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Exploring the ripple effect: Time-frequency dynamics of uncertainty indexes, green bonds, oil, and stocks

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Abstract.

This study investigates the dynamic risk spillover among several uncertainty indices—trade policy uncertainty (TPU), financial policy uncertainty (FPU), and monetary policy uncertainty (MPU)—as well as WTI crude oil prices, the S&P500 stock market, and US green bonds. Utilizing graph theory and the TVP-VAR model, our findings indicate that WTI crude oil, green bonds, and S&P500 stock market returns predominantly act as net transmitters of shocks within the network. In contrast, TPU, FPU, and MPU generally serve as net receivers of these shocks. According to the TVP-VAR-DY analysis, green bonds provide significant benefits for portfolio diversification over the sample period. Nonetheless, the novel graph theory approach reveals that green bonds are not ideal diversifiers in the short term. Additionally, MPU exhibits the highest out-degree in the short term, while FPU shows the highest out-degree in the medium and long term. These results demonstrate the importance of different mathematical approaches, offering valuable insights for investors, policymakers, and academics.

Keywords: Green bonds, stock market, oil, uncertainty index, TVP-VAR and graph theory.

Gel classification: G14

1. Introduction

The attention policymakers give to the environmental issues of economic development has increased due to their compounding effects. In this regard, governments and international institutions have made significant efforts in green investment to address these issues. As a result, green financing has expanded at a considerable pace, particularly in recent decades. Since green bonds offer both economic and environmental benefits, they have become one of the most important green financing instruments and one of the most effective methods for financing the transition to low-carbon economies (Ouyang et al., 2023; Xu et al., 2023; Srivastava et al., 2022; Monasterolo & Raberto, 2018). Considering the important role played by green financing in reducing carbon emissions, as well as the effect of uncertainty policies on green financing, then investigating the role of these variables represents a priority of researchers and policymakers (Su et al., 2022; Khan et al., 2022; Kamal & Hassan, 2022). However, this issue has become a trade-off between economic development and the environment for countries that are on the path to industrialization, and therefore, achieving economic development is a priority for these countries (Zhang et al., 2022; Tian et al., 2020).

Regarding the green bonds, several factors influence the performance of this market, and among the most important of these factors, we can point out uncertainties in various economic fields and the price of oil, which significantly have affected the volatility of financial markets (Eissa et al., 2024; Ahmed et al., 2023; Pham & Nguyen, 2022; Long et al., 2022; Rodriguez et al., 2022; Chousa et al., 2021; Roboredo & Ugolini, 2020; Demirer et al., 2020). On the other hand, examining the dynamic connectedness size and direction between oil prices, macroeconomic variables, and financial markets is fundamental for funds allocation and risk management in recent years (He et al., 2024; Luo et al., 2024; Omri et al., 2024; Jiang et al., 2020; Lee et al., 2020).

The energy sector plays a significant role in all activities on the demand side of the economy, such as industrial activities, transportation, and household consumption (Mensi et al., 2023; Kruel & Ceretta, 2022). With the increase in energy demand and the subsequent release of more carbon dioxide, as well as the rise in global warming, this sector must be adjusted to the environmental requirements (Sadorsky, 2009). Therefore, green bonds can play a vital role in financing sustainable infrastructure. In 2007, in response to serious environmental crises, the green financing mechanism was introduced by the European Investment Bank (EIB). The purpose of green financing has been to finance green projects, such as low-carbon, energy-efficient, and climate-friendly projects (Nguyen et al., 2021).

Therefore, it is necessary to examine the risk spillover between various types of economic uncertainties, oil prices, the stock market, and green bond returns in the US market. This can show which categories of uncertainties in trade, monetary, and financial policies, along with the oil price and the US stock market return, can transfer more risk to the green bond market.

Theoretically, two hypotheses explain the spillover phenomenon. The fundamentals-based hypothesis is the first, which argues that asset prices form fundamentally (such as raising capital, acquisitions, and mergers) and induce a sequential spillover effect between financial assets in different economies. On the contrary, the investor-induced hypothesis shows that the spillover effect between international financial assets is related to investor behavior, which may be the source of contagion behavior (Mensi et al., 2022).

Based on this background, this paper aims to investigate the static and dynamic spillover effects among various uncertainties in the economic policy including financial policy uncertainty (FPU), monetary policy uncertainty (MPU), trade policy uncertainty (TPU), oil price growth rate, the green bonds (GB), and the S&P500 stock return (Stock) in the US, using the quantitative risk spillover approach as well as the graph theory as a mathematical approach implemented for the first time.

This paper uses high-frequency data from January 5, 2013, up to November 22, 2022, which considers major economic and geopolitical events in recent years. To the best of our knowledge, in graph theory approach, unlike other previous studies that used graph theory based on correlation between indicators (Saha et al., 2022; Di Cerbo & Taylor, 2021; Ji & Fan, 2016), the TVP-VAR- Barunik and Krehlik (2018) technique is used. The reason for applying this technique is that the network indicators receive and transmit their effects to each other and the correlation approach does not specify the interconnectedness between them and it only shows the co-movement within the network, so it does not provide robust results. As a result, in this paper, the TVP-VAR-BK approach is used to calculate the edge weights in the graph theory results to analyze the net effect between return series. In addition, one of the weaknesses of graph theory results in previous studies investigating the spillover effect between types of assets is that it provides static results. However, the interrelationship within the network in different time horizons is very important for policymakers and investors. As a result, by applying the TVP-VAR-BK technique in graph theory, dynamic results can be obtained in relation to the interconnectedness between assets, which has significant policy applications for investors and policymakers. Therefore, this paper provides novel results about the BORUVKA-KRUSKAL algorithm in graph theory and fills in the gap in this research field. In this case, investors and speculators with different risk appetites and investment horizons can make better decisions, especially during market turmoil, considering that the US has the largest financial market in the world and is a key player in global financial and emerging equity markets. Moreover, our findings are attractive to investors who seek risk coverage, optimal investment portfolio, and portfolio diversification benefits. In addition, since the policies adopted in the US and the uncertainties resulting from these policies have strong effects on the financial markets of the world (Akinci & Queralto, 2024), the results of this research can be useful and important not only for investors but also for policymakers. Overall, in this research, we seek to show whether investors use green bonds to hedge risk in their portfolio assets including stocks and oil in the presence of various policy uncertainties.

A large body of the studies in the literature addresses the impact of economic policy uncertainty (EPU) and the oil price on green financing as well as carbon emissions, but a few of them investigate the risk spillover between various economic uncertainties and green bonds, especially in extreme conditions. To the best of our knowledge, no study has used the BORUVKA-KRUSKAL algorithm in the graph theory to investigate the connectedness between various economic uncertainties, oil prices, stock, and the green bonds market returns. To be more precise, it should be noted that in the prior approaches that were used in previous studies, the effects of risk spillover have been examined, but in these approaches, it is not possible to determine the direct or indirect transfer of risk between assets, which can be important for policy makers and investors. In addition, the risk contagion between traditional and green bond markets can be affected by various economic policy uncertainties, which will lead to misleading results if they are not considered in the network.

Our results reveal that oil prices and stock market returns are the main net transmitters of shocks to the network. However, trade and monetary policy uncertainties are the main receivers of shocks from the network. Our findings also confirm that all of the policy uncertainty indices are purely receivers of risk, and on the contrary, oil, stock, and green bonds are net transmitters of volatilities to the network. Moreover, green bonds have the weakest net connectedness within the network, therefore, can be used as a portfolio diversifier in portfolios in the presence of all kinds of policy uncertainties. On the other hand, the results of the novel graph theory show that in the longer period, FPU plays the main role in transferring volatilities to the network. Moreover, in the medium term and following FPU, we find that MPU, TPU, and oil returns have the most out degrees in this time span. In the long term, FPU has four outgoing edges, while TPU has only one outdegree; however, the rest of the series have no outdegrees.

Thus, based on the graph theory results, the policy uncertainties considered in this study play a significant role in transferring volatilities to other assets, which underscores the importance of macroeconomic policies in the risk management of asset markets. Moreover, the results of the graph theory in the case of green bonds show that these bonds cannot be considered a good diversifier in a portfolio, especially in the short-term. Consequently, concerning our results in both approaches, our findings based on TVP-VAR-DY are different from what we acquire from the graph theory analysis. This outcome shows that different results can be obtained in a mathematical approach from an econometric methodology, which is of importance for investors and policy makers, and also scholars in their future studies.

Our contributions, which have substantial implications for policymakers, regulators and market participants, are as follows. **(1)** In contrast to other studies, the static risk spillover effects between the different economic uncertainties (including monetary, financial, and trade policy uncertainties), oil prices, the US stock market, and green bond returns have been investigated using the TVP-VAR-DY approach. Moreover, we can observe the pairwise and total connectedness during a considerable time span in which most of the significant events that can affect the spillover in the network are considered. Therefore, this research can provide significant implications for investors with different risk appetites, who seek to manage risk and diversify their portfolios. Moreover, our findings can be beneficial for policy makers to help find out the impacts of different policy uncertainties on asset markets. (**2)** As far as we know, this is the first research that uses the graph theory based on the TVP-VAR-Diebold-Yilmaz (2012) technique as a novel mathematical approach to determine the dynamic risk contagion among green bonds, major traditional asset returns, and economic uncertainties in different investment horizons. Therefore, this research provides fresh evidence about the static and dynamic connectedness between policy uncertainties and main assets (including green bonds, oil, and S&P stock market returns) in the US equity market using these two approaches. (**3)** Moreover, the graph theory as an alternative approach is used to identify the direct or indirect dynamic spillover effects in the network in three investment horizons. As a result, different findings that we achieved from applying the mathematical and TVP-VAR-DY approaches in the network, have important implications for investors and policy makers who seek to find the optimal investment strategies and for scholars in their future studies.

The remainder of this paper is organized as follows. The literature review is presented in Section 2. The data description and methodology are provided in Section 3 and 4. The experimental results are discussed in Section 5. The conclusion and policy suggestions are offered in Section 6.

2. Literature Review

A large body of literature investigates the economic consequences of various uncertainties in the economy and financial markets (Adil & Roy, 2024; Hasan et al., 2023; Tsagkanos et al., 2022). However, the considerable strand of literature addresses the connectedness between economic policy uncertainty (EPU) and carbon emissions (e.g., Jiang et al., 2019; Wang et al., 2020; Sohail et al., 2021; yu et al., 2021; Ayhan et al., 2023; Wu and Qin, 2024). Some studies have examined this relationship from the perspective of the indirect effect of economic policy uncertainty on CO_2 emission. They find that economic policy uncertainty affects the business environment. On the other hand, carbon dioxide emissions are closely linked to production-related decisions of economic entities. Therefore, from this direction, economic policy uncertainty affects the amount of CO_2 emissions. (Jiang et al., 2019). Other studies find a relationship between the policy uncertainty index and CO_2 emissions, which was caused by both the consumption and investment effects (Wang et al., 2020), through the innovation channel (Liu et al., 2021, Zhang et al., 2020), the share of fossil fuels in total energy consumption channel and energy intensity (Yu et al., 2021). More precisely, several research strands have been conducted to review the literature. In the first strand, researchers examine the relationship between various uncertainties and green bonds. However, in this paper, we focus on various categories of economic policy uncertainty, including monetary policy uncertainty (MPU), financial policy uncertainty (FPU), and trade policy uncertainty (TPU). Additionally, we examine oil prices and S&P stock market returns in the US economy.

Wang et al. (2024) addresses the dynamic connectedness among policy uncertainties including monetary, economic, and climate policy and green finance. They focus on green finance issues as a crucial environmental challenge for sustainable development goals. They argue that green finance is affected by policy uncertainties through market stability and investment. Consequently, their empirical results show that monetary and economic policies affected green sustainable finance.

Pham and Nguyen (2022) investigate the effect of economic policy uncertainty (EPU), stock market uncertainty (VIX), and oil price uncertainty (OVX) on the yields of four green bonds. The results show that there is a time-varying and regime-dependent relationship between green bonds and the uncertainties under consideration. During periods of low uncertainty, green bonds and uncertainty are weakly linked, thereby green bonds can be used to hedge against uncertainty. The diversification benefits however are lower during periods of high uncertainty. Long et al. (2022), investigate the quantitative relationship between the stock market uncertainty (VIX), oil market uncertainty (OVX), and green bond market performance in the US, China, and Europe, using the quantile VAR approach. Those authors find that the spillover effects in extreme market conditions are larger than in normal market conditions. They also reveal that VIX and OVX have a higher impact on green bonds, particularly in extreme upward markets. Moreover, the US is the dominant transmitter of spillovers in other green bond markets, while China is constantly the net receiver of the spillovers. Finally, the authors show that the connectedness between green bonds and uncertainties is time-varying and the spillovers at extreme upper and lower quantiles are asymmetric and heterogeneous, especially in the early days of the COVID-19 pandemic. As for Pineiro-Chousa et al. (2021), they show that VIX did not affect the green bond market. Also, within the wavelet-based quantile dependence framework, Wei et al. (2022) demonstrate that the Granger causality from EPU to the green bond market is non-linear and contrasts across time scales. They also show that EPU has no effect on green bonds in the short term, but it has a negative effect in the long term.

Several studies have also investigated the relationship between OVX and the green bond market. Yousaf et al. (2024) investigate the connectedness and dynamic spillover between the green bonds market and crude oil. Using BK-18, DCC-GARCH, BEKK-GJR, and Wavelet coherence methods, they focus on dynamic spillover and transmission of volatility between green bond returns and crude oil. They show different results from applying the aforementioned techniques. Nevertheless, the hedging effectiveness results reveal that green bonds-crude oil-based portfolios benefit portfolio managers and investors who seek portfolio diversification. Using the nonlinear ARDL model, Tian et al. (2022) examine the asymmetric effects of OVX, climate policy uncertainty (CPU), infectious disease equity market volatility (IDEMV), and geopolitical risks (GPR) on green bond prices in the US, Europe, and China. They show that OVX had an asymmetric long-term effect on green bonds in Europe and the US, but it had a symmetric effect in China. In the short-run, only China's green bond market is asymmetrically impacted by uncertainties, while in the long-run, the asymmetric effect displayed by the European green bond market is more widespread and shares comparable features to that of the US.

Other studies have been conducted in the field of the relationship between oil prices and green bonds as more recent studies have paid more attention to green bonds than conventional bonds (Ehlers and Packer, 2017; Dutta et al., 2021; Lee et al., 2021; Liu et al., 2024; Banerjee et al., 2024). Previous studies have investigated the relationship between green bonds and financial markets for portfolio and hedging issues. Roboredo (2018) investigate the co-movement between the green bond and financial markets, using the Copula function and conditional diversification measures. This author find that the green bond market connects with corporate and Treasury bond markets and co-moves with the stock and energy commodity markets. He also finds that green bonds have small diversification benefits for investors in corporate and Treasury markets, while the diversification benefits are substantial for investors in the stock and energy markets. He also confirms that green bonds are influenced by substantial price spillovers from corporate and Treasury fixed-income markets and that large price swings in stock and energy markets have a slight impact on green bond prices.

Roboredo and Ugolini (2020) study the price connectedness between green bonds and financial markets, using a structural vector autoregressive (VAR) model. Using heteroskedasticity to identify the structural VAR model parameters, those authors show that the green bond market is closely linked to the fixed-income and currency markets, thereby receiving substantial price spillovers from those markets and transmitting slight reverse effects. They also show that, in contrast, the green bond market is weakly connected to the energy, stock, and high-yield corporate bond markets.

Roboredo et al. (2020) investigates the spillover between green bonds and financial markets of the United States and the European Union during different time scales. Those authors conclude that green bonds, Treasury, and corporate bonds are related to each other in the short and long terms in the United States and the European Union. Also, green bonds have a weak relationship with corporate bonds, stock market, and energy in all time scales.

Hammoudeh et al. (2020) examine the time-varying relationship between green bonds and three financial assets, the 10-year US Treasury bond index, the WilderHill clean energy stock index, and the price of CO_2 emission permits, using the novel time-varying Granger causality test. The results show that there is a unidirectional Granger causality from these three assets to green bonds in different periods. The authors also find that the causality running from the clean energy index to green bonds is very limited to the year 2019. On the other hand, there is no significant causality running from green bonds to all financial assets under consideration.

A study on the lack of research on how to transfer risk between different uncertainties in various areas of the economy, such as monetary policy uncertainty, financial policy uncertainty, and trade policy uncertainty, along with stock and oil returns, to the green bond market can help fill the gap in the existing literature.

3. Data and preliminary analysis

This study uses three important uncertainty indexes namely monetary policy uncertainty (MPU), financial policy uncertainty (FPU), and trade policy uncertainty (TPU), the West Texas Intermediate (WTI) oil futures prices, the S&P500 index, and the US green bonds return[1]. The sample data ranges from January 5, 2013 to November 22, 2022, and covers major financial, economic and geopolitical events. The daily data related to the policy uncertainty indexes are extracted from the policy uncertainty website, the green bonds from the S&P Global website and the other series are from the Federal Reserve economic data.

As shown in Figure 1, all three kinds of economic uncertainties have experienced a considerable volatility during the sample period. However, we observe a moderate volatilities in the case of oil, S&P stock market, and green bonds returns in the entire period. Moreover, oil and stock returns decreased significantly in the Covid-19 outbreak in the first months of 2020. Furthermore, oil, stock, and GB returns have decreased at the onset of Russia-Ukraine war in early 2022; however, this trend get reversed, and the returns experienced an upward trend afterwards.

١. The price return formula is Ln (Pt/Pt-1), which shows the continuously compounded return of each series.

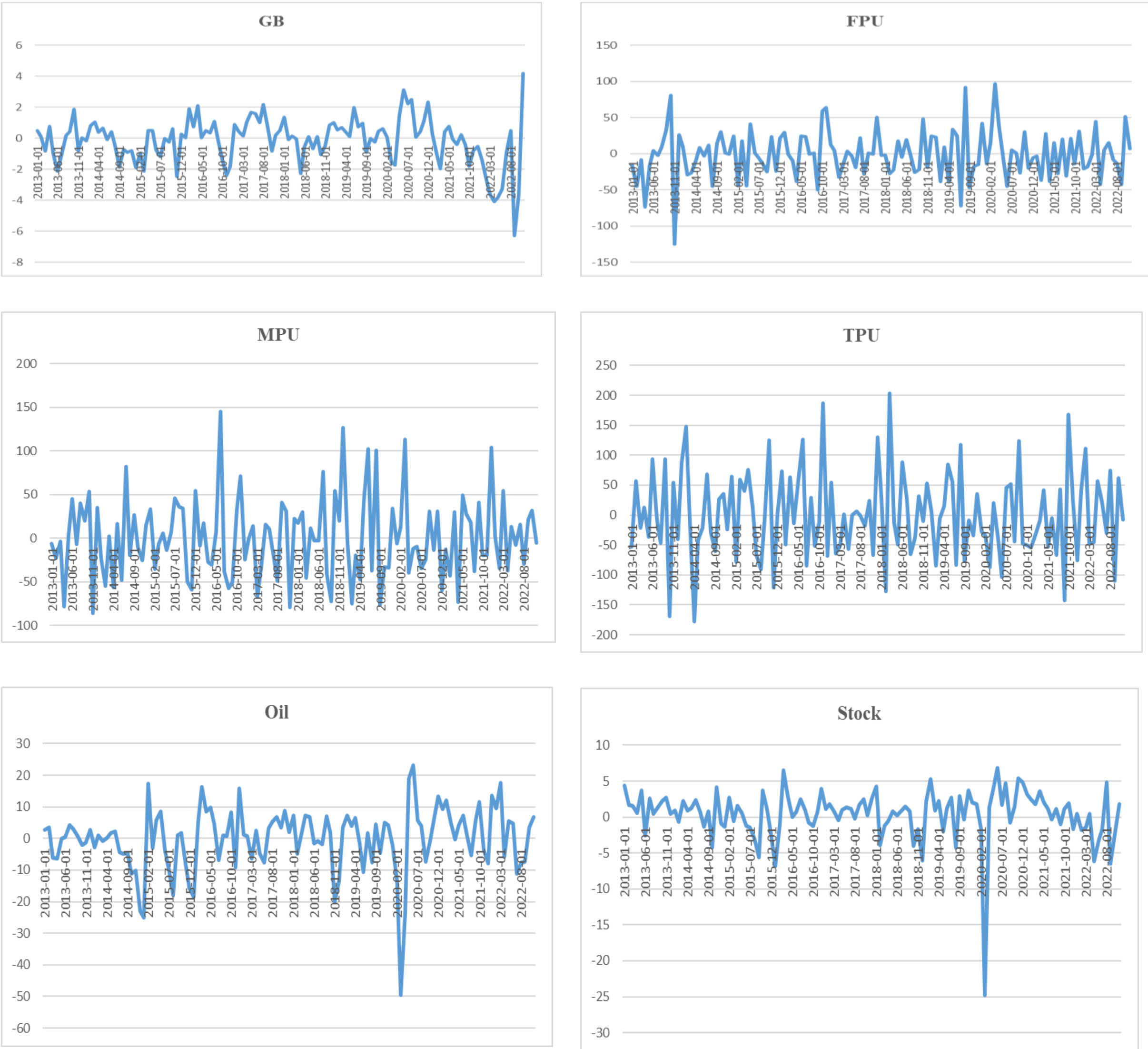

Figure 1. Dynamic returns of GB, FPU, MPU, TPU, Stock, and oil

Table 1 represents the descriptive statistics and unit root tests for all series. As shown in this table, MPU, TPU, and the S&P stock return (Stock) have positive mean; however, GB (the S&P green bonds return), FPU index and the growth rate of oil price have a negative mean. The TPU index is the most volatile variable, whereas GB depicts the lowest unconditional volatility. The skewness values report evidence of asymmetry for GB, MPU, Oil, and Stock. Despite that, we can see the evidence of symmetry for FPU and TPU. The results show significant positive skewness only for MPU; therefore, this is not a risky asset in comparison to other assets during the sample period. The kurtosis values indicate that all returns except MPU and TPU follow a leptokurtic distribution and have fat tails. The excess kurtosis values are positive and greater than zero, indicating that the indices have peaks relative to the normal distribution and, therefore, they are not distributed normally. Moreover, the Jarque-Bera (JB) test exhibits a non-normality distribution for all returns series other than TPU. Finally, the ERS criterion (which is related to the unit root test) shows that all the returns are stationary at the normal level.

Table 1. Descriptive statistics of return series

	GB	**FPU**	**MPU**	**TPU**	**Oil**	**Stock**
Mean	-0.141	-0.954	0.528	0.784	-0.074	0.453
Variance	2.3***	1091.6***	2092.9***	5129.4***	97.5***	12.3***
Skewness	-0.75***	-0.014	0.57**	0.28	-1.26***	-3.27***
Ex.Kurtosis	2.17***	1.54***	0.44	0.13	4.6***	20.8***
JB	34.7***	11.7***	7.43**	1.65	136.9***	2364.2***
ERS	-2.67***	-4.005***	-6.75***	-2.59***	-4.43***	-2.03**

Notes:
(1) ** and *** denote significance at the 5 and 1 percent, respectively.
(2) GB is the S&P green bonds index, FBU is the financial policy uncertainty index, MPU is the monetary policy uncertainty index, TPU is the trade policy uncertainty index, and Stock is the S&P stock return. X, JB is the Jarque-Bera statistic for the normality test and ERS is the Elliott, Rothenberg, and Stock unit root test.

Figure 2 reports the results of the pairwise correlations among research series. We notice that almost all indictors have fat tails with leptokurtic distribution. Figure 1 underlines the existence of a significant and highest correlation between the Stock and the oil price, and this value is 0.59. The pair of FPU and MPU pair exhibits the weakest correlation, which is equal to 0.52. In the end, there are insignificant correlations between other pairs of assets.

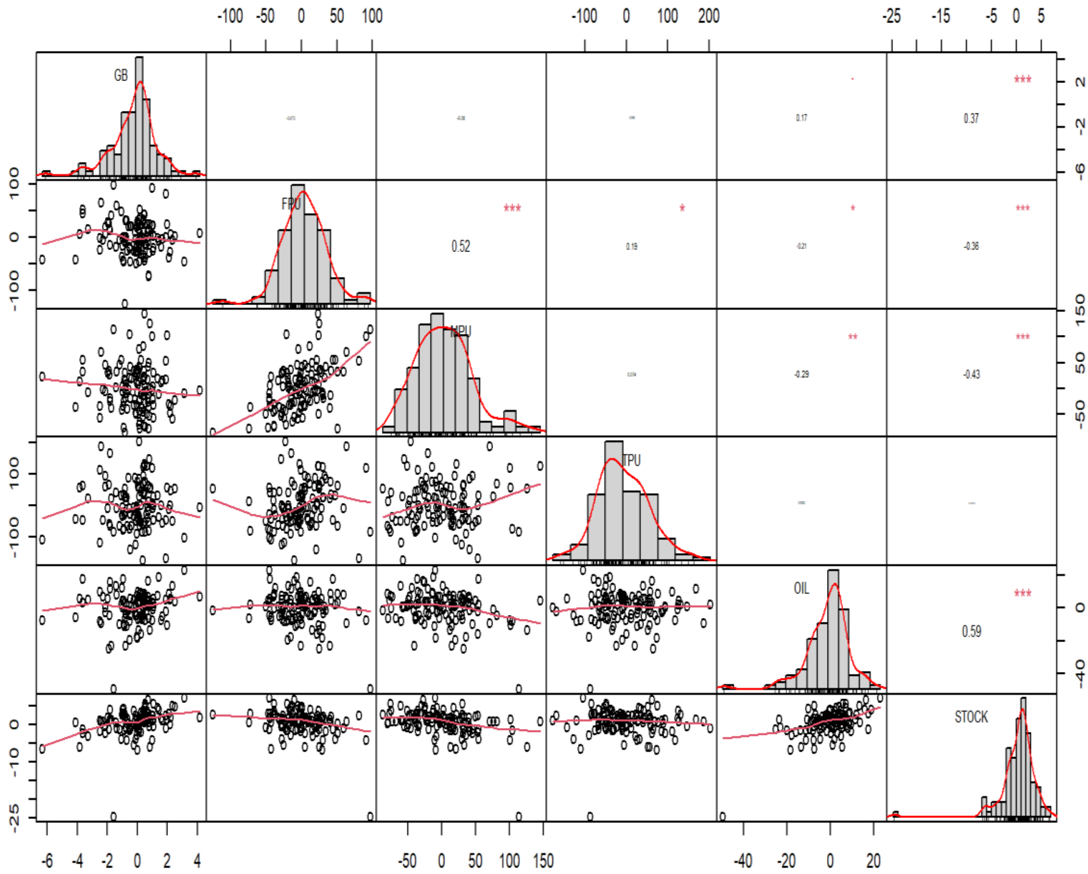

Fig. 2. Pairwise correlations of the return series

Notes: GB, FPU, MPU, TPU, OIL, and STOCK are the indices of the green bond returns, financial policy uncertainty, monetary policy uncertainty, trade policy uncertainty, oil price growth rate, and S&P stock market returns. The small graphs with black dots show the pairwise correlations between assets.

4. Methodology

At first, the risk spillover between the research series has been examined using the TVP-VAR-Diebold-Yilmaz (2012) model. Also, the TVP-VAR-Barunik-Křehlík (2018) model has been used to determine the weights in different time-frequencies to check the centrality as well as the spanning tree in the graph theory[2].

It should be noted that the Diebold -Yilmaz (DY) model in comparison to other econometric models attracts many researchers to investigate inseparable connectedness amidst financial assets. This methodology is suitable for scholars to evaluate network interrelationships between different return series in financial markets in both static and dynamic conditions. It is noteworthy that this approach is different from previous techniques such as VAR models (which only provide static results) and rolling-window VAR models

[۲] To read about the graph theory, refer to Bondy & Murty (2008).

(which provide dynamic results). The TVP-VAR-DY approach was initially put forward by Antonakakis et al. (2020), which benefits from the TVP-VAR version based on the VAR model and not based on the rolling window model. Therefore, the results of this approach are more robust considering that there exists a steady rolling window size. One of the major advantages of this approach is that it eliminates sensitivity to the loss of observations and deviations which is due to using the underlying Kalman filter. Moreover, there is no need to choose the size of the rolling window indiscriminately. Thirdly, there are no missing observations, and finally, the latest advantage of the TVP-VAR approach is related to the collected data so that in this method it is not necessary to enter high-frequency data. It should be noted that all variables have been used as growth rates according to Eq. (1):

$$\left(\frac{t_1 - t_0}{t_0}\right)*100 \tag{1}$$

Based on the Bayesian Information Criterion (BIC), we can represent a dynamic TVP-VAR to explore the time-varying transmission between variables. In the following, we provide its explanation:

$$V_t = \beta_t V_{t-1} + \gamma_t\,,\ \ \gamma_t \sim \mathrm{N}\,(0, D_t) \tag{2}$$

$$\mathrm{vec}\,(B_t) = \mathrm{vec}\,(B_{t-1}) + \mu_t\,,\ \ \mu_t \sim \mathrm{N}\,(0, P_t) \tag{3}$$

where V_t and vec (B_t) are vectors of all variables with different dimensions.

It should be noted that the vectors of V_t, V_{t-1} , together with γ_t are of K×1 dimensions. Other elements are β_t and D_t, which are typical of the K× K dimensional matrixes in Eq. (2). In Eq. (3), vec (B_t) and μ_t represent vectors, that are of the k^2×1 dimensions. Moreover, P_t is a matrix with different dimensions ($k^2 \times k^2$).

Subsequently, the H-step ahead (scaled) Generalized Forecast Error Variance Decomposition (GFEVD) is measured. It assumes that the variable ordering is invariable which is just opposite to orthogonal Forecast Error Variance Decomposition. This version is based on the Wold representation theorem. In this theorem the calculated TVP-VAR approach is transferred to a TVP-VMA process using the below equality:

$$V_t = \sum_{i=1}^{p} B_{it}\ v_{t-i} + \gamma_t = \sum_{j=0}^{\infty} S_{jt}\ \gamma_{t-j} \tag{4}$$

where S_{jt} is the moving average coefficient. Afterward, it is essential to acquire a degree of unity in each row using (the scaled) GFEVD. To that aim, it is necessary to make (unscaled) GFEVD and variance $\sigma^{f}_{ij,t}$ into a normal state. To simplify, $\sigma^{f}_{ij,t}$ (H) informs us about how much asset j is subject to asset i, concerning its share of forecast error variance. To reach this goal, it is crucial to utilize the directional connectedness from j to i, as follows:

$$\sigma^{f}_{ij,t}(H) = \frac{D^{-1}_{ii,t}\sum_{t=1}^{H-1}(l' S_t l_j)^2}{\sum_{j=1}^{k}\sum_{t=1}^{H-1} l_i D_t S_t' l_i} \quad (5a) \ , \ \sigma^{f\prime}_{ij,t}(H) = \frac{\sigma^{f}_{ij,t}(H)}{\sum_{j=1}^{k}\sigma^{f}_{ij,t}(H)} \tag{5}$$

$$\sum_{j=1}^{k}\sigma^{f\prime}_{ij,t}(H) = 1, \sum_{i,j=1}^{k}\sigma^{f\prime}_{ij,t}(H) = k \tag{6}$$

We can make the extraction of spillover calculations in terms of the DY more understandable using the GFEVD. About Eq. (6), spillover is defined as follows:

$$TO_{jt} = \sum_{i=1, i\neq j}^{k}\sigma^{f\prime}_{ij,t}(H) \tag{7}$$

$$FROM_{jt} = \sum_{i=1, i\neq j}^{k}\sigma^{f\prime}_{ji,t}(H) \tag{8}$$

$$NET_{jt} = TO_{jt} - FROM_{jt} \tag{9}$$

$$TCI_t = k^{-1}\sum_{j=1}^{k} TO_{jt} = k^{-1}\sum_{j=1}^{k} FROM_{jt} \tag{10}$$

$$NPDC_{ij,t} = \sigma^{f\prime}_{ij,t}(H) - \sigma^{f\prime}_{ji,t}(H) \tag{11}$$

The total directional interconnection from variable j to other variables is presented by Eq. (7). To be more precise, it evaluates the aggregate effect of transferring a shock from variable j to the network of variables. In the next step, Eq. (8) represents the total effect of all other network variables on variable j. Eq. (9) denotes the net effect of a variable in the network, i.e. it shows whether this variable is a net transmitter or a net receiver according to the sign of NET_{jt}. Therefore, if it is positive (negative), variable j will be the net transmitter (net receiver) in the network. The magnitude of connectedness between variables is depicted by Eq. (10). It simply gives significant information about the level of risk contagion in a system. As a result, if its value is high, it will show that there exists considerable shock transmission between network variables in the sample period.

Finally, Eq. (11) explores the net impact of variable i on variable j which identifies the net directional interconnection between each pair of variables. Considering the sign of $NPDC_{ij,t}$, we can be aware of the role of each variable with the other one. Therefore, if it is positive, we can conclude that variable i is affected by variable j and vice versa for a negative sign of $NPDC_{ij,t}$.

5. Results and Discussion

Table 2 shows the results of the static spillover within the network. Regarding this table, the US stock market return is the main transmitter to the network. Our results show that it imposes the main force (60.95%) on the network, followed by Oil (57.22%), FPU (49.16%), MPU (48.8%), GB (43.04%) and TPU (34.74%), which explain the volatility transmission to the network, respectively. On the other hand, based on the "from" results, the most sensitive asset compared to other assets is also Stock. Our findings show that about 54.43% percent of the volatility in stock market return is related to the network. The other indices have a lower sensitivity in comparison to the stock market index. Moreover, the results about the main net receiver and transmitter of shocks to the network, simply reveal that Oil is the major net volatility transmitter to the system in the sample period. However, our static findings suggest that TPU is the main net shock receiver in the network. Therefore, Oil cannot provide diversification benefits in the investment portfolio during this period.

To investigate the pairwise spillover effect among the assets, Stock is the most volatility shock transmitter to Oil. The spillover effect however is less in the case of the GB, which is 11.47%. It is noteworthy that TPU is the most transmitter of shocks to GB. However, the intensity of the effectiveness of GB from other policy uncertainties is less than that of the TPU shocks. Therefore, our findings underscore the importance of the US trade policy uncertainties in imposing shock to the green bond returns. Moreover, Stock is most affected by the Oil which is about 19.15 percent. This is consistent with Thorbecke (2019) who confirmed that the oil price is a driving factor in the fluctuations of the US stock market returns. Besides, Thorbecke (2019) depicted that the favorable impacts of the oil price have increased, and its harmful effects have also fallen because of the soaring trend of the US oil production after 2010 due to the shale oil revolution. Furthermore, our findings about the driving factors in the variations of Stock express that in contrast to other dimensions of political uncertainty, MPU has the greatest effect (11.79%) on volatilities in Stock.

The results about FPU reveal that it is most affected by the MPU. This result illustrates that the US financial policy uncertainties are the main factor in the variations of the monetary policy index. Thus, this highlights the decisive role of the uncertainties in the financial sector. Furthermore, MPU is mainly affected by FPU, and this underlines the significant nexus between these two indicators. TPU is also most affected by the FPU and this result emphasizes the dominant role of the financial policy uncertainty over other dimensions of policy uncertainty in this country. In total, the results related to Table 2 show that all of policy uncertainty indicators in the sample period are purely receivers of risk and on the contrary, Oil, Stock, and GB are net transmitters of volatilities to the network. In general, our results confirm that GB has benefits for portfolio diversification due to the weakest risk received from the network.

Finally, the total connectedness index (TCI) illustrates a high percentage of connection with the network (48.98%), which implies that there is a strong connectedness amongst GB, Stock, Oil, TPU, FPU, and MPU during the sample period. As a result, focusing on assets that have the lowest connection with other assets in the network (such as GB) can be beneficial for investors who seek risk management and portfolio diversification in the presence of policy uncertainties.

Table 2. Estimates of static spillovers

	GB	FPU	MPU	TPU	OIL	STOCK	From
GB	57.50	6.41	6.28	6.36	11.47	11.98	42.50
FPU	8.88	47.63	13.34	11.28	9.64	9.23	52.37
MPU	6.71	13.40	49.30	7.84	10.95	11.79	50.70
TPU	9.79	11.99	8.22	55.46	5.74	8.80	44.54
OIL	8.49	8.23	9.59	3.89	50.64	19.15	49.36
STOCK	9.17	9.13	11.35	5.37	19.42	45.57	54.43
To	43.04	49.16	48.78	34.74	57.22	60.95	293.90
NET	0.54	-3.21	-1.92	-9.80	7.87	6.52	TCI= 48.98

Notes: The spillovers are from the respective variables to the network which are in the "To" rows, while the spillovers from the network to the respective variables are in the "From" columns. NET is the difference between the "To" row and the "From" column.

5.1. The dynamic net spillover effect of each return series within the network

Figure 3 shows the net impact of the network returns, which can be a net transmitter or receiver of shocks in the network. Generally, it is necessary to say that in the spans where the graph is below the horizontal line, the variable under consideration is a net shock receiver; however, where the graph is above the horizontal line, the variable under consideration is a net transmitter of shocks to the network. The first shadow from the left is related to the net impact of GB on the network. The results show that GB had different impacts on the network during the January 2013 - November 2022 period. Based on the research findings, the GB return mainly received shocks from the network in the span of the Covid-19 pandemic during 2020-2021. However, since the beginning of the Russia-Ukraine conflict in the first months of 2022, its impact has changed and it has become mainly a net transmitter of shocks to the network.

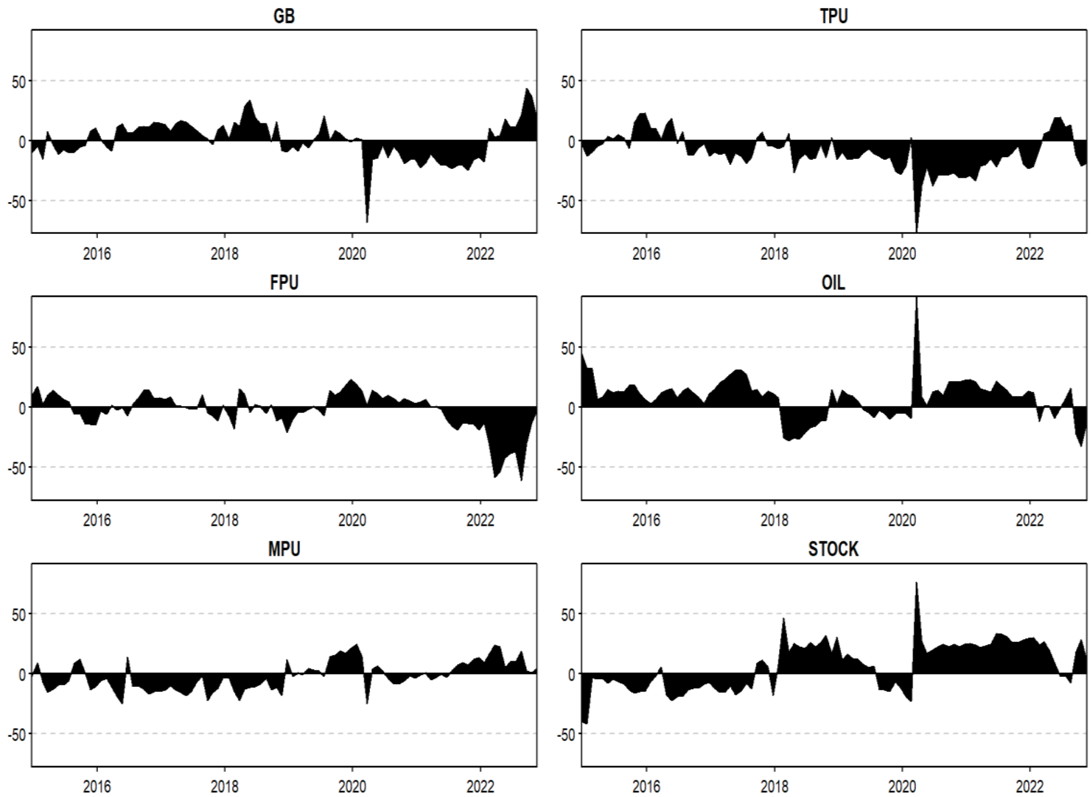

Fig. 3. Time-variations of the net spillover effects
Notes: (1) GB, FPU, MPU, TPU, OIL, and STOCK are indices of green bonds return, financial policy uncertainty, monetary policy uncertainty, trade policy uncertainty, the oil price, and the stock market returns. (2) The results are based on the TVP-VAR model with a lag length order of 1 (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

The TPU has generally played the role of the receiver in most years. However, only in a short period which is related to the US presidential election in 2016 and also during the Russia-Ukraine conflict in 2022, TPU almost became a transmitter of shocks to the network. As shown in Figure 3, the dynamic net spillover of the financial policy uncertainty (FPU) index in the network is mostly volatile. It is worth noting that FPU is a net transmitter of shocks during the Covid-19 pandemic. However, FPU received major shocks from the network during the Russia-Ukraine conflict in 2022. It explores that in the post-COVID-19 era and during the conflict, the uncertainty of financial policies in the US is affected by the uncertainty of other policies, besides GB, Oil, and the Stock.

The result of this study about the net shock transfer of Oil to the network shows that it is a shock transmitter to the network in the major period. However, in the final months of

2022, it turned out to be a shock receiver of the desired network. This indicates that during the period of the Covid-19 pandemic, before and after, Oil is a shock transmitter to the policy uncertainty indices, GB, and Stock. Our dynamic findings about MPU, simply, show that it is a net receiver of shocks from the network and just in 2019 and 2022 its role was reversed and became the net transmitter of a shock to the network (these periods are coincident with increasing investors' concerns about a future decline in the US economic growth and the Russia and Ukraine conflict, respectively). Finally, our results about Stock reveal that it receives major shocks from the network in 2018 and 2020-2022, especially during the Covid-19 outbreak.

In total, based on Figure 3, we should confirm that the reaction of GB, TPU, Oil, and Stock is much more significant to the Covid-19 pandemic, compared to the other indicators. On the other hand, FPU shows the most reaction against the Russia-Ukraine war during the sample period.

5.2. The dynamic spillover effect from return series to the network

Figure 4 shows the impact of each asset on the network in the sample period. The results about GB suggest that its impact increased considerably during the US presidential election in 2016 and especially throughout the Russia-Ukraine conflict in 2022. Moreover, it experienced an upward trend from the middle of 2021 up to the end of 2022, underscoring that the impact of the network on GB has increased in the post-COVID-19 era. The results of TPU indicate that its impact on the network experienced an upward sharp trend in 2016, 2018, 2020, and finally in 2022, which are related to the US presidential election, the expansion in the US economy due to tax cuts by government and stimulation in total demand, Covid-19 outbreak, and the Russia-Ukraine conflict. Therefore, TPU is considerably sensitive to major events in the sampling period. Research findings about the impact of FPU on the network prove that it, despite its high impact on the network in the sample period, experienced a significant decrease at the beginning of 2019 which is related to a considerable decline in the US economic growth because of a decrease in growth rate of investment and consumption against the previous year. Based on the Federal Reserve report (2019), the US nominal Treasury yields decreased significantly during the first half of 2019, which led to increasing investors' concerns about the future. Thus, financial investments slowed during this period, and this fact confirms the drop in TPU impacts on the network in the first half of 2019.

Another decrease in the impacts of FPU on the network is related to the first months of 2022 which is related to the Russia-Ukraine conflict. Moreover, according to the report of the Federal Reserve (2022), a noticeable change in the monetary policies of the US government, which led to a 4% increase in the bank interest rates, took place in early 2020. Also, in the same period, by changing their overdraft policy, banks tried to attract people's financial resources to the banking system and increase savings so that they could reduce poverty. For this reason, in the first months of 2022, the impact of uncertainty resulting from the financial policies decreased, but on the other hand, as seen in Figure 3, the impact of the US MPU on the network is significant.

The effect of Stock on the network is also fluctuating during the sample period, although it experienced a significant decrease in the middle of 2022 which coincides with the Russia-Ukraine conflict. Moreover, the Stock and GB markets experienced the worst period in 2022 since the 2008 global financial crisis. In this year, following the Federal Reserve's decision to control inflation, interest rates increased, consequently, the prices of stocks and bonds fell sharply, despite the predictions made for them. Thus, this has caused a significant reduction in the impact of Stock on network.

Generally, our findings show that various economic uncertainties, and oil, S&P and GB returns are sensitive to shock events in the sampling period. Especially, we observed major shock transmitting from these series to the network during out-break of Covid-19. Therefore, investors and policy makers should pay attention to portfolio diversification during turmoil periods.

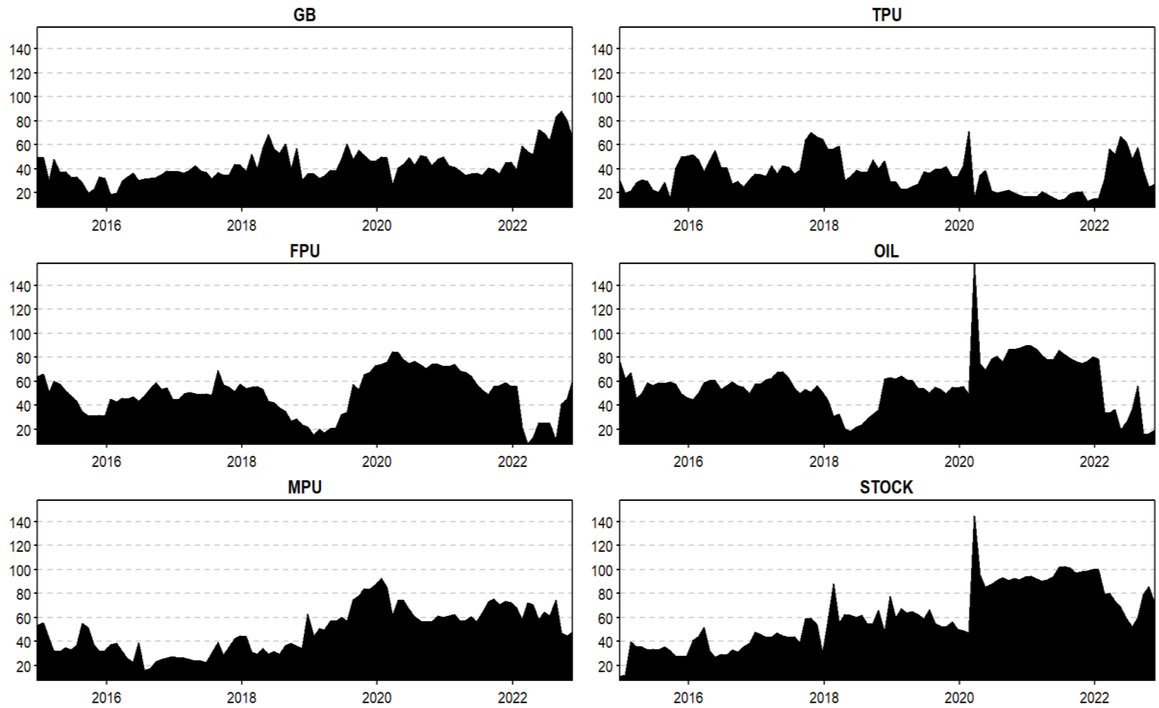

Fig. 4. Dynamic volatility spillovers

Notes: The results are based on the TVP-VAR model with a lag length order of 1 (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

5.3. Time-variations of the spillover effect from the network to each of return series:

Figure 5 shows the dynamic impact of the network on each of the return series in the sample period. As it is clear in this figure, the effectiveness of GB from the network has experienced a significant increase since 2016, which of course is associated with a sudden increase in early 2020. The most critical impact of the network on GB is coincident with the Covid-19 outbreak in 2020 which shows that more than 60 percent of green bonds volatilities are imposed by the network.

Moreover, the results of TPU show that its impact from network is increased from the end of 2019 to the beginning of 2020 and from 2022 onwards. The reason is related to the policies of reducing trading relations due to the spread of the Covid-19 pandemic and the onset of Russia-Ukraine conflict in 2022. The results about the FPU demonstrate that its effect from the network increased significantly from 2020 onwards. This period is coincident with the Covid-19 pandemic, the Russia and Ukraine in 2022 and implementation of contractionary monetary policies by the Federal Reserve (2022) and increase in the bank interest rates, which caused an acceleration in the effectiveness of the FPU from the network. We see similar about the influence of the network on Stock return. As shown in Figure 4, the effectiveness of Stock increases from 2020 until the end of 2022. We observe that it is also influenced by the change in the government's approach to the implementation of the new monetary policies, which has led to the high effectiveness of the stock market return within.

The effect of the network on the oil return started to increase in 2018, and this increase continued until the beginning of 2022. The growth rate of the oil return is strongly influenced by policy uncertainties, due to its financial attributes (Ding et al., 2022), and the results of this research confirm it. Furthermore, it should be noted that the impact of the network on Oil has reached 70 percent during the COVID-19 pandemic. The results related to MPU, simply, reveal that the impacts of the network on it become more significant during the outbreak of Covid-19. Moreover, the network spillover effect on MPU in 2022 shows MPU's sensitivity to the war between Russia and Ukraine., except for oil.

Generally, our findings indicate that all series were significantly influenced by the network during the COVID-19 outbreak. All series were affected by the network from the onset of the Russia-Ukraine war. Therefore, oil can be considered a hedging instrument against other assets in the network during the Russia-Ukraine conflict.

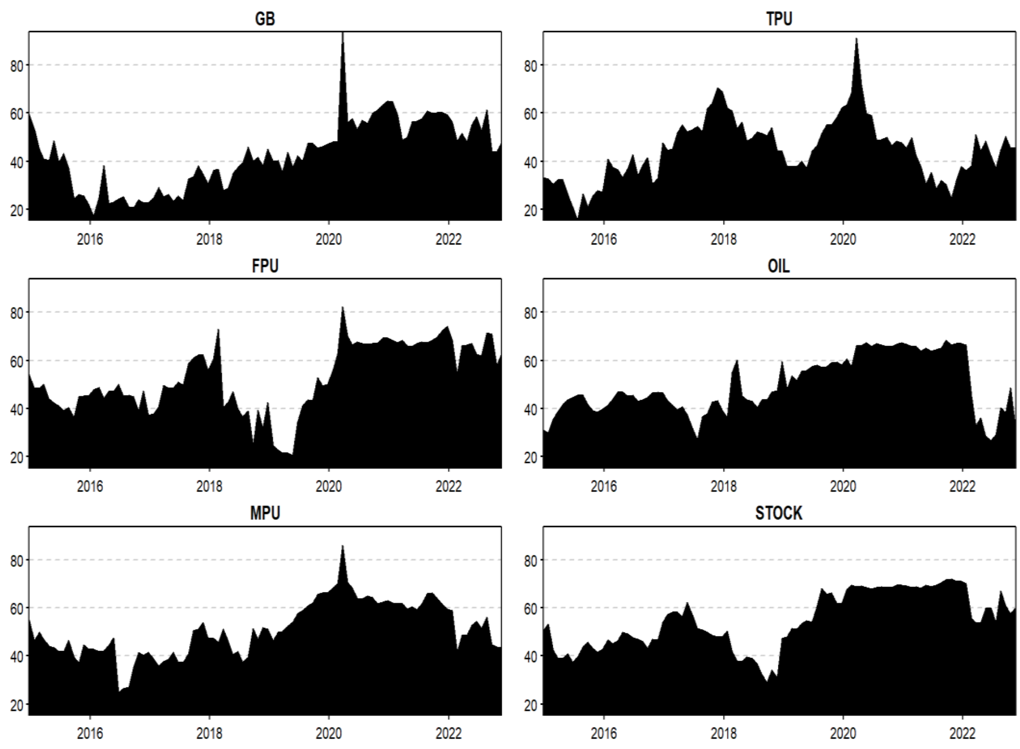

Fig. 5. Time-variations of volatility spillover from the network to each of return series

Notes: See the notes of Figure 4.

5.4.The total spillover between all return series within the network in the entire period

Figure 6 depicts the total spillover and the direction of volatility transmission in the network. As can be shown in this figure, Oil transmits volatilities to the policy uncertainties, including monetary, financial, and trade, as well as to GB. On the other hand, Stock transmits volatilities to TPU and GB. However, GB transmits volatilities only to TPU. In addition, the thickness of these arrows also shows the intensity of transmission of the volatilities. Therefore, it can be said that the intensity of the transfer of volatilities from Stock and GB to TPU has the highest intensity, respectively. Also, the intensity of the transfer of volatilities from Oil to GB is in the next rank. As it is shown in this figure, there is no connectedness between all three policy uncertainties in the network. Moreover, none of the assets under consideration are affected by each kind of policy uncertainty in the sampling period which has policy implications for investors and policy makers.

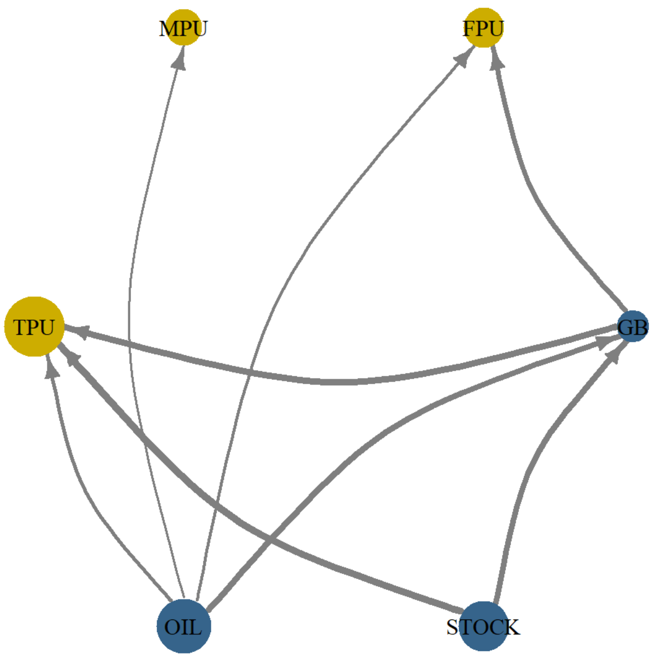

Fig. 6. TVP-VAR pairwise net directional connectedness network

Notes: Blue (yellow) nodes indicate net transmitters (receivers) of the shocks. Th4 vertices were weighted using the averaged net pairwise directional connectedness measures. The node size represents the weighted average net total directional connectedness.

Figure 7 shows the results of the total connectedness index in the network. As it illustrates, the total spillover has experienced an increasing trend up to the end of 2021 and after that, it decreased slowly during 2022 which is coincident with the Russia-Ukraine conflict. Based on this figure, we can conclude that there is a high connectedness in the network. Only in 2022, due to the implementation of the restrictive monetary policies of the Federal Reserve and the increase in oil prices following the worldwide political changes (especially the Russia-Ukraine conflict), the connection in the network decreased. The results, generally, reveal that there is not good opportunity for portfolio diversification, especially during the Covid-19 pandemic.

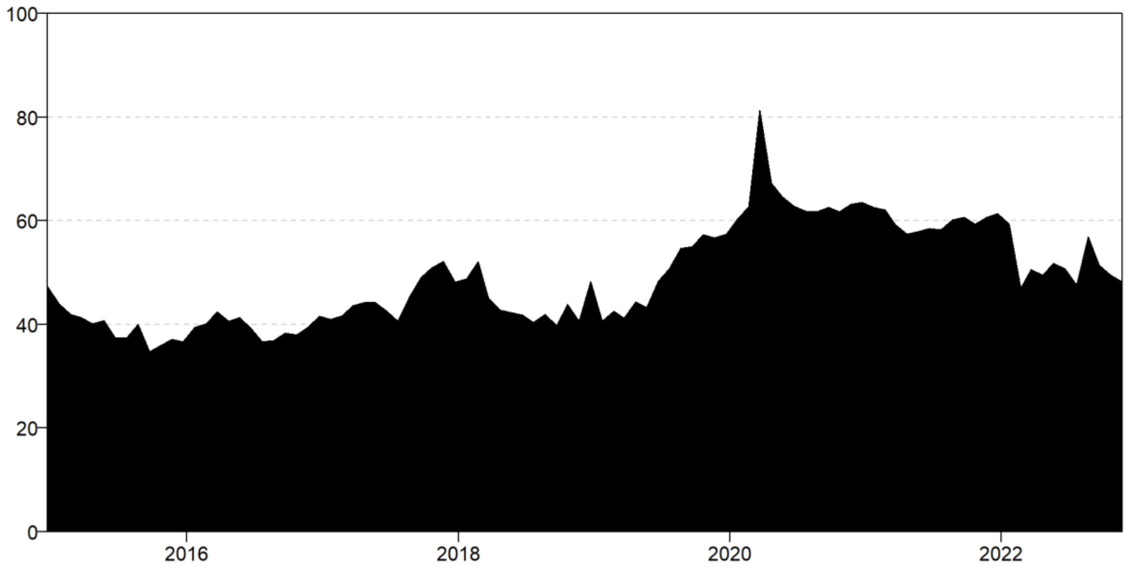

Fig. 7. Total connectedness between all variables in the network based on the TVP-VAR-DY

Notes: See the notes of Figure 4.

5.5.The dynamic net pairwise spillover effect between the network variables in the sample period:

Figure 8 shows the spillover effect in the network during January 5, 2013, up to November 22, 2022 period. As can be seen in the figure of the spillover between GB and FPU, the connectedness is mainly from GB to FPU. Moreover, the interrelationship between them at the beginning of 2020, which is related to the inception of the Covid-19 pandemic, changed again in a very short period, underscoring that this global shock causes the return of green bonds to be affected by the uncertainty of the US government's financial policy.

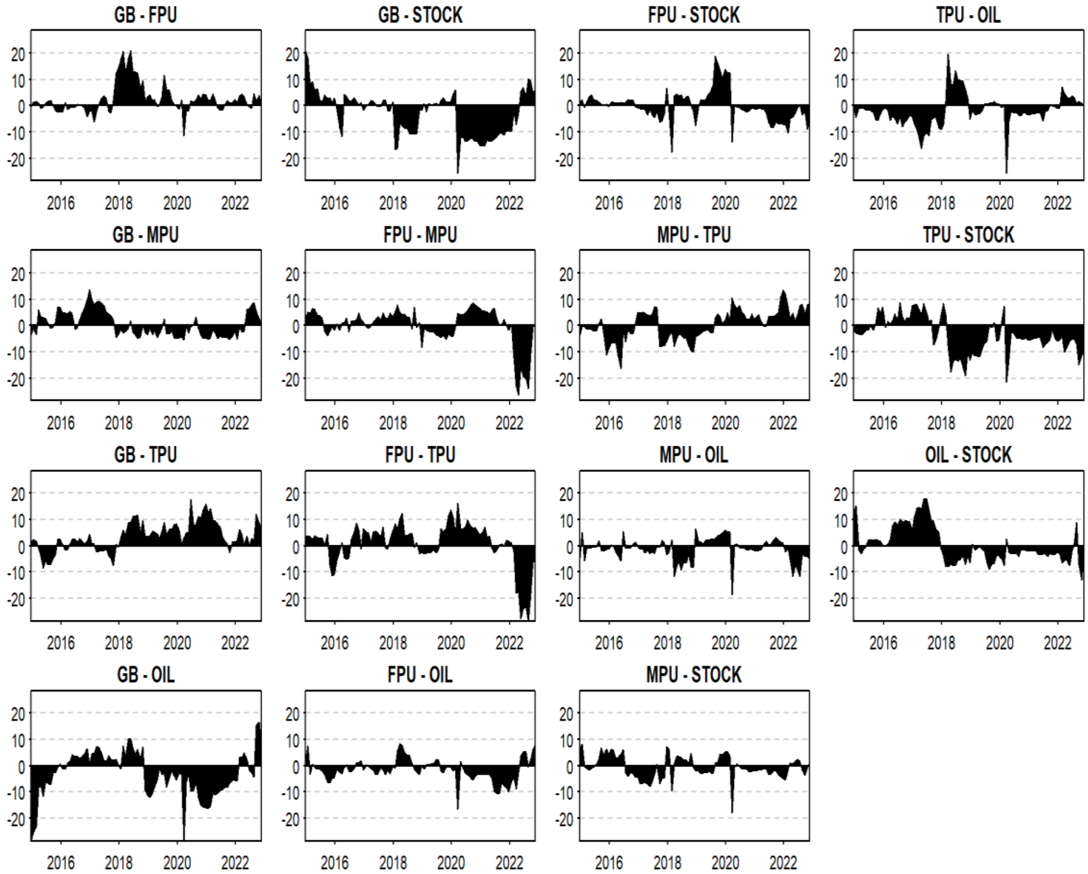

Fig. 8. Net Pairwise spillovers between all the variables in the network based on the TVP-VAR-DY model

Notes: See the notes of Figure 4.

The figure related to the connectedness between GB and Stock shows that the spillover is mainly from GB to Stock, which demonstrates the determining role of GB in transmitting volatility to Stock. The net pairwise connectedness between FPU and Stock depicts that neither of these two assets has a dominant role in transmitting volatilities to the other during the sample period. Of course, it should be noted that from 2020 to the end of November 2022 (which is coincident with the COVID-19 pandemic and the Russia-Ukraine conflict), the dominant role in transmitting shocks is related to Stock. This result shows that in the last three years, the uncertainty of the US government's financial policy has been affected by the changes in the S&P stock market return. The results about TPU and Oil explain that Oil has a dominant role in transmitting volatilities to TPU in the sample period. Its dominant role is accelerated in the first months of 2020 which is related to the spread of the Covid-19 pandemic and the sharp reduction of the oil price in the globe. Moreover, the dynamic spillover between GB and MPU experienced a constant trend during 2018 and up to the first months of 2022 and the MPU has a transmitting role. However, from the first months of 2022 (the beginning of the Russia-Ukraine war) up to the end of this year, the trend is reversed, and GB determined the variations of MPU.

The mutual interrelationship between FPU and MPU fluctuated throughout the entire period. However, in 2022, MPU has a dominant role in transmitting volatilities to the government's financial policy uncertainty. This period is coincident with the Russia-Ukraine conflict. As shown in Figure 8, the pairwise connectedness between MPU and TPU has a volatile trend. However, TPU transmits volatilities to MPU from 2020 and up to the end of 2022 which are related to the Covid-19 pandemic and the conflict between Russia and Ukraine, respectively. The pairwise spillover between TPU and Stock shows that Stock has a dominant role in transmitting TPU volatilities, especially from 2018 and up to the end of 2022.

Our findings also show that TPU is mainly a receiver of volatilities from GB and FPU in the entire period. However, this role is reversed about MPU in 2022 which is associated with the Russia-Ukraine conflict. Our research findings simply, explore that TPU has a dominant role in transmitting volatilities to MPU during 2022. Moreover, the results about the dynamic connectedness between MPU and FPU with Oil show that none of them had a dominant role in the changes of the other variables during the entire period. It is only necessary to mention that in the last months of 2022, Oil is a transmitter of the shock to MPU and is a recipient of shock from FPU. The results about the net pairwise interrelationship between the Oil and Stock underline that spillover is mainly from Stock to Oil. However, this result is reversed when it comes to the connectedness between GB and Oil. Based on our findings, Oil is the most transmitter of shocks to GB. In the end, the dynamic net pairwise spillover between MPU and Stock explains that there exists a volatile connectedness between them. However, the spillover is mostly from the Stock to the MPU.

In summary, Figure 8 shows that GB is the net transmitter of shocks to all series during Russia-Ukraine war. However, FPU is the net receiver of shocks within the network in that time period. The minimum interrelationship is observed in the MPU-Stock and the GB-FPU pairs during the Covid-19 pandemic and the Russia-Ukraine conflict, which shows Stock and GB’s potential in minimizing portfolio risk with regard to these two economic uncertainties at this time period.

Before presenting the results of the directional graph and the spanning tree, it should be mentioned that the weight (risk) in the short-term, medium-term, and long-term periods is based on the results of the TVP-VAR- BK (2018) model, which is included in the appendix.

5.6. Results of the graph theory

5.6.1. The short-term results of the directions and weights of return series in the network:

We require a simple graph G for using the BORUVKA-KRUSKAL Algorithm. As a consequence, the tree (V, F) returned by this algorithm is a spanning tree of G without a direction. In this paper, to make the results more usable for readers, the directed tree is used. Using the TVP-VAR-BK technique, we evaluate the directions and weights of the interconnection amidst all variables by calculating the net volatility contagion in this model in different time horizons.

With regard to the number of outdegrees for each return series in Figure 9, it is clear that

$d_{T_1}^{+}(MPU) = 2, d_{T_1}^{+}(TPU) = 0, d_{T_1}^{+}(FPU) = 0, d_{T_1}^{+}(GB) = 1$, $d_{T_1}^{+}(STOCK) = 1$, and $d_{T_1}^{+}(OIL) = 0$.

Therefore, the MPU is the most effective factor in the short term. If the goal of policy makers is minimizing the short-term risk spillover in the network, MPU should be controlled. The results of the spanning tree and BORUVKA-KRUSKAL's algorithm reveal that the highest outgoing edges (transmitting of volatility) are caused by MPU in the short-term. Our findings from graph theory in the short-term, simply, depict that Stock and TPU are the main receivers of volatilities from the network. Moreover, GB and Oil have the least interconnection in the network and their connection is only observed with Stock. Therefore, concerning our findings, GB and Oil are not affected by policy uncertainties in the short run.

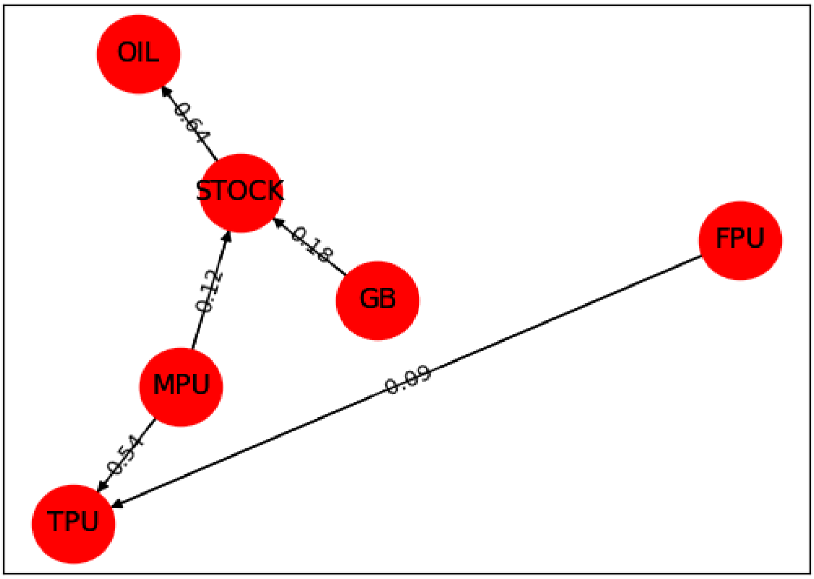

Fig. 9. An optimal tree $\boldsymbol{T_1}$ returned by the BORUVKA-KRUSKAL Algorithm in the short-term

Notes: The vertices show the return series under estimated in the network. The direction of edges shows the net effect between each pairs of return series in the network and their weights are shown on each of edges.

5.1.1. The medium-term results of the directions and weights of return series in the network:

Figure 10 shows the results of the spanning tree based on the BORUVKA-KRUSKAL's algorithm in the medium term. Regarding the number of outgoing edges of each return series in Figure 10, it is evident that:

$d^+_{T_2}(MPU) = 1$, $d^+_{T_2}(TPU) = 1$, $d^+_{T_2}(FPU) = 2$, $d^+_{T_2}(GB) = 0$, $d^+_{T_2}(STOCK) = 0$, and $d^+_{T_2}(OIL) = 1$.

Therefore, FPU is the most effective factor in the medium term. If policymakers aim at minimizing the medium-term risk spillover in the network, the FPU should be controlled. The results of the spanning tree and BORUVKA-KRUSKAL's algorithm reveal that the highest outgoing edges (transmitting of volatility) are caused by FPU. In other words, in the medium term, FPU is the main driver. However, Stock has the most input degree, and it is the main receiver of volatilities in this network. Moreover, there is no connection between GB and other network variables with the exception of FPU. Furthermore, there is no interrelationship between Oil and MPU, FPU, and GB in the medium term. In addition, contrary to the results obtained in the short term, GB and Oil in the medium term are affected by political uncertainties that affect GB by FPU, and TPU in the case of Oil. These findings are of importance for investors who seek portfolio diversification and also for policy makers in forecasting the impacts of their policies on the US financial markets.

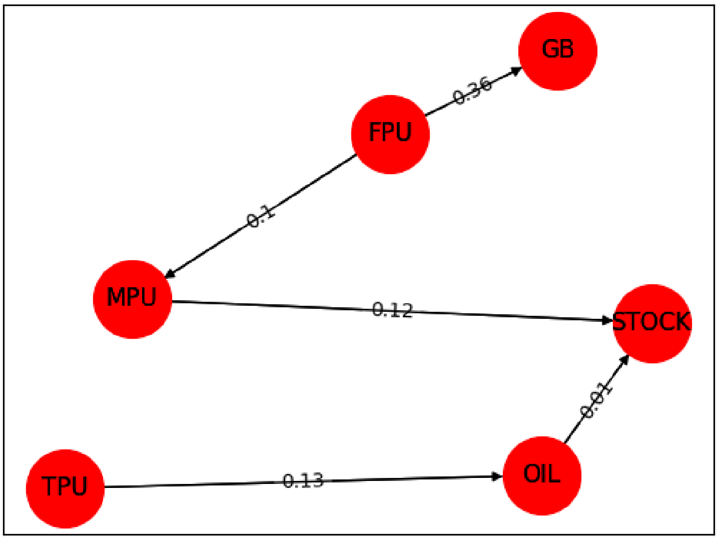

Fig. 10. An optimal tree T_2 returned by the BORUVKA-KRUSKAL Algorithm in the medium-term

Note: The vertices show the return series under estimated in the network. The direction of edges shows the net effect between each pairs of return series in the network and their weights are shown on each of edges.

5.1.2. The long-term results of the directions and weights of return series in the network:

Figure 11 shows the results of the spanning tree based on the BORUVKA-KRUSKAL's algorithm in the long term.

Concerning the number of outgoings of each return series that is shown in Figure 10, it is apparent that:

$d^+_{T_3}(MPU) = 0$, $d^+_{T_3}(TPU) = 1$, $d^+_{T_3}(FPU) = 4$, $d^+_3(GB) = 0$, $d^+_{T_3}(STOCK) = 0$, and $d^+_{T_3}(OIL) = 0$.

Thus, FPU is the most effective factor in this period. An important point is that in the long term as well as in the medium term, the highest outgoing edge is related to the FPU. But in the long term, FPU has four outgoing edges and two in the medium term. Based on these findings, in the longer period, the role of FPU in transferring volatilities (outdegree) in the network is greater, and more attention should be paid to it for risk management. In the mid-term after FPU, the MPU, TPU, and Oil have the most outgoing edges. In the long term, after the FPU with four outgoing edges, the TPU has only one outdegree and the rest of the variables have no outdegree. The results of the graph theory show that the policy uncertainties play a significant role in transferring volatilities to the network which shows the critical role of the US macroeconomic policies in risk management in asset markets.

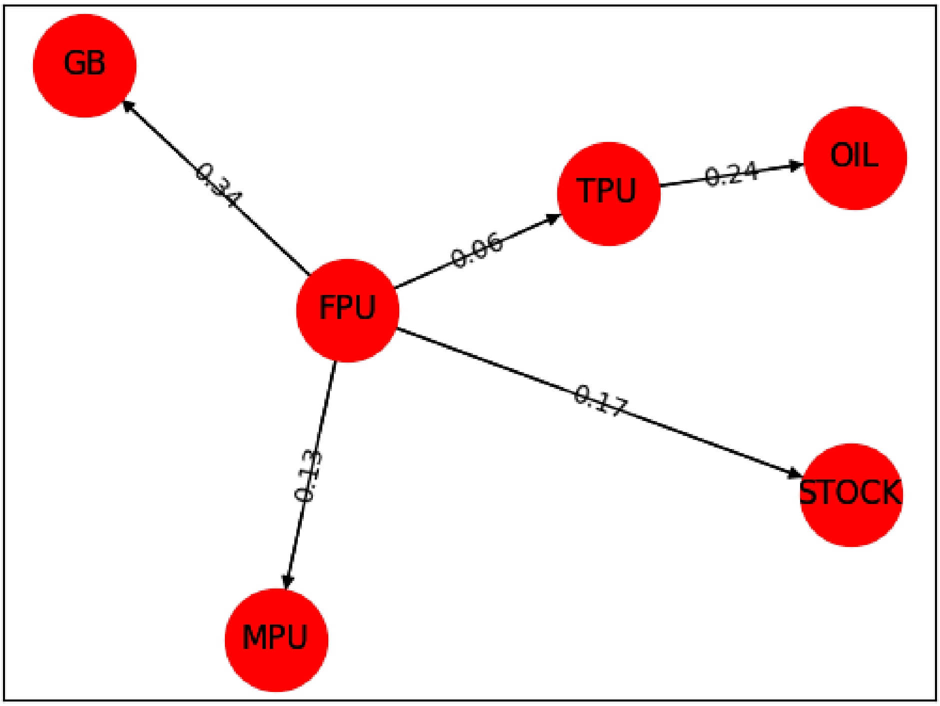

Fig. 11. An optimal tree T_3 returned by the BORUVKA-KRUSKAL Algorithm in the long-term
Note: The vertices show the return series are underestimated in the network. The direction of edges shows the net effect between each pairs of return series in the network and their weights are shown on each of edges.

6. Conclusion and policy implications

The connectedness between traditional and green bond assets along with policy uncertainties is one of the key concepts in financial issues. It should be noted that investing in green bonds (as a fixed-income asset) has found a special place in investors' portfolios, especially during the last two decades. Considering the importance of this issue, this paper investigates the static and dynamic spillover effects of financial asset returns (green bonds and S&P stocks), the return of oil price, and all kinds of policy uncertainties in the US economy, using TVP-VAR- Diebold-Yilmaz (2012) approach and the Graph theory from January 5, 2013, to November 22, 2022.

Concerning the empirical evidence, there is a mutual interrelationship between the price of oil, the return of green bonds, and the S&P stock market, and these assets are all influenced by policy uncertainties. In the current study, policy uncertainty means the uncertainty of trade policy, financial policy, and monetary policy, which have been analyzed separately in the studied network. It should be noted that an issue that is of particular importance is green financing, which can help each economy achieve sustainable growth and development and increase economic resilience (Cao & Tao, 2023). In addition, from the perspective of investors and policymakers, understanding the static and dynamic effectiveness of portfolio assets including traditional and green assets from different kinds of uncertainties has considerable advantages in portfolio diversification and managing risk.

The results show that Stock and Oil are the main net transmitters of shocks to the network. On the other hand, TPU is the main net receiver of shocks from the network in the sample period. The research shows that during the COVID-19 pandemic (2020-2021), GB mainly received network shocks, but since the Russia-Ukraine conflict began in early 2022, it has become a shock transmitter. Additionally, GB's weak network connections provide benefits for portfolio diversification. Our dynamic results about Stock reveal that it receives major shocks from the network in 2018 and 2020-2022, especially during the COVID-19 outbreak. Generally, our dynamic results about the net spillover effect from each variable to the network show that GB and TPU are major net receivers, and Oil and Stock are net transmitters of shocks during the COVID-19 pandemic. On the other hand, FPU is a major net receiver of shocks from the network during the Russia-Ukraine conflict.

The results of the pairwise dynamic spillover show that among the uncertainties, MPU transmits major shocks to green bonds especially during the COVID-19 pandemic. Moreover, oil transmits more shocks to GB than Stock and the intensity of this transmission during the period of COVID-19 is very considerable. Our results about the total connectedness index (TCI) in the network show that, on average, it is more than 40 percent which is increased considerably during the COVID-19 pandemic. The research highlights that GB has the weakest net connectedness in the network, offering advantages for portfolio diversification during the sample period. However, contrary to TVP-VAR-DY findings, graph theory results show GB as a key short-term contributor to the network, making it unsuitable as a hedge asset. Policy uncertainties, especially financial policy uncertainty (FPU), significantly transfer volatility to assets, emphasizing the impact of US macroeconomic policies on asset market risk management. Discretionary policies can affect stock and green asset returns by creating uncertainties, altering their portfolio weights. The dynamic graph theory results underscore that policy uncertainties, particularly FPU, have the most intense spillover effects. Thus, the US government should consider the impact of economic policy uncertainties if prioritizing environmental policy and green growth.

In the end, it should be noted that different results can be obtained from TVP-VAR-DY approach and graph theory based on the TVP-VAR-BK technique as a novel mathematical approach in financial markets. Acquiring different results from these two approaches has important implications for investors, policymakers, and scholars in their future studies. It should be noted that, unlike previous studies which used graph theory based on correlation between indicators, in the current paper, the graph theory based on the TVP-VAR-BK technique is applied. It is worth noting that finding dynamic spillover connectedness among assets is crucial for investors and policymakers and the reason for applying the TVP-VAR-BK technique in graph theory is related to its advantages in providing novel results. However, the results of graph theory based on correlation among indicators are unable to investigate the net transmission of volatility between each pair of assets in the network and it only shows the co-movement among network variables. Moreover, the other shortcoming of previous research is that they were unable to provide spillover effects in graph theory in different investment horizons. However, finding interconnectedness among network variables in different time horizons is very crucial for investors and policy makers. As a result, in this paper, the TVP-VAR-BK approach is used to calculate the edge weights in the graph theory to analyze the net effect between series in the short-, medium-, and long-term horizons. In general, our research findings are of importance for investors, policymakers, and portfolio managers, and have important implications for scholars in their future studies.

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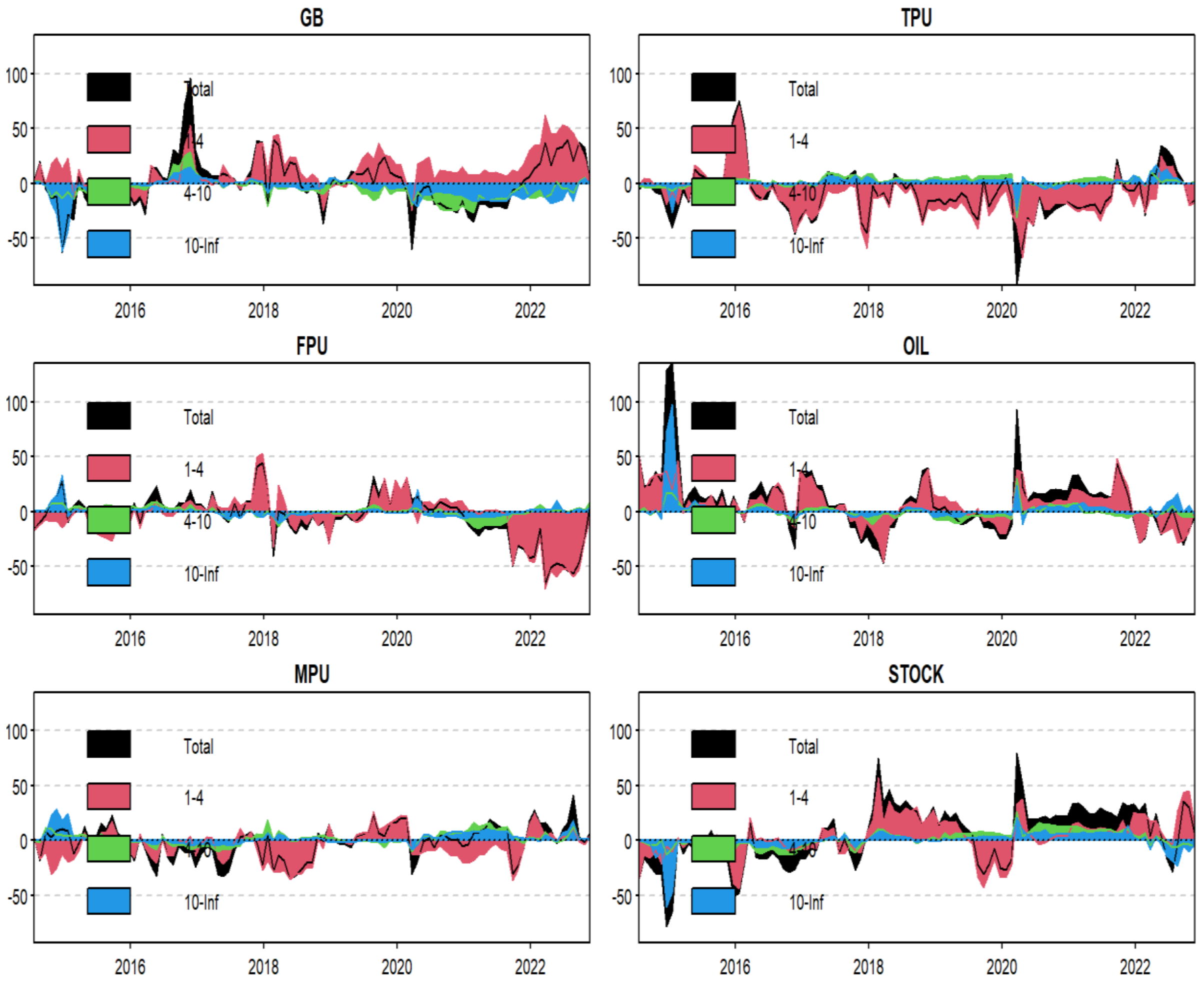
Appendix

Figure A1. Net- Time Frequency



Notes: The pink color represents the net-time frequency of each variable in the short term, the green color captures the medium term, and the blue color characterizes the long term. Also, the black color symbolizes the total of all periods.

Figure A2. Short-run Network Analysis

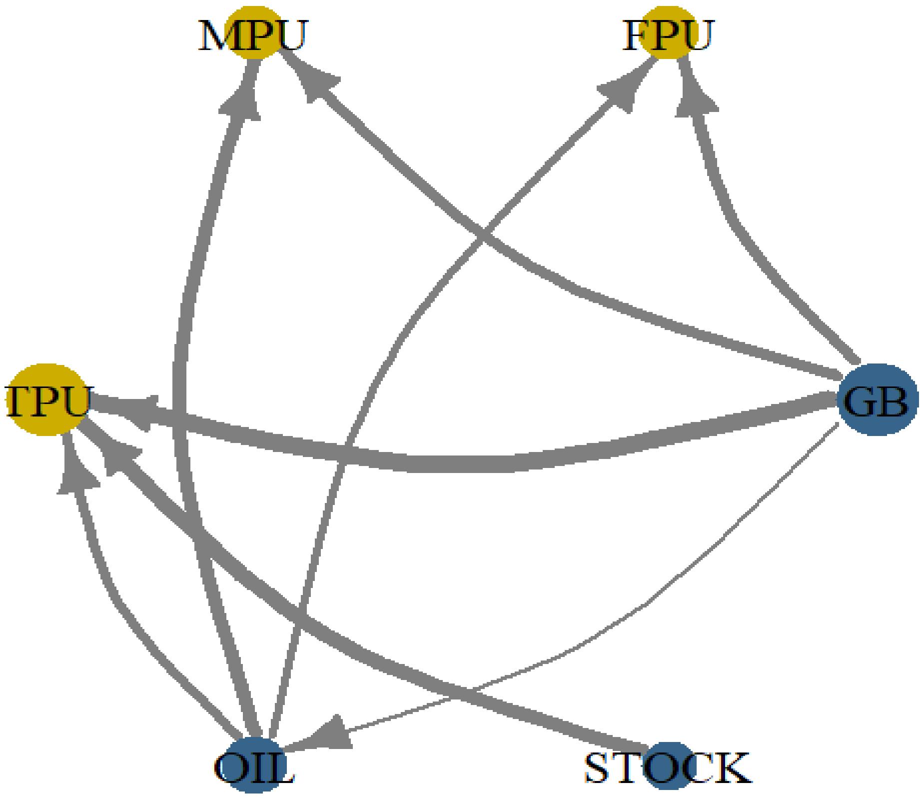


Figure A3. Medium-run Network Analysis

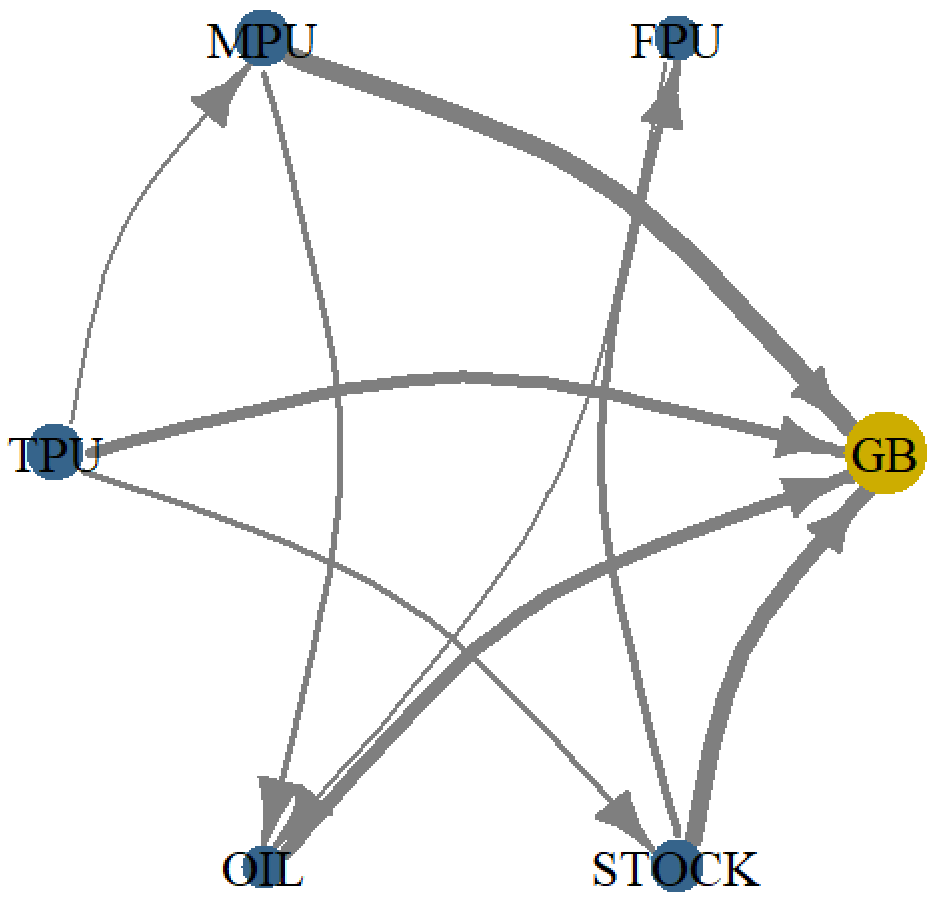


Figure A4. Long-run Network Analysis

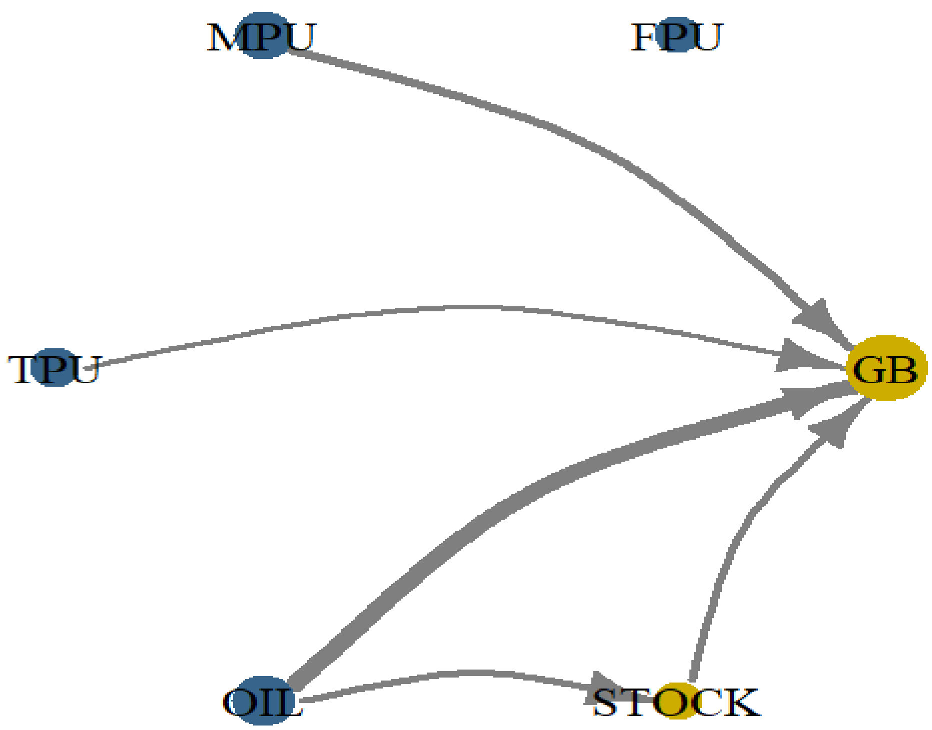
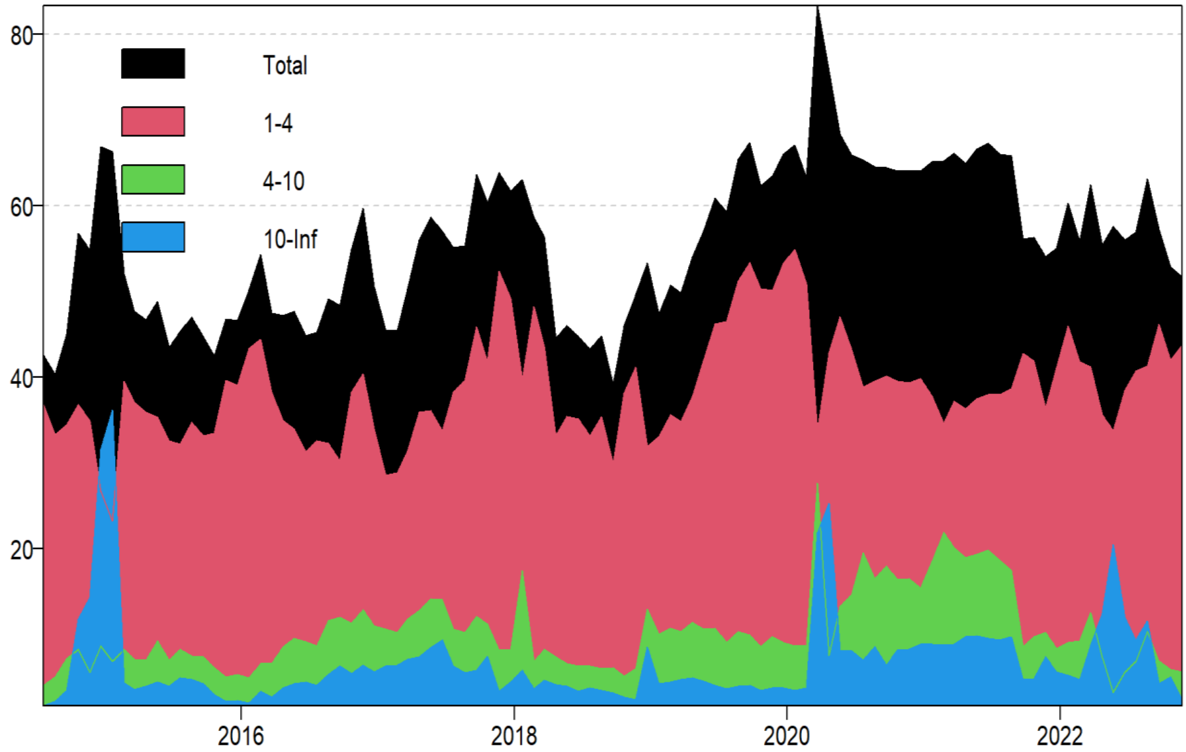


Figure A5. Total Connectedness Index (TCI)



Notes: The pink color represents the total connectedness in the short term, the green color captures the medium term, and the blue color characterizes the long term. Also, the black color symbolizes the total of all periods.