policy uncertainty and clean energy stock, the literature examining such a nexus is limited with Ji *et al*. (2018) and Zhao *et al.* (2020) being the only

exception. However, these previous studies do not consider how green investments across different sectors respond to economic policy uncertainty. From a risk management and energy policy perspective, such heterogeneous analysis is important to make any informed portfolio diversification decisions and determining hedging strategies.

Against this background, our study contributes to the literature on clean energy stock market performance by examining the interactions between clean energy sectors in the presence of economic policy uncertainty. Particularly, we make three notable contributions to the literature. First, using the wavelets approach, we provide an in-depth analysis of the dependence and directional predictability from economic policy uncertainty to the performance of clean energy sectors across different time scales. Particularly, unlike past studies that have investigated the relationship between clean energy stocks and other financial assets using composite market indexes that cover the entire green energy market (see Henriques & Sadorsky, 2008; Uddin *et al.,* 2019), and regional green energy markets such as in Urom *et al.* (2021), we focus on six clean energy sectors including the building, economy, edge, financial, technology, and transport sectors. We examine the co-variance and co-movement of their performance with economic policy uncertainty across different time domains. In doing so, we consider in detail, how the performance of each clean energy sector may be influenced by the changes in the level of economic policy uncertainty across three different investment horizons such as short-, medium, and long term.

Methodologically, our study differs from both Ji *et al.* (2018) and Zhou *et al.* (2019) which, respectively, use CoVar and VAR models but do not consider sectoral heterogeneities in clean energy investments. Secondly, we measure the strength of dependence and directional predictability of the performance of each clean energy sector from economic policy uncertainty across the short-, medium- and long-term investment horizons. To serve this objective, we rely on the cross-quantilogram approach of Han *et al.* (2016). This method extends the single time-series quantilogram introduced in Linton and Whang (2007). This enables us to quantify the heterogeneous dependence and influence of changes in investors' perception of the impact of fluctuations in the general macroeconomic conditions on green energy investments across different sectors. Besides, the empirical design of the cross-quantilogram approach permits us to examine dependence and directional predictability across nine quantiles of each returns distribution, enabling us to investigate the dynamics in dependence and directional

predictability across both the bearish, normal, and bullish market conditions for each green energy sector.

Thirdly, we characterize the degree of integration among the performance of investments in green energy across the six chosen sectors in the presence of economic policy uncertainty using the set of eight-time scales, representing more detailed information of the true data. Specifically, we examine the corresponding time-varying integration of green energy sectors and uncertainties in the general macroeconomic condition in each scale and time horizon using the Time-Varying Parameter VAR (TVP-VAR) model with stochastic volatility. By so doing, we provide crucial insights on the heterogeneous level of integration, net-directional spillovers, diversification opportunities, and the vulnerability of each green energy sector to shocks in other green energy sectors under uncertainties in economic policy uncertainties across different investment horizons.

The rest of the paper is structured as follows. The next section presents an overview of the extant literature examining the interaction between renewable energy stocks and economic policy uncertainties. The research design including the data and empirical strategy is described in section three. Section four presents and discusses the results of the empirical analysis, while section five presents the conclusion of the study.

2 Literature review

Although the empirical analysis of the performance of clean energy stocks is somewhat nascent, existing studies are humongous, and an exhaustive survey of this literature is beyond the scope of the current study. However, within the broad literature, our research relates closely with those that deal with the interaction between clean energy stock prices and EPU. Empirical evidence on the impact of EPU impacts on other asset classes appears relatively scanty and not difficult to find (Lundgren *et al*., 2018). Conceptually, while EPU intensifies financing friction in the capital market, clean energy compared to fossil fuels is nascent and highly dependent on government policies, making them more vulnerable to policy uncertainties. To this end, Ji *et al*. (2018) compared the impact of uncertainty from the financial market, oil market, and economic policy on the energy stock market. They conclude that policy uncertainty has a weaker effect than the other two factors. They also find that policy uncertainty is more important in the context of renewable energy stocks than for conventional energy stocks.

On the other hand, Zhao (2020) investigates both the effects of oil price shocks and policy uncertainty on the stock returns of clean energy companies using a structural VAR model. The results underline that oil supply shocks and aggregated demand shocks have a positive effect on the returns of clean energy companies, while policy uncertainty shocks and oil shocks have a negative effect. In addition, the effects of oil shocks on the returns of clean energy stocks are amplified by the addition of political uncertainty as an endogenous factor in the model, the impact of which is mainly transmitted by the uncertainty of inflation. Somewhat differently, Liu *et al*. (2020) test the differential impact of EPU on investment energy enterprises in China and find that EPU significantly inhibits traditional energy enterprises' investment but promotes the investment of renewable energy enterprises. Moreover, Sendstad and Chronopoulos (2020) develop a real options framework to analyze the impact of technological, policy, and electricity price uncertainty on the decision to invest in clean energy technologies. Results from the empirical exercise suggest that greater policy uncertainty affects incentives to invest in clean energy technologies.

Furthermore, Henriques and Sadorsky, (2008) estimate a four-variable VAR model to investigate the empirical relationship between clean energy stock prices, technology stock prices, oil prices, and interest rates. They find that movements in oil prices, technology stock prices, and interest rates explain the movements of clean energy stock prices. Simulation results, however, reveal that a shock to technology stock prices has a larger impact on clean energy stock prices than does a shock to oil prices. Applying a similar approach as in Henriques and Sadorsky (2008) to a more updated dataset, Kumar *et al.* (2012) confirmed similar influential abilities of oil and technology in explaining variations in clean energy stock prices. Sadorsky (2012), for instance, employed four different multivariate GARCH models to analyze the volatility spillovers between oil prices and the stock prices of clean energy companies and technology companies. The results show that the stock prices of clean energy companies correlate more highly with technology stock prices than with oil prices.

From the foregoing, it is safe to argue that the extant studies may offer some important insights into the impact of EPU on clean energy stock market prices. Despite this, these studies are limited in that they largely focus on aggregate clean energy stocks, suggesting that we still have a limited understanding of the heterogeneous response of different clean energy sector stocks to changes in EPU. In this paper, we aim to contribute to the literature on clean energy stock market performance by examining the impact of EPU on sectoral clean energy stocks in the

United States. More specifically, we use wavelet and cross-quantilogram approaches to provide an in-depth analysis of the dependence and directional predictability from economic policy uncertainty to sectoral clean energy stock prices under different time scales and market conditions. We also use the Time-Varying Parameter (TVP-VAR) model with stochastic volatility to characterize the level of integration between these clean energy sectors and EPU under different investment horizons. In this way, and as an extension of previous studies, we provide a more comprehensive analysis of the heterogeneous response of different sectoral clean energy stock prices to EPU under different time scales and investment horizons.

3. Data and empirical strategy

3.1 Data

To examine the dependence and directional predictability from economic policy uncertainty to sectoral renewable energy stocks in the U.S., we rely on the NASDAQ OMX Green Economy Index family which contains sector-level green energy equity indexes. Specifically, we use the NASDAQ OMX Green Building (bld), NASDAQ OMX Green Economy (eco), NASDAQ Clean Edge Green Energy (edge), NASDAQ OMX Green Financial (fin), NASDAQ OMX Green IT (tech), and NASDAQ OMX Green Transportation (trn) as representatives of sector-level U.S. green equity market performance for building, economy, edge, financial, technology and transport sectors, respectively. These Indexes are designed to capture the performance of companies across the range of industries most closely connected with the economic model around sustainability.

Descriptively, the NASDAQ OMX Green Building Index tracks companies participating in advanced designs for retrofits and new buildings that lead to dramatic efficiency gains in energy and water consumption. NASDAQ OMX Green Economy Index tracks the performance of companies across the spectrum of industries most closely associated with the economic model around sustainable development through every economic sector. NASDAQ Clean Edge Green Energy (edge) tracks the performance of companies that are primarily manufacturers, developers, distributors, and/or installers of clean energy technologies. NASDAQ OMX Green IT tracks companies that provide solutions that help companies decrease energy consumption by enabling collaboration online, efficient data centers, computer networks, and virtualization software. Finally, NASDAQ OMX Transportation Index tracks companies focused on efficiency gains and pollution reduction associated with automobiles, trains, and other modes of transportation.

We rely on the Economic Policy Uncertainty Index for the U.S. (EPU) of Baker *et al.* (2016) as proxies for uncertainties in the U.S. macroeconomic space. By considering companies across the sectors of the U.S. economy, these indexes offer closer views of the dependence of each sector's green energy equity market on uncertainties in economic policy. We sourced the daily spot prices on sectoral NASDAQ OMX Green Economy Indexes from Quandl while data for epu are from the St. Louis FRED database. All data series covers the period from November 10, 2010 (due to the start date for NASDAQ OMX Green Economy index) to August 19, 2020. All daily series are converted to log returns by taking the log difference of index values. We present the evolution of EPU in Figure 1 and sectoral green equity market prices and returns in Figure 2. In all cases, we can deduce that sectoral green energy equity prices are trending upwards, especially in recent times. Regarding the uncertainty index, we observe an increased level of EPU during the recent volatile economic situation orchestrated by the COVID-19 health crisis. There is also clear evidence of the impact of the pandemic on returns for all the sectoral green energy markets as shown by high volatility clusters around the period of the pandemic.

[Insert Table 1 about here]

Furthermore, Table 1 presents the descriptive statistics for all return series. We observe that all the sectors of green energy stocks have positive mean returns and that the financial (fin) and Information Technology (tech) sectors exhibit the highest mean return while it is least for the Edge (edge) sector. All the return series are negatively skewed and have excess Kurtosis. Also, following the Jarque-Bera (J-B) and ADF tests, we can reject the null hypothesis of normality and the presence of unit root for all the series. The ADF test confirms that all the return series are stationary while the Brock-Dechert-Scheinkman (BDS) test for non-linearity proposed by Brock *et al*. (2001) suggests that all sector returns are non-linear in nature. This is because we can reject the hypothesis of linearity for all the series. The stationarity and non-linearity of all the series permit us to apply a non-linear econometric approach such as the cross-quantilogram going forward. In Figure 3, we present the unconditional correlations using a heat map. We can find that correlation are positive across all sectors and EPU.

3.2 *Empirical strategy*

3.2.1 *Wavelet multiscale decomposition*

The wavelet analysis decomposes an original time series into different time-frequency domain data, thereby conveying crucial information in the time and frequency domain. Unlike most financial econometric approaches, the wavelet transform allows a two-dimensional analysis that captures the multiscale information content of a time series. This property has made wavelet analysis an effective mathematical tool in the analysis of dynamic interactions between two-time series under different time-frequency domains. Traditionally, wavelet analysis requires both the orthogonal and normalized bases derived from a dyadic categorization and translation of a pair of specially designed functions φ and ψ, named father wavelet and mother wavelet respectively. The father wavelet may be defined as:

$$\varphi_{j,k} = -2^{-j/2}\varphi\left\{\frac{t-2^{j}k}{2^{j}}\right\} \; with \int \varphi(t)dt = 1, \qquad (1)$$

,

while the mother wavelet is expressed as follows:

$$\psi_{j,k} = -2^{-j/2}\psi\left\{\frac{t-2^{j}k}{2^{j}}\right\} \; with \int \psi(t)dt = 0 \qquad (2)$$

The father wavelet captures the smooth and low-frequency parts of the time series while the detail and high-frequency series are captured by the mother wavelet. The smooth coefficient derived from the father wavelets is denoted as follows:

$$S_{j,k} = \int f(t)\varphi_{J,k} \qquad (3)$$

The detail coefficients derived by the mother wavelet are defined as follows:

$$d_{j,k} \int f(t)\psi_{J,k} \; with\, j = 1 \ldots\ldots\ldots J \qquad (4)$$

The maximal scale of the father wavelets is 2^j while the detailed series derived from the mother wavelets are captured from at all scales from 1 to J. The function $f(\cdot)$ of a time series may be defined as follows:

$$f(t) = \sum_k s_{j,k}\varphi_{j,k}(t) + \sum_k d_{j,k}\psi_{j,k}(t) + \sum_k d_{j-1,k}\psi_{j-1,k}(t) + \cdots + \sum_k d_{1,k}\psi_{1,k}(t) \qquad (5)$$

where φ and ψ are father and mother wavelets while $s_{j,k}d_{j,k}$. Equation 5 may be simplified as follows:

$$f(t) = S_J + D_J + D_{J-1} + \cdots + D_j + \cdots + D_1 \qquad (6)$$

while the orthogonal components are defined as follows:

$$S_J = \sum_k S_{j,k}\varphi_{j,k}(t) \qquad (7)$$

$$D_J = \sum_k d_{j,k}\psi_{j,k}(t)\,. \;\; j = 1, \ldots j \qquad (8)$$

where D_j denotes the frequency components that capture short-, medium- or long-term changes due to shocks from the time scale 2^j while the residual derived after removing $D_1 \ldots D_j$ from the original series is captured by S_j. Given that we used daily data and that a moderate filter is arguably most suitable for financial data such as clean energy equity returns, we specify $J = 8$ for the multi-resolution level J. This multiscale decomposition enables us to capture eight levels of detail corresponding to the highest frequency component D_1 realized from a time scale of $2^1 = 2$ days, representing the daily effects. More so, the D_2 corresponds to variations in the time scale $2^2 = 4$ days, showing the weekly effects while components $D_3, D_4, D_5, D_6, D_7,$ and s_7 capture variations across the medium $2^3 = 8$ days to the long-term periods $2^8 = 256$ days, respectively.

We rely on the Maximal Overlap Discrete Wavelet Transform (MODWT) to estimate the scales and wavelet coefficients. The MODWT has become widely used in previous studies for several

reasons. For instance, Mishra *et al*. (2019) note that unlike the Discrete Wavelet Transform (DWT), it does not suffer from any limitation regarding the sample size. Also, whereas the DWT employs weighted differences and makes an average of attached sets of observations, MODWT employs moving difference and average operator, thus keeping the exact number of observations at each wavelet decomposition scale.

3.2.2 *The wavelet-based cross-quantilogram*

After retrieving the wavelet decomposed series for all the variables used in this study, we proceed to use the cross-quantilogram of Han *et al.* (2016) for testing the dependence between each sectoral clean energy stock returns and EPU. Specifically, we examine whether significant positive or negative dependence exists between these variables across different time scales and different quantiles of their distributions. To do this, we rely on the cross-quantilogram approach proposed by Han *et al.* (2016), which extends the single time-series quantilogram technique of Linton and Whang (2007). Assume that the conditional distribution function of two strictly stationary time series (θ_{1t}) given θ_{2t} with density function $f_{\theta_i|x_i}(.|X_{it})$, the corresponding conditional quantile function may be defined as:

$$q_{i,t}(\alpha_i) \equiv inf v: F_{\theta_i|x_i}(.|X_{it} \geq \alpha_i)\ for\ \alpha_i \in (0,1), for\ i = 1,2 \tag{9}$$

In this paper, we set θ_{1t} as epu and θ_{2t} as different scales of each sectoral clean energy stock (bld, eco, edge, fin, tech, trn) respectively. If α is the range of quantiles, the cross-quantilogram measures the serial dependence between two events such as $\{\theta_{1t} \leq q_1(\alpha_1)\}$ and $\{\theta_{2t} \leq q_2(\alpha_2)\}$ for arbitrary quantiles. The quantile-hit or quantile-exceedance process for $i = 1,2$ may be expressed as $\{\ 1[\theta_{it} \leq q_i[\cdot]]\ \}$. Consequently, the cross-quantilogram which is measured as the cross-correlation of the quantile-hit process of α-quantile with k lags may be defined as follows:

$$\rho_\alpha(k) = \frac{E[\Psi_{\alpha 1}^2(\theta_{1,t} - q_1(\alpha_1))\Psi_{\alpha 2}(\theta_{2,t-k} - q_2(\alpha_2)]}{\sqrt{E[\Psi_{\alpha 1}^2(\theta_{1,t} - q_1(\alpha_1))]}\sqrt{E[\Psi_{\alpha 2}^2(\theta_{2,t} - q_2(\alpha_2))]}} \tag{10}$$

For $k = 0, \pm 1, \pm 2, \ldots$ where $\Psi_\alpha(v) \equiv 1[v < 0] - \alpha, 1[\cdot]$ is the indicator function, and $1[\theta_{1,t} \neq q_i(\alpha_i)]$ denotes the quantile-hit or quantile-exceedance process. Given $\alpha = (\alpha_1, \alpha_1) = (\alpha_{1N}, \alpha_{0N})$ as an instance, $\rho_\alpha(1)$ captures the cross-correlation between epu that

are below or above quantile $q_{0N}(\alpha_{0N})$ on day t and the sectoral clean energy returns on day t being below or above quantile $q_{1N}(\alpha_{IN})$. Ideally, if $\rho_\alpha(1) = 0$, epu being below or above quantile $q_{0N}(\alpha_{0N})$ on day t does not always permit the prediction of whether the subsequent returns on sectoral clean energy will be above or below quantile $q_{1N}(\alpha_{IN})$ on the next day. Contrarily, $\rho_\alpha(1) \neq 0$ reflects one-day directional predictability from epu to the returns on sectoral clean energy at $\alpha = q_1(\alpha_1)$

As noted in Zhou *et al.* (2019), a sampled analog of the cross-quantilogram given the series $\{\theta_{1t}, \theta_{1t}\}_{t=1}^{T}$, may be realized by solving the following sets of minimization problems to estimate the unconditional quantile functions:

$$\hat{q}_1(\alpha_1) = \arg min_{v_1 \in R} \sum_{t=1}^{T} \pi_{\alpha_1}(\theta_1 - v_1)$$

$$\hat{q}_2(\alpha_2) = \arg min_{v_2 \in R} \sum_{t=1}^{T} \pi_{\alpha_2}(\theta_2 - v_2)$$

where, $\pi\alpha(\mu) \equiv \mu(\alpha - 1[\mu < 0])$. The cross-quantilogram of the sample counterpart is estimated as follows:

$$\hat{\rho}_\alpha(k) = \frac{\sum_{t=k+1}^{T} \Psi_{\alpha 1}\,(\theta_{1,t} - \hat{q}_{1,t}(\alpha_1))\Psi_{\alpha 2}(\theta_{2,t-k} - \hat{q}_{2,t-k}(\alpha_2)}{\sqrt{\sum_{t=k+1}^{T} \Psi_{\alpha 1}^2\,(\theta_{1,t} - \hat{q}_{1,t}(\alpha_1))}\sqrt{\sum_{t=k+1}^{T} \Psi_{\alpha 2}^2\,(\theta_{2,t-k} - \hat{q}_{2,t-k}(\alpha_2))}} \qquad (11)$$

where $k = 0, \pm 1, \pm 2, \ldots, \rho_\alpha(\hat{k}) = 0$ denotes no directional predictability from epu to sectoral clean energy returns. Also proposed by Han *et al.* (2016), relying on the hypothesis of $H_0: \rho_\alpha(k) \neq 0$ for all $k \in 1, \ldots, p$ against the alternative $H_1: \rho_\alpha(k) \neq 0$ for some $k \in 1, \ldots, p$ the quantile-based version of the LjungBox-Pierce statistics may be represented as follows:

$$\hat{Q}_\alpha^{(p)} \equiv \frac{T(T+2)\sum_{k=1}^{p} \hat{\rho}_\alpha^2}{T - K} \qquad (12)$$

where $\hat{Q}_{\alpha}^{(p)}$ represents the portmanteau test that is used to test for directional predictability at a pair of quantiles $\{\theta_1, \theta_2\}$ up to p lags. As the asymptotic distribution of the cross-quantilogram may contain noise parameters under the assumption of no directional predictability, we rely on Han *et al*. (2016) by using the stationary bootstrap of Politis and Romano (1994) to approximate the distribution of the Portmanteau test statistics.

3.3 *Wavelet-based network system analysis*

After retrieving the frequency components from the wavelet technique (see annexes), we proceed towards achieving the third objective of this study using the Bayesian TVP-VAR dynamic spillover model of Antonakakis and Gabauer (2017). This empirical framework extends the spillover techniques of Diebold and Yılmaz (2012; 2014). Indeed, we are concerned with examining the network system of connectedness among green energy sectors and EPU across different time scales. The TVP-VAR model specifies the distribution of a time series, r_{it}, to depend on its lags and the lags of covariates of interest and introduces variations in the variances via a stochastic volatility Kalman Filter estimation with forgetting factors proposed in Koop and Korobilis (2014). Therefore, this approach circumvents the burden of setting the rolling window size arbitrarily and the loss of observations. Consequently, this model has been increasingly adopted in past studies (see e.g. Dahir *et al.,* 2019; Ji *et al.,* 2019; Urom *et al.,* 2020; Urom *et al.,* 2021; Bouri *et al.,* 2021; Adekoya & Oliyide, 2021).

In its traditional form, the TVP-VAR model may be expressed as follows:

$$y_t = C_t v_{t-1} + \mu_t \mu_t | \rho_{t-1} \sim N(0, \tau_t) \tag{13}$$

$$vec(C_t) = vec(C_{t-1}) + \gamma_t \gamma_t | \rho_{t-1} \sim N(0, \varepsilon t_t) \tag{14}$$

with

$$v_{t-1} = \begin{pmatrix} y_{t-1} \\ y_{t-2} \\ \vdots \\ y_{t-p} \end{pmatrix} \; and \; C_t = \begin{pmatrix} C_{it} \\ C_{2t} \\ \vdots \\ C_{pt} \end{pmatrix}$$

where, for Eq. 13, y_t and v_{t-1}denote $n \times 1$ and $np \times 1$ vectors (which in our case include the frequency components of the price index for a chosen sector, conditionally on the set of

available information up to $t - 1, \rho_{t-1}$. C_t and C_{it} are $n \times np$ and $n \times n$ are dimensions of time-varying coefficient matrices respectively while μ_t is an $n \times 1$ vector of the error term. γ_t is an $np \times 1$ dimensional vector while the time-varying variance-covariance matrices, τ_t, and ε_t correspond to $n \times n$ and $n^2p \times n^2p$ dimensional matrices respectively. Lastly, the vectorization of C_t denoted by $vec(C_t)$ is, however, an $n^2p \times 1$ dimensional vector.

To derive the generalized impulse response functions and the generalized forecast error variance decomposition (GFEVD) which form the basic inputs for generating the generalized spillover index (see Koop & Korobilis, 2014), the VAR model in Eq. 13 is transformed into a moving average following the Wold theorem stated as follows:

$$y_t = K'(N_t(v_{t-2} + \phi_{t-1}) + \phi_t) \tag{15}$$

$$= K'(N_t(N_t(v_{t-3} + \phi_{t-2}) + \phi_{t-1})\phi_t) \tag{16}$$

$$\vdots \tag{17}$$

$$= K'\left(N_t^{k-1} v_{t-k-1} + \sum_{j=0}^{L} N_t^j \, \phi_{t-j}\right) \tag{18}$$

With

$$N_t = \begin{pmatrix} C_t & \\ l_{n(p-1} & 0_{n(p-1)\times n} \end{pmatrix} \phi_t = \begin{pmatrix} \mu_t \\ 0 \\ \vdots \\ 0 \end{pmatrix} = K\mu_t K = \begin{pmatrix} l \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$

where N_t, ϕ_t, and L correspond to $np \times np \times 1$ and $np \times n$ dimensional matrices. Following Adekoya and Oliyide (2021) by deriving the limit of Eq.18 as k tends to ∞, we get the following:

$$y_t = lim_{k\to\infty} K'\left(N_t^{k-1} v_{t-k-1} + \sum_{j=0}^{L} N_t^j \, \phi_{t-j}\right) = \sum_{j=0}^{\infty} K' N_t^j \, \phi_{t-j} \tag{19}$$

such that it follows directly

$$y_t = \sum_{j=0}^{\infty} K' N_t^j K \, \mu_{t-j} \quad A_{jt} = K'^{N_t^j} K, \quad j = 0,1, \ldots \tag{20}$$

$$y_t = \sum_{j=0}^{\infty} A_{jt} \mu_{t-j} \tag{21}$$

where A_{jt} denotes an $n \times n$ matrix.

Following the generalized forecast error variance decomposition (GFEVD), the generalized impulse response function (GIRFs) $\omega_{ij,t}(H)$captures the responses of all variables j to a shock in the variable i. Bouri *et al.* (2021) note that given the lack of a structural model, the *H*-step-ahead forecast for which variable i is shocked and another where variable i is not shocked are computed. Hence, this difference is taken to be related to the shock in variable i, which is defined as follows:

$$GIRF_t\left(H, \vartheta_{j,t}\rho_{t-1}\right) = E\left(y_{t+H} | d_j = \vartheta_{j,t}\rho_{j,t}\right) - E\left(y_{t+K} \middle| \rho_{j,t}\right) \tag{22}$$

$$\Psi_{ij,t}(H) = \frac{A_{H,t} \sum_t d_j}{\sqrt{\sum_{jj,t}}} \frac{\vartheta_{j,t}}{\sqrt{\sum_{jj,t}}} \qquad \vartheta_{j,t} = \sqrt{\sum_{jj,t}} \tag{23}$$

$$\omega_{ij,t}(H) = \sum_{jj,t}^{-\frac{1}{2}} A_{H,t} \sum_t d_j, \tag{24}$$

where d_j represents an $n \times 1$ selection vector with 1 in the jth position, and zero otherwise. The *GFEV D*($\tilde{\gamma}_{ij,t}(H)$) which is estimated and normalized, permits it to be interpreted as the share of variance that a variable has on the system. Therefore, each roll of the normalized variance share adds up to one, implying that all the variables in the system jointly explain 100% of variable *i*'s forecast error variance. The GFEVD is estimated as follows:

$$\tilde{\gamma}_{ij,t}(H) = \frac{\sum_{t=1}^{H-1} \omega_{i,j,t}^2}{\sum_{j=1}^{n} \sum_{t=1}^{H-1} \omega_{i,j,t}^2} \tag{25}$$

Where $\sum_{j=1}^{n} \tilde{\gamma}_{ij,t}^{n}(H) = 1$ while $\sum_{i,j=1}^{n} \tilde{\gamma}_{ij,t}^{n}(H) = n$. Further, the numerator term represents the cumulative effect of a shock in variable i, while the denominator term represents the cumulative effect of all the shocks. Thereafter, we compute the total connectedness index through the use of the GFEVD thus:

$$T_t(H) = \frac{\sum_{ij=1,i\neq j}^{n} \tilde{\gamma}_{ij,t}(H)}{\sum_{i,j=1}^{n} \tilde{\gamma}_{ij,t}(H)} = \frac{\sum_{ij=1,i\neq j}^{n} \tilde{\gamma}_{ij,t}(H)}{n} \tag{26}$$

3.3.1 *Decomposition of the total connectedness*

The connectedness technique in Eq.26 above mainly describes how a shock on one variable spills over to other variables in our sample. To offer deeper insights on the directional connectedness, this approach is further decomposed into directional connectedness to others; directional connectedness from others; and net total directional connectedness.

First, the total directional connectedness "To" others defines how a shock in one of the variables *i* transmits to all other variables *j*. This may be computed as follows:

$$T_{i\rightarrow j,t}(H) = \frac{\sum_{ij=1,1\neq j}^{N} \tilde{\gamma}_{ji,t}(H)}{\sum_{ij=1}^{n} \tilde{\gamma}_{ji,t}(H)} \tag{27}$$

Similarly, the total directional connectedness variable *i* receives from other variables *j* corresponds to total directional connectedness from others and may be defined as follows:

$$T_{i\leftarrow j,t}(H) = \frac{\sum_{j=1,i\neq j}^{n} \tilde{\gamma}_{ij,t}(H)}{\sum_{i=1}^{n} \tilde{\gamma}_{ij,t}(H)} \tag{28}$$

Lastly, given the above measures, we proceed to derive the net directional connectedness by subtracting the total directional connectedness to others from the total directional connectedness from others. As noted in Urom *et al*. (2021), this may be taken to denote the strength or influence of variable *i* over other variables within the network. This may be computed as:

$$T_{i,t} = T_{i\rightarrow j,t}(H) - T_{i\leftarrow j,t}(H) \tag{29}$$

Apparently, the above expression indicates that a positive $T_{i,t}$ suggests that the sphere of influence of variable i over the network is beyond the sphere of influence of the network wields over variable i. Contrarily, a negative $T_{i,t}$ denotes that the influence from the network variable i is greater than the influence from variable i on the network.

Lastly, we distill the net directional pairwise connectedness to offer more insights into the bidirectional interactions among green energy sectors and EPU by computing the net pairwise directional connectedness (*NPDC*) defined as:

$$NPDC_{ij}(H) = \left(\tilde{\gamma}_{ji,t}(H) - \tilde{\gamma}_{ij,t}(H)\right) \tag{30}$$

where $NPDC_{ij}(H) < 0$, indicates that variable i is dominated by variable j while $NPDC_{ij}(H) > 0$ corresponds to the variable i dominating variable j.

4 Results and discussion

4.1 *Dependence between clean energy sectors and economic policy shocks*

Our empirical analysis begins with the investigation of the degree of dependence between green energy sectors and the U.S economic policy shocks. First, we focus on the covariance and correlations between each green energy sector and economic policy shocks before proceeding to explore the predictive power of economic policy shocks on the performance of each green energy sector across different market conditions using the cross-quantilogram. Figures 4 Panel A to F presents the covariance (i) and correlations (ii) between each green market sector and economic policy shock using the following time bounds 1-8 days, 8-64 days, and 64 days and above corresponding to short-, medium- and long-term, respectively. The dotted black lines denote the evolution of covariance while U and L represent the upper and lower bounds of the 95% confidence interval across the chosen time scales.

Across all the cases, results show the dotted black lines lie within the upper and lower bounds. The results show that in the short-run, green energy sectors exhibit positive covariance with economic policy shock while covariances become zero in both the medium- and long-term. This result suggests that a shock in economic policy has an immediate but short-lived significant effect on the performance of green energy across all sectors. In particular, this effect

appears to be strongest in the building sector followed by the transport sector while it is least for the green edge sector which embodies companies that are mainly concerned and involved in the electric grid; electric meters, devices, and networks; energy storage and management; and enabling software used by the smart grid and electric infrastructure sector.

On the contrary, the results also show that correlations are asymmetric across sectors and market conditions; and are mostly weak in the short-run but strengthen in the medium- and long term. In particular, across all the sectors, correlations are positive but low in the short-run but increase in the medium-term. However, correlations are negative in the long-term and are least in the edge sector, followed by the financial sector. This implies that economic policy shock has strong detrimental effects on the performance of green energy sectors in the long term. This is, however, not the case for the technology sector where the negative effects of economic policy shocks are detrimental both in the medium- and long-term. This implies that economic policy shocks impact the performance of companies that offer solutions that help firms decrease energy consumption by enabling collaboration online, efficient data centers, computer networks, and virtualization software negatively both in the short- and long-term.

4.1.1 *Quantile directional predictability across different time-scales*

Moving forward, we examine the directional predictability of the performance of green energy sectors from economic policy shocks across different market situations using estimates from the cross-quantilogram as defined previously in Eq 11- 12. The estimates of the cross-quantilogram are presented in Table 2 for each sector. We consider the cross-quantilogram $\hat{\rho}_{\alpha}(k)$ and the Portmanteau test $\hat{Q}_{\alpha}^{(p)}$ under nine quantiles covering both the bear and bull market conditions as well as the mean of the performance distribution for each sample cross-quantilogram up to 60-day lags for all the different time scales from $d_1 - s_7$. For the bear market states, we consider low quantiles ranging from 0.05, 0.1, and 0.2 quantiles, while for the bull market, we consider high quantiles from 0.8, 0.9, and 0.95. For the shoulders of performance distribution, we consider the 0.3, 0.5, and 0.7 quantiles. Each value in the table denotes the strength of an event of an increase in economic policy shock over a certain percentile following the next day's performance of green energy sectors above the corresponding percentile.

In particular, values in the table denote the strength of directional predictability from economic policy shock to returns in each green energy sector across nine quantiles and time scales considered with the statistical significance of each value determined using the portmanteau test statistic as defined in Eq 12. Some important general insights may be derived from the results in Table 2. For instance, the directional predictability from economic policy shocks to green energy sectors appears to be mostly negative and stronger in the long term. Also, across all sectors, these values are more statistically significant at various levels as shown by the portmanteau test statistic. Besides, the percentage of significant directional predictability from economic policy shock is shown in the last row; which corroborates that predictability becomes more significant towards the long-term across all sectors.

Specifically, directional predictability appears to be stronger for the economy sector but least in the transport sector. This implies that in the short run, economic policy shocks exhibit stronger information content for the performance of firms in the green economy sector. This comprises companies that are most closely associated with the economic model around sustainable development. Moreover, during this market period, predictability is mainly negative at lower quantiles but positive at higher quantiles. This implies that economic policy shocks appear to be detrimental to green energy firms during bearish market conditions but may enhance their performance during bullish market conditions, especially for firms in the green economy sector. However, this may not be the case for firms in the financial, technology, and transport sectors where directional predictability from economic policy shock is not significant during bullish market periods.

However, in the medium-term, predictability from economic policy shock is strongest for firms in the financial sector but least for those in the transport sector. Moreover, predictability appears to be very heterogeneous both across sectors and market conditions. For instance, whereas predictability from economic policy shock is mainly negative and stronger towards the end of the medium-term, it is, however, mostly positive for the building and financial sectors. This is also the case for the transport sector at the end of this term (d_5) from 0.7 quantiles upwards. These findings suggest that in the medium-term, economic policy shock may exhibit asymmetric effects on green energy firms across different sectors.

Particularly, an increase in economic policy shock tends to mostly impact negatively on the performance of firms in all the sectors during bearish to normal market conditions but

positively during bullish market periods, especially on firms in the building and financial sectors. For firms in the other sectors, results are mixed during bullish market periods. For instance, for companies in the green economy, transport, and technology sectors, there is positive directional predictability from economic policy shock towards the end of the medium-term while for firms in the edge sector, this may be found at the beginning of the medium-term. In sum, in the medium term, across all quantiles considered and regardless of the direction of predictability, the strength of predictability from economic policy shocks appears to be strongest for firms in the transport, followed by those in the financial sectors but least for those in the edge sector.

Regarding the long-term, results show that predictability across the sectors is mainly negative and strengthens towards higher quantiles and the very long-term. Negative predictability suggests that an increase in economic policy uncertainty is harmful to the performance of green energy firms, especially those in the building, economy, and transport sectors, where values are high and negative across all frequencies and quantiles. Results also show that across all the sectors, there is positive predictability from economic policy uncertainty in the lowest quantile (0.05) and up to the (0.1) quantile for financial and transport sectors at the beginning of the long term. This implies that when market conditions are very poor, economic policy uncertainty may have positive long-term effects on green energy firms, especially those in the transport and financial sectors. Intuitively, the result may be viewed in the light of the lasting positive effects of favorable economic policy changes introduced by national governments during an economic downturn.

There are some other notable exceptions characterized by positive predictability from economic policy uncertainty across all quantiles for some sectors including financial and the technology sectors. For instance, for the financial sector, results show that across all quantiles in the long-term as shown by the d_7 frequency, there is positive predictability from economic policy uncertainty to the performance of firms in the financial sector. This suggests that an increase in the long-term economic policy uncertainty may be beneficial to green energy firms in the financial sector irrespective of the market condition. Apparently, this may not be unconnected with the very close ties between the economic and financial sectors. Besides, most economic policy changes such as macroeconomic intervention measures which gives rise to economic policy shocks are mainly executed through the financial sector. The implication is that most of

these macroeconomic measures often affect other sectors through the financial sector, thereby improving the performance of the firms involved in the implementation of the measures.

Moreover, positive predictability may also be seen in the very long-term (s_7) for the financial sector in the upper quantiles (above 0.8) and across all quantiles for the technology sector except for the mid quantiles (0.5-0.7). These results suggest that during bullish market periods, green energy firms in the financial sector may benefit from economic policy uncertainty in the very long term while during both bearish and bullish market conditions, economic policy uncertainty appears to be beneficial for green energy firms in the technology sector in the very long-term. This finding is intuitively plausible, given the close linkages between the financial and technology sectors in the process of green energy development and deployment. Indeed, the increasing awareness about environmental quality and the transition to clean energy has led to increasing support for green energy firms in the technology sector, mainly through the use of favorable economic policies that improve the access of these firms to investment funds in the financial market. Lastly, regardless of the direction of predictability, results show that economic policy uncertainty has the strongest information content for green energy firms in the building sector across both market conditions and under bearish market conditions for the financial sector.

4.2 *Network-system analysis*

In this section, we are primarily concerned with the dynamics of integration among the performance of green energy sectors and EPU across different investment horizons. Indeed, we present results of spillovers as defined in Eq. 26 to 29 for different frequency scales. While many existing empirical studies have investigated the level of market integration among different asset classes using both aggregate and sector-specific market indexes, [37] acknowledges that most of these studies have neglected the level of interactions across different time domains. Consequently, in this study, we rely on the frequency signals that we retrieve using the MODWT approach to perform the multi-frequency resolution analysis of integration among green energy sectors and EPU. This permits us to shed light on the short- (approximately 1-8 days), medium- (approximately 8-64 days), and long-term (64 days and above) levels of market integration while identifying which time-frequency domain dominates spillovers in the network of green energy sectors in the presence of uncertainties in economic policy.

Table 3 presents the results of the level of integration across the respective time scales while Figure 5 displays the net pairwise directional spillover that enables us to examine directional spillovers between each pair of green energy sectors and EPU across the eight-time scales considered. As may be seen in Table 3, results show that although the level of connectedness among green energy sectors and EPU appears to be weak in the short-term periods, it becomes stronger in the medium- and long-term. In particular, the total connectedness index (TCI) shows that under the short-term investment horizons ($d_1 - d_2$), the degree of integration ranges from about 0.403 to 0.496. Intuitively, this result implies that in the short term as characterized by higher frequencies, the mean level of integration is approximately 0.45. This suggests that across this investment horizon, about 45% of error variance in the forecast of returns for green energy investments may be attributed to risk spillovers from other green energy sectors and EPU.

Moreover, under these time scales, results show that at the beginning of the short-term (d_1), all the green energy firms are net transmitters of risk as shown by the *net* column, except those in the edge and technology sectors. However, towards the end of the short-term (d_2), results suggest that among green energy sectors, the financial and technology sectors become the only net receivers of risk spillover from the system. Besides, in the short term, although EPU is a net receiver of risk spillover under the (d_2) time scale, it is a net transmitter of shock in the (d_1) time scale. Apparently, this is not unconnected with the swift transfer of economic policy shocks to the financial markets, especially shocks from negative macroeconomic news. This result also demonstrates that the information content of EPU may be relevant in the forecast of short-term returns for investment in green energy stocks.

Regarding the medium-term time scales ($d_3 - d_5$), results show that under this investment horizon, the degree of integration lies between 0.523 to 0.583. Specifically, although the total connectedness index is about 0.583 at the start of the medium-term, it drops to 0.523 but rises to 0.570 towards the end of this term. Intuitively, the mean degree of integration across this investment horizon is about 0.56, implying that in the medium-term, about 56% of error variance in the forecast of returns for investments in green energy stocks may be attributed to risk spillovers from other green energy stocks and EPU. Results are mixed concerning the net-transmitters and net-receivers of shocks across the frequency scales that comprise the medium-term, especially in the (d_5) frequency scale. For instance, although the building, economy, and

edge sectors are the net transmitters of shocks while the financial and transport sectors are the net receivers of shocks across the (d_3) and (d_4) frequency scales. However, under the (d_5) scale, only the economy and transport sector become net transmitters while the remaining sectors become net receivers of shocks.

This suggests that only green energy firms in the economy sector remain net transmitters while those in the financial sector remain net receivers of shocks throughout the medium-term investment horizon. Intuitively, this demonstrates that the performance of green energy stocks in the economy sector is very crucial in the prediction of the medium-term performance of other green energy firms across the other sectors considered in this study. Also, it demonstrates that the returns of green energy stocks in the financial sector can sufficiently be predicted in this investment horizon using the performance of green energy investment across the other green energy sectors, especially the economy sector. Moreover, results also demonstrate that under this investment horizon, EPU remains a net receiver of shocks from the system across the three frequency scales. This result suggests that although EPU exhibits more information content in the prediction of the performance of green energy stocks in the short term, in the medium term, it becomes a weak predictor as it receives more shocks than it transmits to green energy investment.

Lastly, for the long-term time scales ($d_6 - d_7$), the degree of integration is highest, ranging from 0.615 to 0.639 while it decreases to about 0.531 in the very long-term (s_7). Taken together, the mean level of integration under this investment horizon is approximately 0.60, implying that about 60% of error variance in the forecast of returns for investment in green energy investment may be attributed to shock spillover from other green energy sectors in the presence of EPU. Regarding the net transmitters and net receivers of shocks, results show that under the long-term scales, the building, economy, and transport sectors are the net transmitters of shocks while in the very long term, the building, economy, and edge sectors are the net-transmitters of shocks. However, at the beginning of the long-term (d_1), the technology sector is a net transmitter of shocks but becomes a net receiver beyond this time scale.

In sum, these findings demonstrate that the information content of the performance of green energy firms in the building and economy sectors in the prediction of returns for long-term investments in the remaining green energy sectors is stronger than the information content of

the system of the green energy sectors considered in the presence of uncertainties in economic policy. In the very long-term, this conclusion applies to the edge sector which becomes a net transmitter of shocks too. However, concerning EPU, results show also that across the long-term time scales ($d_1 - d_7$) and the very long-term scale (d_1), EPU remains a net receiver of shocks from the system. This suggests that the performance of green energy firms, especially those in the building and economy sectors contain a significant predictive influence on the level of uncertainty in macroeconomic policy. These findings may not be unconnected to the increasing influence of green energy technology at the backdrop of impressive trends in the transition to cleaner energy sources.

Moving forward, in Figure 5, Panel a - h, we present the network graphs of the mean net pairwise directional connectedness across the 8 frequency scales for all pairs of green energy sectors and EPU as defined in Eq. 29. Indeed, we rely on the size of the node to demonstrate the magnitude of the net-pairwise directional connectedness while the color of the nodes indicates whether the sector or uncertainty index is a net transmitter (blue) or net-receiver (red). Moreover, the colors of the arrows rank the strength of the net-pairwise directional connectedness from red (strongest) to blue, green, and purple (weakest). The arrow thickness also indicates the strength of the net-pairwise directional connectedness. As shown in Figure 5, Panel a to b contains the network graphs for the ($d_1 - d_2$) frequency scales that correspond to the short-term horizon; Panel c to e contain network graphs for the medium-term ($d_3 - d_5$); Panel f and g ($d_6 - d_7$) corresponds to the long-term while Panel h is for the very long-term (s_7).

The graphical evidence corroborates the results in Table 3 which show that shocks from green energy firms in the economy sector dominate risk spillovers in the system. Particularly, these graphs demonstrate that in the short-term, the strongest shocks spill over from green energy firms in the economy sector (red arrows) to those in the technology sector (d_1) and those in the financial sector (d_2). Besides, shocks from the transport sector also spill substantially over to the edge and technology sectors (d_1) and from the building sector to the financial sector as shown by blue arrows. However, as shown by the purple arrows, the weakest net pairwise shock spillover is exhibited by the spillover of shocks from the building sector to EPU (d_1) and from green energy firms in the financial sector to EPU (d_2). Taken together, these results

demonstrate that the short-term integration of the sampled green energy sectors with EPU is mainly driven by shock transmission from the economy, transport, and building sectors.

Regarding the network graphs for the medium-term frequency scales, evidence from Panel c to e shows that although green energy firms in the edge sector dominated the spillover of shocks at the beginning of this investment horizon as shown in (d_3), firms in the economy sector dominated the remaining frequency scales ($d_4 - d_5$) while firms in the financial and transport sectors were the main receiving firms. In particular, Panel c shows that the strongest spillover emanates from the edge sector to the financial sector while Panels d and e demonstrate that the strongest shocks spill from the economy sector to the financial sector as shown by the red arrows. Moreover, as shown by the blue arrows, substantial shocks also spill from firms in the building and transport sectors to firms in the financial sector. Contrarily, the weakest shocks flow from the technology sector to the financial sector as shown by the purple arrow in Panel c; it manifests in the shocks from EPU to firms in the edge sector (Panel d) while it is exhibited from the financial sector to the technology sector at the end of this investment horizon (Panel e). Intuitively, these results demonstrate that the degree of integration among the included green energy sectors and EPU is largely driven by shocks spillover from firms in the edge, economy, and financial sectors. Given the level of shock spillovers among these firms, the performance of firms in the edge and economy sectors appears to substantially drive the performance of green energy investments in other sectors, especially those in the financial sector.

Considering the network graphs for the long-term investment horizon as shown in Panel f - h. Graphical evidence demonstrates that the degree of shocks spillover is mainly led by shock spillovers from firms in the economy sector to those in the financial sector at the beginning of the long-term (Panel f); from firms in the economy sector to the edge sector (Panel g) and from firms in the building sector to the financial sector in the very long-term (Panel h) as shown by red arrows. Substantial shocks also spill from green energy firms in the edge sector. In contrast, at the beginning of the long-term, the weakest shocks spill over from EPU to the economy sector as shown by the purple arrow in Panel f. This may also be seen in Panel g with the weakest shocks from green energy firms in the building sector to those in the transport sector while in the very long-term, the weakest shock spills from the technology sector to firms in the building sector.

5 Conclusion

In this paper, we contribute to the extant literature on green energy stock market performance by examining the interactions among the U.S. clean energy sectors including the building, economy, edge, financial, technology, and transport sectors in the presence of uncertainties in macroeconomic policies. First, we used the wavelet approach and the cross-quantilogram methodology for a thorough analysis of the dependence and directional predictability from EPU to the performance of clean energy sectors across different time scales and both the bearish, normal, and bullish market conditions. Also, we examined the degree of integration among the performance of investments across these green energy sectors in the presence of EPU across times scale and horizon using the Time-Varying Parameter VAR (TVP-VAR) model with stochastic volatility. These enabled us to offer crucial insights on the heterogeneous level of integration, net-directional spillovers, diversification opportunities, and the vulnerability of each green energy sector to shocks in other green energy sectors under uncertainties in the macroeconomic space across different investment horizons.

Results from the analysis of dependence and directional predictability from EPU demonstrate that in the short-run, green energy sectors exhibit positive covariance with EPU while covariances become zero in both the medium- and long-term. Covariance with EPU appears to be strongest with green energy firms in the building sector followed by those in the transport sector while it is least with those in the green edge sector. Regarding correlations with EPU, results show that across all the sectors, correlations are positive but low in the short-term but increase in the medium-term while it becomes negative in the long-term and is least in the edge sector, followed by the financial sector. Taken together, these results suggest that the strength of predictability from EPU to the returns of green energy firms appears to be heterogeneous across sectors.

Furthermore, results from the analysis of the degree of integration and directional net-pairwise connectedness corroborate the earlier results as it shows that the degree of integration strengthens in the long term. Particularly, we find that the mean level of integration is about 45%, 56%, and 60% for the short-, medium- and long-term, respectively. Moreover, across both the short and medium-term investment horizons, green energy firms in the building, economy, and transport sectors are the consistent net transmitters of shock spillover while on the long-term horizon, firms in the building, economy, and technology sectors become the net-transmitters of shocks. In contrast, across all the investment horizons, firms in the edge and

financial sectors are consistent net receivers of shocks from the system. Regarding EPU, results show that in the short-term, EPU is a net transmitter of shocks to the system while across both the medium- and long-term, EPU becomes a net receiver of shocks from the system.

Overall, our results suggest that clean energy stock prices respond heterogeneously to uncertainties in macroeconomic policies, with the direction and magnitude of responses varying across sectors, market conditions, and investment horizons. This offers investors and portfolio managers that may be interested in investing in clean energy equities the opportunity of diversifying their portfolio across sectors, market conditions, and horizons to reap the benefits thereof. Along this line, for instance, our finding that the covariance between EPU and clean energy stock prices are strongest in the building sector followed by those in the transport sector while it is least with those in the green edge sector offers insight into such a potential cross-sectoral portfolio diversification in clean energy equities. Similarly, the heterogeneous predictability from EPU on these clean energy stock prices also points to macroeconomic conditions such investors and portfolio managers should be aware of across time scales. In particular, our results would suggest that investors and portfolio managers that are interested in the short-term return on clean energy stocks should be more concerned about EPU than those interested in the long-term returns on clean energy stocks.

References

[1] O. B. Adekoya and J. A. Oliyide. How covid-19 drives connectedness among commodity and financial markets: Evidence from TVP-VAR and causality-in-quantiles techniques. *Resources Policy*, 70, 2021.

[2] G. Akhmat, K. Zaman, T. Shukui, and F. Sajjad. Does energy consumption contribute to climate change? evidence from major regions of the world. *Renewable and Sustainable Energy Reviews*, 36, 2014.

[3] Antonakakis, N., & Gabauer, D. (2017). *Refined measures of dynamic connectedness based on TVP-VAR*. MPRA Paper No. 78282.

[4] M. Arouri, C. Estay, C. Rault, and D. Roubaud. Economic policy uncertainty and stock markets: Longrun evidence from us. *Finance Research Letters*, 18, 2016.

[5] M. Auffhammer and T. Mansur. Measuring climatic impacts on energy consumption: A review of the empirical literature. *Energy Economics*, 46, 2014.

[6] S. R. Baker, N. Bloom, and S. J. Davis. Measuring economic policy uncertainty. *The quarterly journal of economics*, 131(4), 2016.

[7] E. Bouri, X. Lei, N. Jalkh, Y. Xu, and H. Zhang. Spillovers in higher moments and jumps across us stock and strategic commodity markets. *Resources Policy*, 72, 2021.

[8] W. Brock, W. Dechert, J. Scheinkman, and B. LeBaron. A test for independence based on the correlation dimension'. growth theory, non-linear dynamics, and economic modeling: *scientific essays of William Allen Brock*, 15, 2001.

[9] W. A. Brock, W. Dechert, and J. Scheinkman. A test for independence based on the correlation dimension. *Working paper, University of Wisconsin at Madison, University of Houston, and University of Chicago*, 1996.

[10] J. Brogaard and A. Detzel. The asset-pricing implications of government economic policy uncertainty. *Management Science*, 61(1), 2015.

[11] A. M. Dahir, F. Mahat, B. A. A. Noordin, and N. H. Ab Razak. Dynamic connectedness between bitcoin and equity market information across BRICS countries. *International Journal of Managerial Finance*, 16, 2019.

[12] F. X. Diebold and K. Yılmaz. On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182, 2014.

[13] X. Diebold and K. Yilmaz. Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1), 2012.

[14] B. Elie, J. Naji, A. Dutta, and G. S. Uddin. Gold and crude oil as safe-haven assets for clean energy stock indices: Blended copulas approach. *Energy*, 178, 2019.

[15] L. Eyraud, A. Wane, C. Zhang, and B. Clements. Who's going green and why? trends and determinants of green investment. *IMF Working Papers*, 2011.

[16] B. N. E. Finance. Global trends in clean energy investment, 2018.

[17] H. Han, O. Linton, T. Oka, and Y. J. Whang. The cross-quantilogram: Measuring quantile dependence and testing directional predictability between time series. *Journal of Econometrics*, 193(1), 2016.

[18] I. Henriques and P. Sadorsky. Oil prices and the stock prices of alternative energy companies. *Energy Economics*, 30, 2008.

[19] Q. Ji, E. Bouri, C. K. M. Lau, and D. Roubaud. Dynamic connectedness and integration in cryptocurrency markets. *International Review of Financial Analysis*, 63, 2019.

[20] Q. Ji, B.-Y. Liu, H. Nehler, and G. Uddin. Uncertainties and extreme risk spillover in the energy markets: a time-varying copula-based covar approach. *Energy Economics*, 76, 2018.

[21] . R. R. Kang, W. Oil shocks, policy uncertainty, and stock market return. *Journal of International Financial Markets, Institutions, and Money*, 26, 2013.

[22] W. Kang, F. Gracia, and R. Ratti. Oil price shocks, policy uncertainty, and stock returns of oil and gas corporations. *Journal of International Money and Finance*, 70, 2017.

[23] B. Kocaarslan and U. Soytas. Dynamic correlations between oil prices and the stock prices of clean energy and technology firms: The role of reserve currency (us dollar). *Energy Economics*, 84, 2019.

[24] G. Koop and D. Korobilis. A new index of financial conditions. *European Economic Review*, 71, 2014.

[25] S. Kumar, S. Managi, and A. Matsuda. Stock prices of clean energy firms, oil, and carbon markets: A vector autoregressive analysis. *Energy Economics*, 34, 2012.

[26] O. Linton and Y. J. Whang. The quantilogram: With an application to evaluating directional predictability. *Journal of Econometrics*, 141(1), 2007.

[27] . Z. T. Liu, L. Economic policy uncertainty and stock market volatility. *Finance Research Letters*, 15, 2015.

[28] R. Liu, L. He, X. Liang, X. Yang, and Y. Xia. Is there any difference in the impact of economic policy uncertainty on the investment of traditional and renewable energy enterprises? a comparative study based on regulatory effects. *Journal of Cleaner Production*, 255, 2020.

[29] A. Lundgren, A. Milicevic, G. Uddin, and S. Kang. Connectedness network and dependence structure mechanism in green investments. *Energy Economics*, 72, 2018.

[30] S. Mishra, A. Sharif, S. Khuntia, M. S. Meo, and S. A. R. Khan. Does oil prices impede Islamic stock indices? fresh insights from wavelet-based quantile-on-quantile approach. *Resources Policy*, 62, 2019.

[31] D. Phan, S. Sharma, and V. Tran. Can economic policy uncertainty predict stock returns? global. *Journal of International Financial Markets, Institutions, and Money*, 55, 2018.

[32] D. N. Politis and J. P. Romano. The stationary bootstrap. *Journal of the American Statistical Association*, 89, 1994.

[33] C. Reboredo and S. Uddin. Do financial stress and policy uncertainty have an impact on the energy and metals markets? a quantile regression approach. *International Review of Economics Finance*, 43, 2016.

[34] P. Sadorsky. Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. *Energy Economics*, 34, 2012.

[35] L. H. Sendstad and M. Chronopoulos. Sequential investment in renewable energy technologies under policy uncertainty. *Energy Policy*, 137, 2020.

[36] G. S. Uddin, M. Rahman, A. Hedström, and A. Ahmed. Cross-quantilogram-based correlation and dependence between renewable energy stock and other asset classes. *Energy Economics*, 80, 2019.

[37] C. Urom, I. Abid, K. Guesmi, and J. Chevallier. Quantile spillovers and dependence between bitcoin, equities, and strategic commodities. *Economic Modelling*, 93, 2020.

[38] C. Urom, G. Ndubuisi, and J. Ozor. Economic activity, and financial and commodity markets' shocks: an analysis of implied volatility indexes. *International Economics*, 165, 2021.

[39] E. Z. Wang and C. C. Lee. Dynamic spillovers and connectedness between oil returns and policy uncertainty. *Applied Economics*, 52, 2020.

[40] X. Zhao. Do the stock returns of clean energy corporations respond to oil price shocks and policy uncertainty? *Journal of economic structures*, 2020.

[41] Z. Zhou, Y. Jiang, Y. Liu, L. Lin, and Q. Liu. Does international oil volatility have directional predictability for stock returns? evidence from BRICS countries based on cross-quantilogram analysis. *Economic Modelling*, 80, 2019.

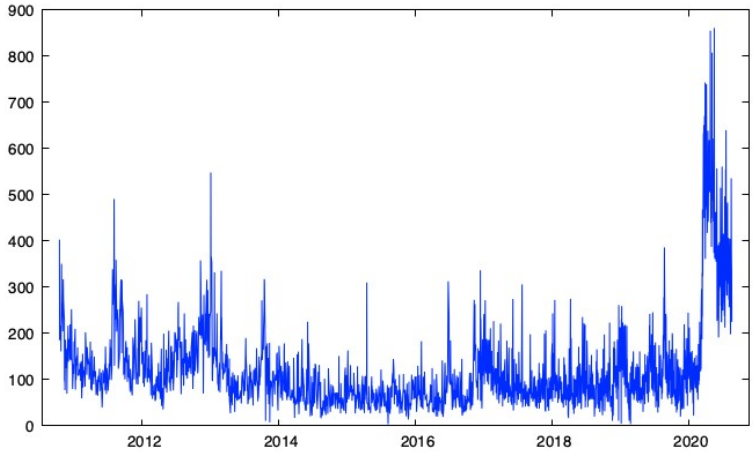
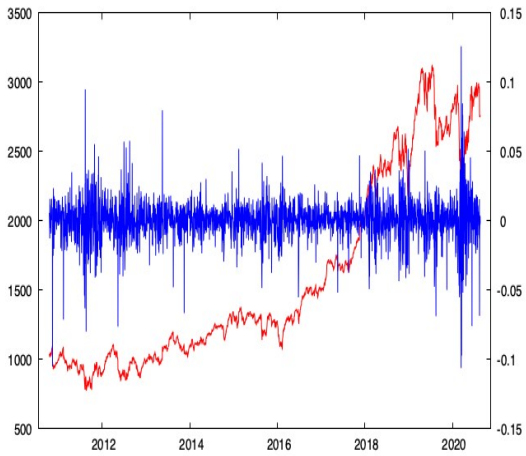
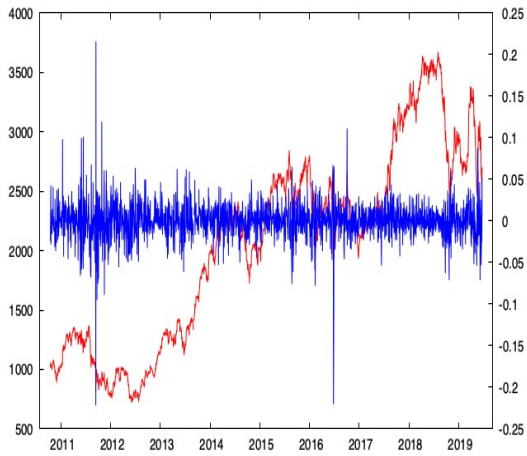


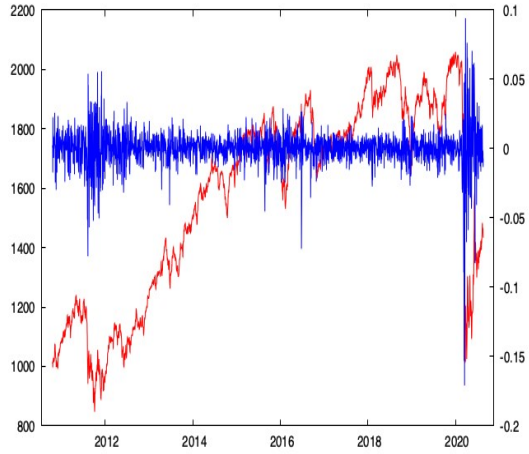
Figure 1: Plot of Economic Policy Uncertainty



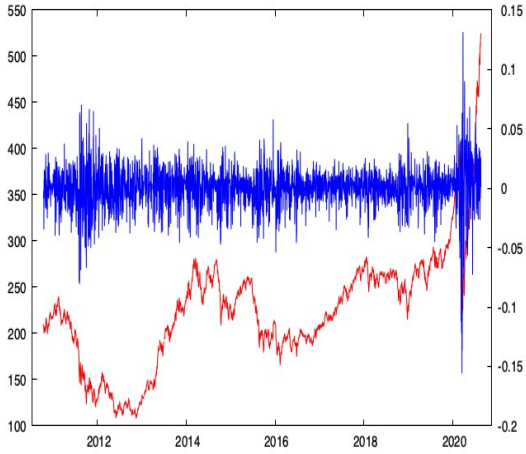
(a)(i) Prices and returns of TECH



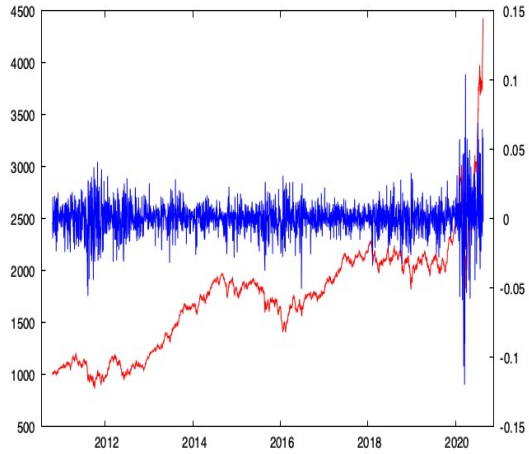
(ii) Prices and returns of FIN



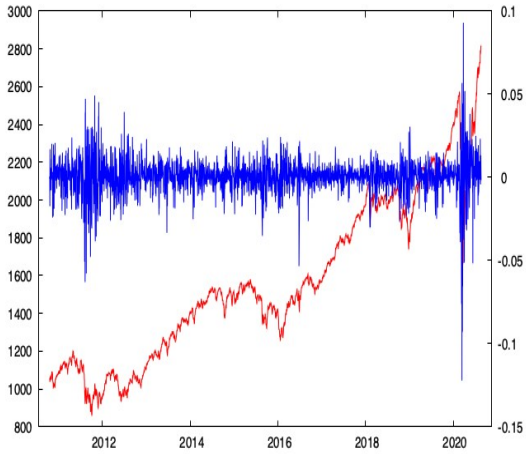
(b)(i) Prices and returns of BLD



(ii) Prices and returns of EDGE



(c)(i) Prices and returns of TRN



(ii) Prices and returns of ECO

Figure 2: Plots of prices and returns series for sectoral U.S. clean energy market

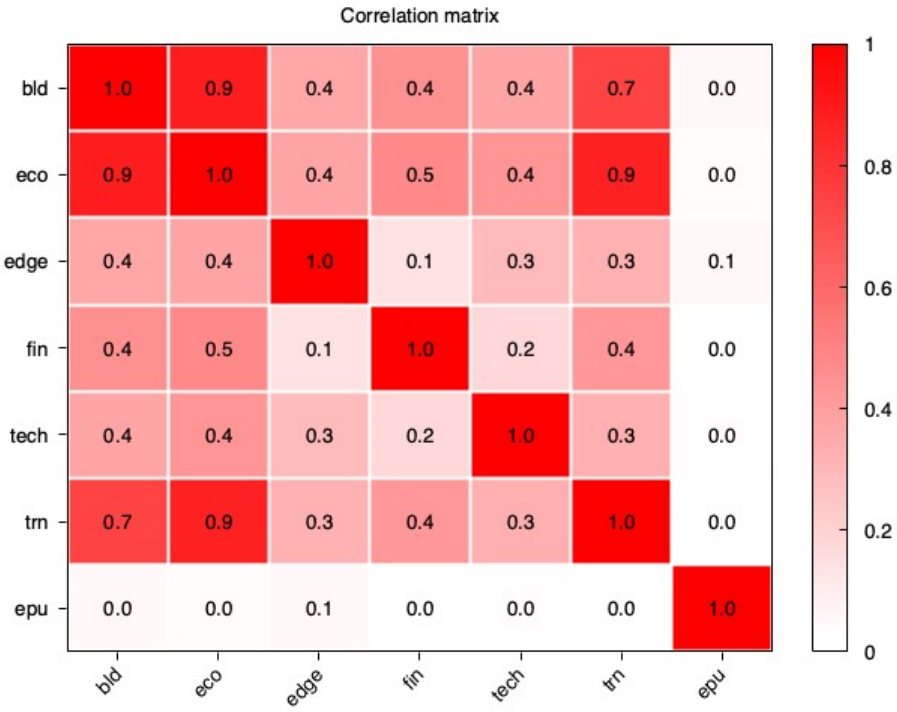
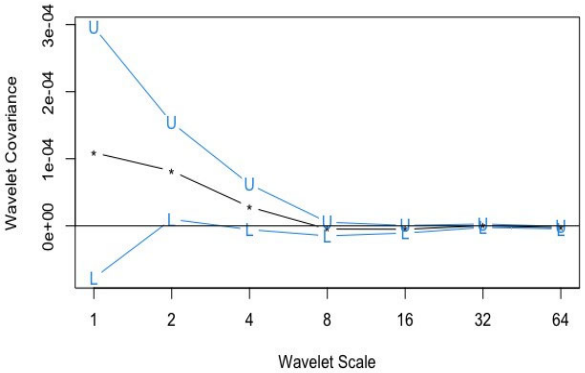
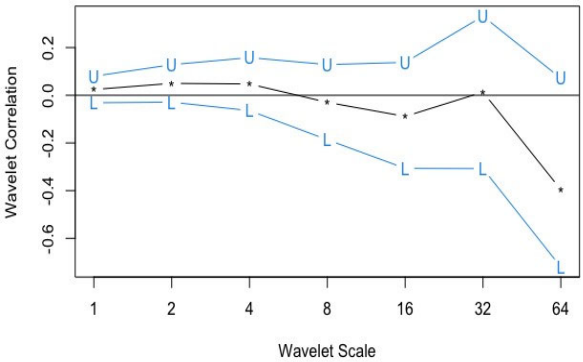


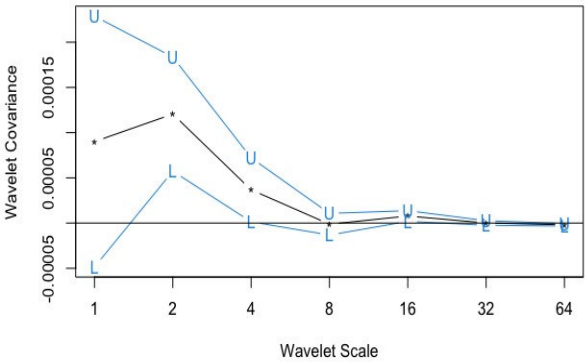
Figure 3: Correlation matrix

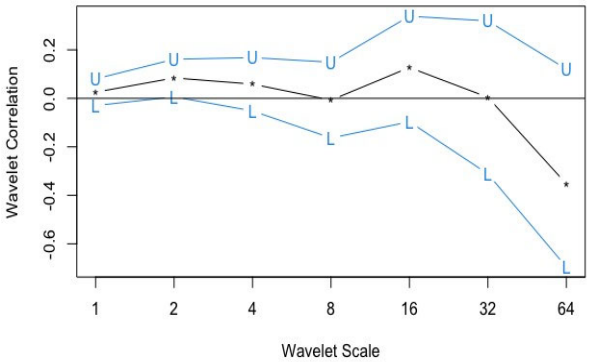




(a)(i) Covariance of TECH sector with EPU

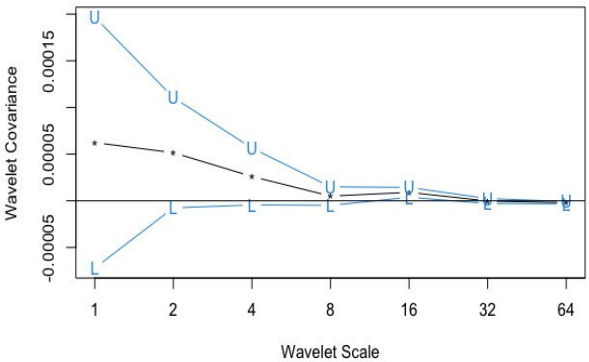
(ii) Correlation of TECH sector with EPU

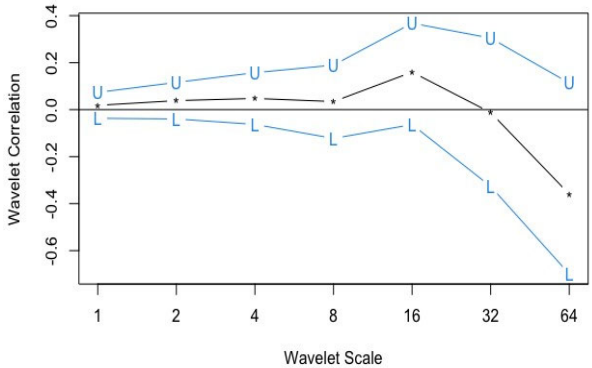




(b)(i) Covariance of BLD sector with EPU

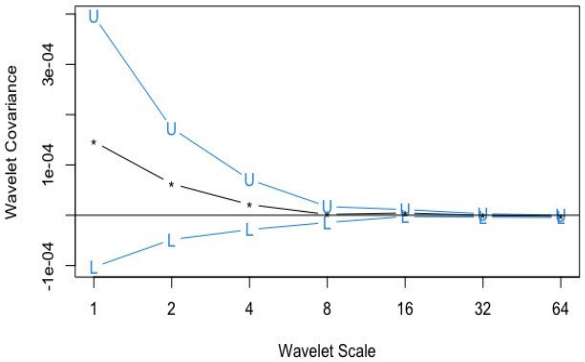
(ii) Correlation of BLD sector with EPU

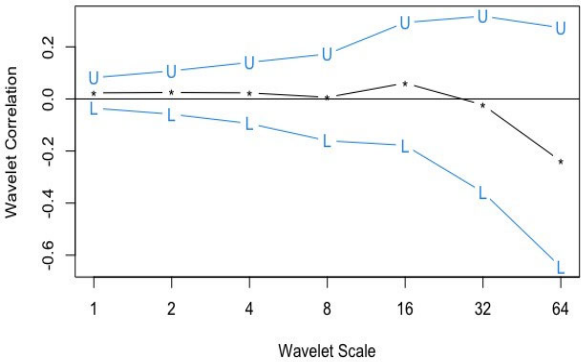




(c)(i) Covariance of TRN sector with EPU

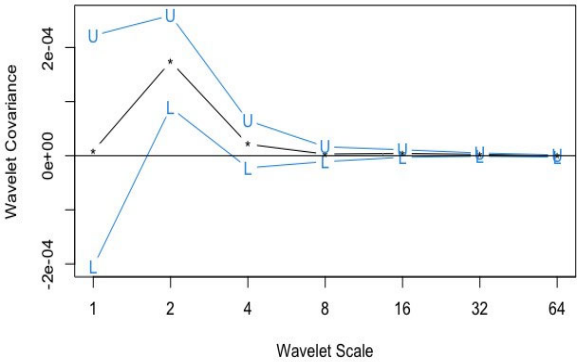
(ii) Correlation of TRN sector with EPU

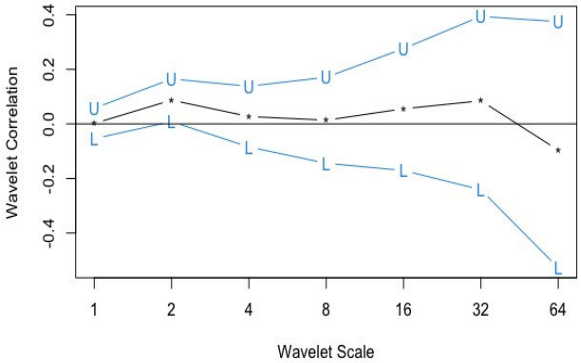




(d)(i) Covariance of FIN sector with EPU

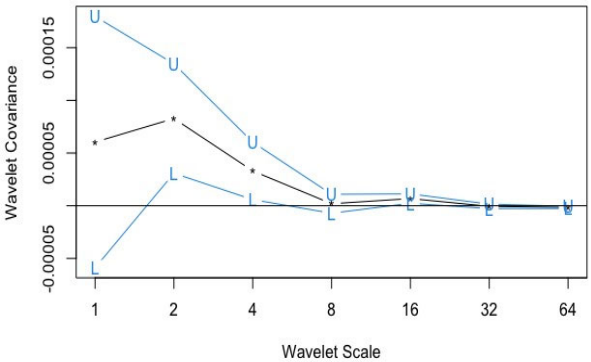
(ii) Correlation of FIN sector with EPU

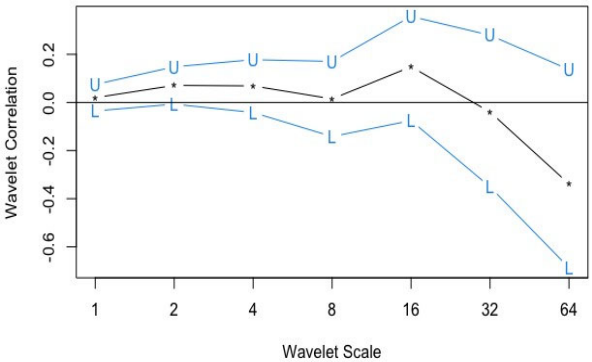




(e)(i) Covariance of EDGE sector with EPU

(ii) Correlation of EDGE sector with EPU

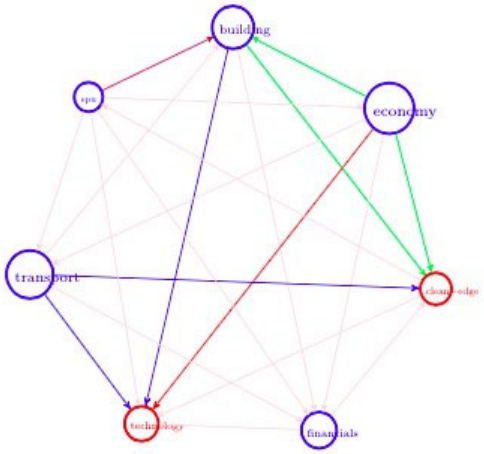




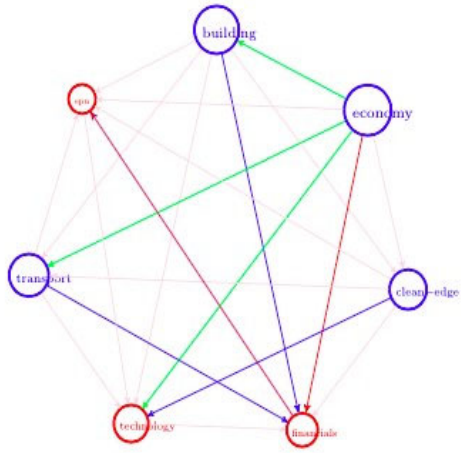
(f)(i) Covariance of ECO sector with EPU

(ii) Correlation of ECO sector with EPU

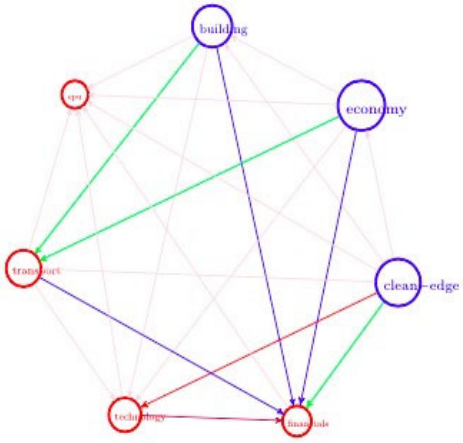
Figure 4: Plots of covariance and correlations with epu



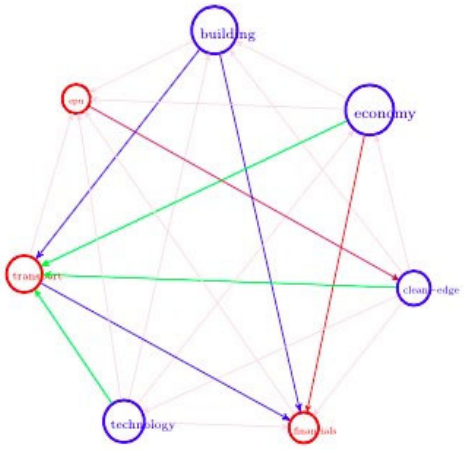
(a) Net pairwise directional spillovers under d_1



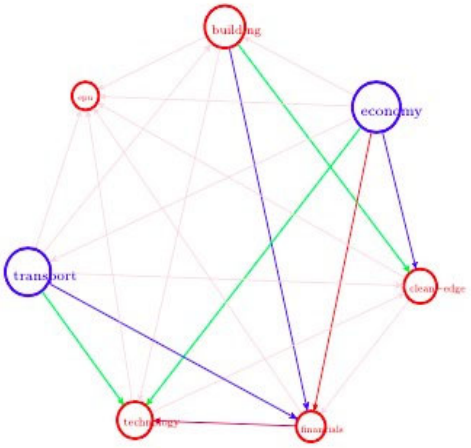
(b) Net pairwise directional spillovers under d_2



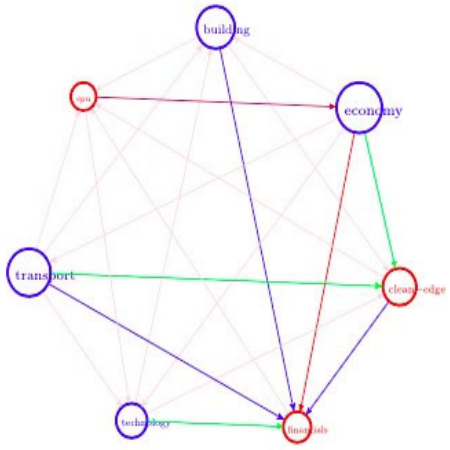
(c) Net pairwise directional spillovers under d_3



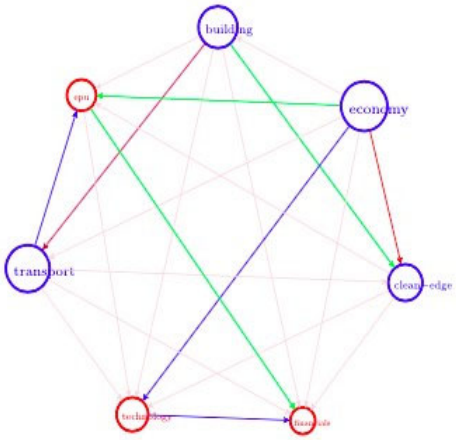
(d) Net pairwise directional spillovers under d_4



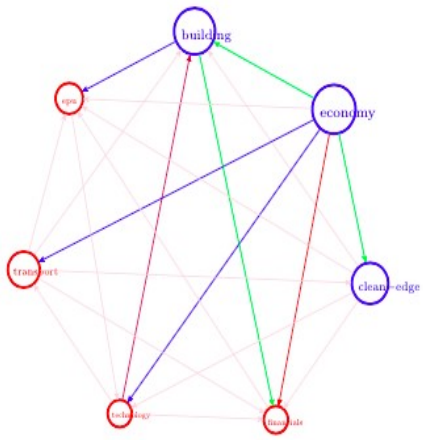
(e) Net pairwise directional spillovers under d_5



(f) Net pairwise directional spillovers under d_6



(g) Net pairwise directional spillovers under d_7



(h) Net pairwise directional spillovers under s_7

Figure 5: Plots of network pairwise directional spillovers across different frequencies

Table 1: descriptive statistics

	Mean	Max.	Min.	Std. Dev.	Skewness	Ex. Kurt.	J-B	ADF	BDS Stats.
bld	0.0003	0.0558	-0.0776	0.0101	-0.6086	6.4346	3986.58***	-44.05***	0.0629***
							(0.0000)	(0.0001)	(0.0000)
eco	0.0003	0.0492	-0.0630	0.0092	-0.4732	4.9123	2326.42***	-43.16***	0.0708***
							(0.0000)	(0.0000)	(0.0000)
edge	0.0001	0.0703	-0.0807	0.0158	-0.2819	1.7208	304.83***	-45.07***	0.0548***
							(0.0000)	(0.0001)	(0.0000)
fin	0.0004	0.2159	-0.2219	0.0215	-0.4895	16.4080	25116.8***	-48.91***	0.0391***
							(0.0000)	(0.0001)	(0.0000)
tech	0.0004	0.0949	-0.1050	0.0135	-0.4424	6.5890	4108.57***	-46.87***	0.0591***
							(0.0000)	(0.0001)	(0.0000)
trn	0.0003	0.0412	-0.0554	0.0098	-0.3970	2.3080	553.78***	-41.40***	0.0493***
							(0.0000)	(0.0000)	(0.0000)
epu	109.7	586.6	3.32	69.04	1.75	4.99	393.63***	-48.59***	0.0426***
							(0.0000)	(0.0001)	(0.0000)

Note: BDS statistic denotes the Brock-Dechert-Scheinkman test for non-linearity proposed by Brock *et al.* 1996. This is defined as $BDS(\delta, m, T) = \sqrt{T\frac{C(\delta,m,T)-C(\delta,1,T)^m}{\sigma(\delta,m,T)}}$, where $C(\delta, m, T)$ as a U- statistics is a minimum variance unbiased and while $\sigma(\delta, m, T)$ is a nontrivial function of the correlation integral. Lastly, ***, ** and * represent significance at 1%, 5% and 10% respectively. bld, eco, edge, fin, tech, trn correspond to the returns of the Building, Economy, Clean-edge, Financial, Technology, and Transport sectors, respectively, while epu denotes economic policy uncertainty in the U.S.

Table 2: Directional predictability from economic policy uncertainty to sectoral clean energy stocks across different time scales and quantiles

Sector	Quantiles	Time scales							
		Short-term		Medium-term			Long-term		
bld									
		bld.d1	bld.d2	bld.d3	bld.d4	bld.d5	bld.d6	bld.d7	bld.s7
	0.05	-0.015	-0.012‡	-0.005†	0.003	-0.039‡	0.006†	0.005	-0.078
	0.1	-0.012	-0.009†	-0.007†	-0.005†	-0.028	-0.020‡	0.025	-0.113‡
	0.2	-0.006	-0.007	-0.010†	-0.005†	-0.017	-0.037‡	-0.024‡	-0.162‡
	0.3	-0.001	-0.001	-0.004†	-0.001†	-0.020‡	-0.030‡	-0.050‡	-0.134‡
	0.5	0.003	0.003	0.000†	0.001†	-0.032‡	-0.016‡	-0.090‡	-0.106‡
	0.7	0.007†	0.003	0.005†	0.003†	0.001‡	-0.014‡	-0.195‡	-0.185‡
	0.8	0.005	0.004	0.008†	0.002†	0.005†	-0.038‡	-0.280‡	-0.253‡
	0.9	0.007	0.004†	0.006†	0.009†	0.011‡	-0.083‡	-0.297‡	-0.344‡
	0.95	0.009	0.012‡	0.007†	0.009	0.024	-0.146‡	-0.357‡	-0.474‡
	% of sig. quant.	11.1%	44.4%	100%	77.8%	66.7%	100%	77.8%	88.9%
	Strength of Pred.	0.007	0.037	0.054	0.025	0.108	0.389	1.293	1.772
eco									
		eco.d1	eco.d2	eco.d3	eco.d4	eco.d5	eco.d6	eco.d7	eco.s7
	0.05	-0.016‡	-0.013‡	0.002†	0.000†	-0.026‡	0.002†	0.077	-0.077‡
	0.1	-0.014‡	-0.013	0.002†	0.001 †	-0.038‡	-0.007	0.049	-0.096‡
	0.2	-0.008	-0.010	-0.001†	0.009†	-0.032‡	-0.021‡	-0.015‡	-0.131‡
	0.3	-0.005	-0.005	0.001†	0.009†	-0.041‡	-0.037‡	-0.050‡	-0.102‡
	0.5	0.002	0.000	0.000†	0.005†	-0.002†	-0.027‡	-0.116‡	-0.022‡
	0.7	0.007	0.006†	-0.002	-0.010†	0.012‡	-0.029‡	-0.210‡	-0.095‡
	0.8	0.010‡	0.009†	-0.001†	-0.007†	0.026‡	-0.034	-0.270	-0.166‡
	0.9	0.009†	0.013‡	-0.003†	-0.002	0.032‡	-0.064‡	-0.309‡	-0.307‡
	0.95	0.010	0.012‡	0.004	-0.002	0.021‡	-0.093‡	-0.272‡	-0.349‡
	% of sig. quant.	44.4%	55.6%	77.8%	77.8%	100%	100%	88.9%	100%
	Strength of Pred.	0.049	0.054	0.010	0.042	0.231	0.314	1.291	1.344
edge									
		edge.d1	edge.d2	edge.d3	edge.d4	edge.d5	edge.d6	edge.d7	edge.s7
	0.05	-0.011‡	-0.017‡	-0.008†	0.004†	-0.018‡	0.033‡	0.040‡	-0.070‡
	0.1	-0.009‡	-0.015	-0.014‡	0.002†	-0.012‡	-0.003	0.028	-0.082‡
	0.2	-0.003	-0.014	-0.011‡	0.005†	0.005	-0.033‡	-0.005	-0.095‡
	0.3	-0.003	-0.008	-0.008†	0.007†	0.003	-0.045‡	-0.030	-0.061‡
	0.5	-0.001	0.001	0.001†	0.009†	0.017	-0.036‡	-0.108‡	0.000†
	0.7	0.003	0.008†	0.010†	0.001†	0.016	-0.045‡	-0.195‡	-0.059‡
	0.8	0.006	0.009	0.012‡	-0.001†	-0.001†	-0.057‡	-0.233‡	-0.105‡
	0.9	0.013‡	0.012	0.008†	0.002†	0.004†	-0.089‡	-0.244‡	-0.143‡
	0.95	0.011	0.016	0.009†	0.006	0.013	-0.117‡	-0.216‡	-0.219‡
	% of sig. quant.	33.3%	22.2%	100%	88.9%	44.4%	100%	77.8%	100%
	Strength of Pred.	0.032	0.025	0.080	0.032	0.035	0.458	1.064	0.834
fin									
		fin.d1	fin.d2	fin.d3	fin.d4	fin.d5	fin.d6	fin.d7	fin.s7
	0.05	-0.013‡	-0.008	0.008†	-0.015‡	-0.042‡	0.024‡	0.434‡	-0.078‡
	0.1	-0.007	-0.006	0.008†	-0.016‡	-0.040‡	0.001†	0.245‡	-0.073‡
	0.2	-0.005	-0.009†	0.007†	-0.010†	-0.035‡	-0.025‡	0.156‡	-0.056‡
	0.3	-0.002	-0.005	0.003†	-0.009†	-0.017‡	-0.040‡	0.184‡	-0.080‡
	0.5	0.000	-0.002	0.001†	0.003†	0.001†	-0.003†	0.200‡	-0.098‡
	0.7	0.002	0.003†	0.002†	0.009†	0.027‡	0.015‡	0.089‡	-0.024

	0.8	0.003	0.006	0.000†	0.014‡	0.039‡	-0.016‡	0.081‡	0.061‡
	0.9	0.004	0.005	-0.006†	0.009†	0.042‡	-0.074‡	0.079‡	0.112‡
	0.95	0.009	0.011	-0.008†	0.020‡	0.037‡	-0.138‡	0.087‡	0.078‡
	% of sig. quant.	11.1%	22.2%	100%	100%	100%	100%	100%	88.9%
	Strength of Pred.	0.013	0.012	0.043	0.104	0.279	0.336	1.555	0.636
tech									
		tech.d1	tech.d2	tech.d3	tech.d4	tech.d5	tech.d6	tech.d7	tech.s7
	0.05	-0.004	-0.008	-0.006	0.001†	-0.013‡	0.007†	0.090	0.056‡
	0.1	-0.003	-0.010	-0.001	0.004†	-0.021‡	-0.033‡	0.038	0.058‡
	0.2	-0.001	-0.010	0.004†	0.001†	-0.012‡	-0.069‡	-0.019‡	0.123‡
	0.3	-0.002†	-0.006	0.005†	0.006†	0.007†	-0.084‡	-0.043‡	0.080‡
	0.5	0.004†	0.003	0.001†	0.007†	0.014‡	-0.082‡	-0.081‡	0.033
	0.7	0.000†	0.007	-0.003†	0.000†	0.029‡	-0.035‡	-0.146‡	0.035
	0.8	0.006	0.005	0.005†	-0.001†	0.026‡	-0.029‡	-0.222‡	0.164‡
	0.9	0.004	0.009	0.002	0.002†	0.023	-0.048‡	-0.311‡	0.109‡
	0.95	0.003	0.002	0.000	-0.012‡	0.017‡	-0.042‡	-0.340‡	0.078‡
	% of sig. quant.	33.3%	0%	55.6%	100%	88.9%	100%	77.8%	77.8%
	Strength of Pred.	0.006	0	0.018	0.034	0.139	0.429	1.163	0.669
trn									
		trn.d1	trn.d2	trn.d3	trn.d4	trn.d5	trn.d6	trn.d7	trn.s7
	0.05	-0.007	-0.005	0.000	0.008	-0.033‡	0.020	0.097‡	-0.078‡
	0.1	-0.009	-0.010	0.004	0.007†	-0.049‡	0.002	0.043‡	-0.102‡
	0.2	-0.006	-0.005	0.008	0.011‡	-0.049‡	0.002	-0.030‡	-0.133‡
	0.3	-0.005	-0.001	0.006	0.004†	-0.042‡	-0.009†	-0.087‡	-0.165‡
	0.5	-0.002	-0.002	-0.001	-0.002†	-0.021	-0.016‡	-0.139‡	-0.197‡
	0.7	0.006†	0.006	-0.004	-0.011‡	0.013‡	-0.009†	-0.221‡	-0.231‡
	0.8	0.006	0.004	-0.007†	-0.009	0.037‡	-0.027‡	-0.272‡	-0.161‡
	0.9	0.009	0.007	-0.008†	-0.005	0.035‡	-0.057‡	-0.259‡	-0.287‡
	0.95	0.006	0.007	-0.002	-0.003	0.010‡	-0.104‡	-0.295‡	-0.233‡
	% of sig. quant.	11.1%	0%	22.2%	55.6%	88%	66.7%	100%	100%
	Strength of Pred.	0.006	0	0.016	0.034	0.269	0.222	1.442	1.587

Notes: Values in the table represent the strength of prediction under nine quantiles from epu to renewable energy sectors. The closer the values to ±1, the stronger the predictive ability of epu under a particular quantile. Bold values are estimated coefficients that are significant at least 5%; where † and ‡ denote significance at 5% and 1%, respectively. bld, eco, edge, fin, tech, trn correspond to the returns of the Building, Economy, Clean-edge, Financial, Technology, and Transport sectors, respectively

Table 3: Market integration with economic policy uncertainty

	bld	eco	edge	fin	tech	trn	epu	*From*	*Net*
d1									
bld	NA	0.288	0.027	0.062	0.040	0.212	0.004	0.633	0.061
eco	0.254	NA	0.022	0.065	0.048	0.268	0.004	0.661	0.210
edge	0.082	0.091	NA	0.021	0.022	0.096	0.003	0.316	-0.207
fin	0.061	0.074	0.006	NA	0.018	0.061	0.005	0.224	0.002
tech	0.110	0.139	0.027	0.022	NA	0.099	0.005	0.401	-0.241
trn	0.184	0.278	0.020	0.054	0.029	NA	0.005	0.570	0.166
epu	0.002	0.001	0.007	0.002	0.002	0.001	NA	0.015	0.010
To	0.694	0.871	0.109	0.226	0.160	0.736	0.025	TCI=0.403	
d2									
bld	NA	0.260	0.082	0.089	0.054	0.180	0.005	0.670	0.097
eco	0.237	NA	0.085	0.083	0.070	0.224	0.005	0.703	0.207
edge	0.083	0.095	NA	0.021	0.102	0.076	0.012	0.388	0.092
fin	0.169	0.179	0.040	NA	0.021	0.134	0.003	0.545	-0.256
tech	0.076	0.104	0.168	0.020	NA	0.068	0.011	0.446	-0.142
trn	0.193	0.264	0.080	0.074	0.050	NA	0.004	0.665	0.020
epu	0.009	0.009	0.023	0.003	0.009	0.004	NA	0.058	-0.018
To	0.767	0.910	0.479	0.289	0.305	0.685	0.039	TCI=0.496	
d3									
bld	NA	0.229	0.132	0.090	0.091	0.160	0.007	0.708	0.038
eco	0.212	NA	0.144	0.093	0.101	0.194	0.007	0.750	0.128
edge	0.090	0.106	NA	0.067	0.151	0.097	0.017	0.530	0.283
fin	0.157	0.183	0.126	NA	0.065	0.161	0.007	0.699	-0.291
tech	0.074	0.092	0.259	0.045	NA	0.060	0.020	0.551	-0.069
trn	0.190	0.241	0.131	0.089	0.056	NA	0.006	0.713	-0.019
epu	0.023	0.027	0.020	0.024	0.018	0.022	NA	0.134	-0.070
To	0.746	0.878	0.813	0.408	0.481	0.693	0.064	TCI=0.583	
d4									
bld	NA	0.281	0.056	0.067	0.091	0.142	0.017	0.654	0.078
eco	0.232	NA	0.073	0.063	0.096	0.214	0.009	0.687	0.178
edge	0.055	0.041	NA	0.034	0.243	0.039	0.039	0.451	0.093
fin	0.139	0.207	0.051	NA	0.086	0.136	0.019	0.638	-0.380
tech	0.035	0.044	0.258	0.031	NA	0.015	0.022	0.405	0.176
trn	0.240	0.265	0.075	0.048	0.037	NA	0.011	0.675	-0.108
epu	0.030	0.026	0.031	0.015	0.028	0.023	NA	0.153	-0.037
To	0.731	0.865	0.544	0.258	0.580	0.568	0.116	TCI=0.523	
d5									
bld	NA	0.289	0.060	0.074	0.063	0.208	0.008	0.701	0.001
eco	0.200	NA	0.081	0.073	0.096	0.241	0.007	0.697	0.410
edge	0.135	0.174	NA	0.035	0.157	0.153	0.006	0.659	-0.186
fin	0.088	0.167	0.056	NA	0.072	0.118	0.005	0.507	-0.196
tech	0.093	0.184	0.147	0.078	NA	0.133	0.010	0.645	-0.152
trn	0.176	0.275	0.090	0.042	0.067	NA	0.003	0.652	0.214
epu	0.011	0.019	0.038	0.011	0.039	0.012	NA	0.129	-0.090
To	0.702	1.107	0.473	0.311	0.493	0.866	0.039	TCI=0.570	
d6									
bld	NA	0.215	0.131	0.086	0.126	0.191	0.015	0.765	0.002
eco	0.169	NA	0.138	0.073	0.160	0.211	0.014	0.765	0.244
edge	0.155	0.193	NA	0.052	0.156	0.184	0.004	0.743	-0.040
fin	0.150	0.175	0.120	NA	0.104	0.147	0.002	0.697	-0.362
tech	0.116	0.183	0.149	0.046	NA	0.142	0.021	0.656	0.033
trn	0.162	0.230	0.133	0.066	0.135	NA	0.013	0.740	0.158

epu	0.014	0.013	0.032	0.013	0.009	0.023	NA	0.105	-0.035
To	0.766	1.009	0.704	0.336	0.690	0.898	0.070	TCI=0.639	
d7									
bld	NA	0.223	0.126	0.002	0.107	0.194	0.091	0.743	0.117
eco	0.207	NA	0.146	0.010	0.134	0.203	0.069	0.768	0.214
edge	0.168	0.205	NA	0.004	0.112	0.196	0.053	0.738	-0.117
fin	0.025	0.039	0.015	NA	0.058	0.024	0.042	0.203	-0.159
tech	0.138	0.187	0.114	0.016	NA	0.128	0.056	0.639	-0.079
trn	0.197	0.224	0.158	0.004	0.107	NA	0.068	0.759	0.098
epu	0.125	0.104	0.061	0.008	0.043	0.112	NA	0.453	-0.074
To	0.860	0.983	0.620	0.044	0.561	0.857	0.379	TCI=0.615	
s7									
bld	NA	0.168	0.044	0.120	0.017	0.025	0.192	0.566	-0.012
eco	0.103	NA	0.226	0.065	0.069	0.208	0.030	0.702	0.308
edge	0.027	0.261	NA	0.061	0.040	0.267	0.002	0.657	0.077
fin	0.155	0.124	0.104	NA	0.052	0.022	0.025	0.482	-0.145
tech	0.013	0.121	0.063	0.043	NA	0.025	0.018	0.283	-0.062
trn	0.014	0.258	0.286	0.014	0.029	NA	0.015	0.617	-0.036
epu	0.242	0.077	0.010	0.035	0.014	0.034	NA	0.412	-0.130
To	0.554	1.010	0.734	0.338	0.221	0.581	0.282	TCI=0.531	

Notes: epu denotes economic policy uncertainty in the U.S; *From* and *To* represents the strength and direction shock spillovers while *TCI* is the total connectedness index. bld, eco, edge, fin, tech, trn correspond to the returns of the Building, Economy, Clean-edge, Financial, Technology, and Transport sectors, respectively.

UNU-MERIT Working Papers
ISSN 1871-9872

Maastricht Economic and social Research Institute on Innovation and Technology
UNU-MERIT

UNU-MERIT Working Papers intend to disseminate preliminary results of research carried out at UNU-MERIT to stimulate discussion on the issues raised.

The UNU-MERIT WORKING Paper Series

2022-01 *Structural transformations and cumulative causation towards an evolutionary micro-foundation of the Kaldorian growth model* by André Lorentz, Tommaso Ciarli, Maria Savona and Marco Valente

2022-02 *Estimation of a production function with domestic and foreign capital stock* by Thomas Ziesemer

2022-03 *Automation and related technologies: A mapping of the new knowledge* base by Enrico Santarelli, Jacopo Staccioli and Marco Vivarelli

2022-04 *The old-age pension household replacement rate in Belgium* by Alessio J.G. Brown and Anne-Lore Fraikin

2022-05 *Globalisation increased trust in northern and western Europe between 2002 and 2018* by Loesje Verhoeven and Jo Ritzen

2022-06 *Globalisation and financialisation in the Netherlands, 1995 – 2020* by Joan Muysken and Huub Meijers

2022-07 *Import penetration and manufacturing employment: Evidence from Africa* by Solomon Owusu, Gideon Ndubuisi and Emmanuel B. Mensah

2022-08 *Advanced digital technologies and industrial resilience during the COVID-19 pandemic: A firm-level perspective* by Elisa Calza Alejandro Lavopa and Ligia Zagato

2022-09 *The reckoning of sexual violence and corruption: A gendered study of sextortion in migration to South Africa* by Ashleigh Bicker Caarten, Loes van Heugten and Ortrun Merkle

2022-10 *The productive role of social policy* by Omar Rodríguez Torres

2022-11 *Some new views on product space and related diversification* by Önder Nomaler and Bart Verspagen

2022-12 *The multidimensional impacts of the Conditional Cash Transfer program Juntos in Peru* by Ricardo Morel and Liz Girón

2022-13 *Semi-endogenous growth in a non-Walrasian DSEM for Brazil: Estimation and simulation of changes in foreign income, human capital, R&D, and terms of trade* by Thomas H.W.Ziesemer

2022-14 *Routine-biased technological change and employee outcomes after mass layoffs: Evidence from Brazil* by Antonio Martins-Neto, Xavier Cirera and Alex Coad

2022-15 *The canonical correlation complexity method* by Önder Nomaler & Bart Verspagen

2022-16 *Canonical correlation complexity of European regions* by Önder Nomaler & Bart Verspagen

2022-17 *Quantile return and volatility connectedness among Non-Fungible Tokens (NFTs) and (un)conventional assets* by Christian Urom, Gideon Ndubuisi and Khaled Guesmi

2022-18 *How do Firms Innovate in Latin America? Identification of Innovation Strategies and Their Main Adoption Determinants* by Fernando Vargas

2022-19 *Remittance dependence, support for taxation and quality of public services in Africa* by Maty Konte and Gideon Ndubuisi

2022-20 *Harmonized Latin American innovation Surveys Database (LAIS): Firm-level microdata for the study of innovation* by Fernando Vargas, Charlotte Guillard, Mónica Salazar and Gustavo A. Crespi

2022-21 *Automation exposure and implications in advanced and developing countries across gender, age, and skills* by Hubert Nii-Aponsah

2022-22 *Sextortion in access to WASH services in selected regions of Bangladesh* by Ortrun Merkle, Umrbek Allakulov and Debora Gonzalez

2022-23 *Complexity research in economics: past, present and future* by Önder Nomaler & Bart Verspagen

2022-24 *Technology adoption, innovation policy and catching-up* by Juan R. Perilla and Thomas H. W. Ziesemer

2022-25 *Exogenous shocks and proactive resilience in the EU: The case of the Recovery and Resilience Facility* by Anthony Bartzokas, Renato Giacon and Corrado Macchiarelli

2022-26 *A chance for optimism: Engineering the break away from the downward spiral in trust and social cohesion or keeping the fish from disappearing* by Jo Ritzen and Eleonora Nillesen

2022-27 Dynamic dependence between clean investments and economic policy uncertainty by Christian Urom, Hela Mzoughi, Gideon Ndubuisi and Khaled Guesmi