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Research article

How do the uncertainties affect the connectedness between the green bond market and conventional financial markets? Evidence from the Russian-Ukrainian war

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Abstract: In this study, we address the dynamics of connectedness between the green bond market and conventional financial markets during crisis periods and uncertainty factors influencing it. Recently, most researchers have focused on the impact of uncertainties on green bond, green finance, and conventional bond markets, and only a few of them on the impact of uncertainties on the connectedness of financial markets. Moreover, this phenomenon is underexplored during crisis periods. In response to this, we assessed the change in the connectedness between green bond and conventional financial markets, as well as the impact of uncertainties on connectedness during the Russian-Ukrainian war. The Diebold and Yilmaz's (2012, 2014) spillover index was used to assess the connectedness between green bond and conventional financial markets. Dynamic model averaging (DMA), proposed by Koop and Korobilis (2012), was applied to assess the impact of uncertainties on the connectedness. The study revealed that the total spillover index increased significantly during the Russian-Ukrainian war. Moreover, the green bond market was a receiver of shocks during the pre-war period, but a transmitter during the war period. This may indicate that it has become a less predictable and more sensitive market. Total spillover was positively affected by Economic Policy Uncertainty (EPU) and Twitter-Based Economic Uncertainty (TEU) indices, and negatively by Geopolitical Risk (GPR) and Volatility (VIX) indices. Uncertainties increased with the start of the war. The GPR index peaked the most. All uncertainty indices had a greater impact on total spillover during the war. The greater impact can be explained by increased market sensitivity, rising levels of financial stress, shifts in investor behavior, and the accelerated dissemination of information during times of crisis. The findings provide implications for portfolio managers in terms of risk management and portfolio decisions at a global level.

Keywords: green bond market; conventional financial markets; connectedness; uncertainties; economic crises

JEL Codes: G15, G01, G11

Abbreviations: EPU: Economic Policy Uncertainty; TEU: Twitter-Based Economic Uncertainty; GPR: Geopolitical Risk; Volatility index (VIX); DMA: dynamic model averaging; VAR: vector autoregression; GFEVD: generalized forecast error variance decomposition; DLM: dynamic linear model

1. Introduction

Global financial markets experienced several crises in the 21st century, such as the 2008 global financial crisis, the COVID-19 pandemic, and the Russian invasion of Ukraine. The latter event significantly increased geopolitical risk and uncertainty in the global economy and financial markets. Moreover, in the 21st century, there is the problem of climate change. Sustainable investing can help fight climate change, and green bonds are considered one of the promising instruments for sustainable financing. The assessment of the connectedness of the green bond market with other financial markets under uncertainties can provide important insights into the resilience of this investment during periods of economic and financial turmoil. Environmentally friendly investors, who are motivated at least in part by non-monetary motives, usually invest in green bonds. These investors view them as less risky securities in the long term. As a result, green bond prices are less vulnerable to market sentiment under conditions of increased uncertainty. This is important for potential investors who are looking for ways to protect their portfolios from risk. Understanding how the green bond market connects with other financial markets during crisis periods and how the uncertainties affect this connectedness provides information on risk management and possible investment strategies.

One of the key questions addressed by researchers is the dynamism of the connectedness between the green bond market and other financial markets, and the impact of various uncertainty factors on this connectedness. Recently, scientists have focused on the changes in connectedness between the green bond market and other financial markets in crisis periods such as the oil price crash, the China-US trade conflict, the COVID-19 pandemic, and the Russian-Ukrainian war. Total spillovers are usually driven by short-term volatilities and exhibit a significant increase during periods of economic and financial turmoil (Chen et al., 2024; Mensi et al., 2024; Xu et al., 2024; Zhao and Park, 2024; Oliyide et al., 2023). Mensi et al. (2024) found that total connectedness is stronger during extreme bearish or bullish conditions than during normal market conditions. Periods of major crises are associated with unusually high connectedness. This phenomenon is known as the contagion effect. According to Xu et al. (2024), financial turmoil significantly strengthens the spillover effects between the green bond market and other markets. This is particularly evident during the COVID-19 pandemic. The stock, oil, and gold markets are the major transmitters of shocks to the US green bonds, while currencies and cryptocurrencies are the major receivers of shocks from the US green bonds. Similar research results were presented by Zhao and Park (2024): The green bond market acts as a net spillover transmitter to conventional bond and currency markets in the short term during the COVID-19 pandemic, and conversely, acts as a net spillover receiver in the long term. Even though spillover effects become stronger during the economic and financial turmoil, they fluctuate temporarily because market fundamentals begin to recover and uncertainty diminishes. As a result, the risk spillover effect exhibits a decreasing trend (Chen et al., 2024). Asymmetric connectedness between the green bond market and other financial markets was found by Mensi et al. (2024) and Naeem et al. (2021).

Uncertainty indices help gauge market sentiment, investor confidence, and the level of risk that may arise in extreme market conditions. Several scholars have studied the impact of uncertainties on the connectedness of financial markets. The impact of different uncertainties on the connectedness of various financial markets was investigated by Wang et al. (2024), Sheenan (2023), Tang et al. (2023), Zhang et al. (2023), and Sohag et al. (2022). Tang et al. (2023) investigated the impact of uncertainty indices on the green bond market. They pointed out that fund managers and retail investors can utilize green bonds to mitigate economic policy uncertainty, geopolitical threats, and volatility in the WTI oil market. Wang et al. (2024) examined the linkage and spillover relationship between green finance and uncertainty indices measuring economic, monetary, and climate policies. They found a significant influence of all uncertainty indices on the market of green finance. In addition, economic and monetary policy uncertainty had a stronger impact compared to climate policy uncertainty. Zhang et al. (2023) studied the time-varying causal relationship between geopolitical risk and green finance. They found time heterogeneity in the causal relations between geopolitical risk and green finance; a more prolonged impact of geopolitical risk on the volatility of green bonds and renewable energy than the return; a more sustained impact on the return and volatility of renewable energy than clean energy; and a diminishing impact of geopolitical risk on the return of the European clean energy market. Sohag et al. (2022) stated that geopolitical events negatively affect the green equity and green bond markets through the asset price and return channels, as the beginning and escalation of wars. Sheenan (2023) analyzed linkages between green, conventional bond markets and geopolitical risk in high and low volatility periods. They concluded that green bonds behave differently from conventional bonds and may be more susceptible to geopolitical risk and contagion.

Some publications are related to the impact of uncertainties on the connectedness of global financial markets during the COVID-19 pandemic (Polat et al., 2024; Wei et al., 2024; Elsayed et al., 2022). Elsayed et al. (2022) examined dependence structure and dynamic connectedness between the green bond market and other financial markets before and during the COVID-19 pandemic. Their research covered four uncertainty indices to measure financial uncertainty, financial stress, and economic uncertainty. Polat et al. (2024) explored the time-varying interconnectedness among green bonds, Twitter-based economic uncertainty indices, and the S&P 500 Composite Index. They observed the negative impact of market sentiment on the green bond market, especially in the early stages of the COVID-19 pandemic. Wei et al. (2024) studied the impact of market volatilities on the relative performance of green bonds. The scholars revealed that when volatilities coincide with oil shocks, they influence the relative performance of green bonds consistently more. This phenomenon is particularly evident in the post-COVID-19 period. Some studies have shown that EPU promotes the connectedness of conventional financial markets (Benlagha and Hemrit, 2022; Mokni et al., 2020).

There are a couple of studies related to the impact of uncertainties on the connectedness of global financial markets during the Russian–Ukrainian war. Wan et al. (2023) explored the dynamics of connectedness among six global financial markets, including crude oil spot price, the US dollar index, G7 MSCI, EFM MSCI, the global bond index, and gold price in the empirical research. The financial stress index and VIX consistently hold significant influence among the five chosen uncertainties throughout the sample period. Moreover, GPR and TEU demonstrated significance during the conflict period. In addition, the scholars noticed the divergence of uncertainties: The financial stress index and

TEU strengthen connectedness, whereas VIX and GPR weaken. Yousaf et al. (2023) examined the impact of the Russian–Ukrainian war uncertainty on the connectedness between global stock and commodity markets and showed a significant and positive impact on the total volatility connectedness index. Gyamerah and Asare (2024) wrote a literature review of the impact of economic policy uncertainty on green bonds. They noticed that it had a strong impact on the green bond. The scholars suggested conducting the study to understand how economic policy uncertainty evolves during various geopolitical events.

Table 1. Summary of studies on the impact of uncertainties on financial markets and their connectedness.

Authors and year	Uncertainty indices	Impact on	Study period
Tang et al. (2023)	EPU, Geopolitical Threats (GPRT), Geopolitical Acts (GPRA)	Green bond market	2012–2022
Polat et al. (2024)	TEU	Green bond market	COVID-19 pandemic and the Russian-Ukrainian war
Wei et al. (2024)	VIX, Crude Oil ETF Volatility Index (OVX), Intercontinental Exchange U.S. Bond Market Option Volatility Estimate (MOVE)	Green bond market	2014–2023 and COVID-19 pandemic
Sheenan (2023)	GPR	Green and conventional bond market	2014–2022
Wang et al. (2024)	EPU, Monetary Policy Uncertainty (MPU), Climate Policy Uncertainty (CPU)	Green finance market	2013–2022
Zhang et al. (2023), Sohag et al. (2022)	GPR	Green finance market	2012–2022, 2014–2021
Benlagha and Hemrit (2022)	EPU	Connectedness within the international sovereign bond yields	2015–2019
Mokni et al. (2020)	EPU	Connectedness between oil price shocks and gold price	1997–2019
Elsayed et al. (2022)	VIX, World Financial Stress Index (FSI), TEU	Connectedness between green bond and conventional financial markets	COVID-19 pandemic
Wan et al. (2023)	VIX, FSI, GPR, TEU	Connectedness of global financial markets	The Russian-Ukrainian war

Table 1 summarizes the studies related to the impact of various uncertainties on different financial markets and the connectedness between them. The information shows that scholars investigated different sets and numbers of uncertainty indices, among which EPU, GPR, TEU, and VIX dominate. It should be pointed out that the impact of uncertainties on green bond, green finance, and conventional bond markets is investigated in most studies. To our knowledge, only a few studies are focused on the connectedness between markets, and only one of them is focused on the connectedness between green bonds and conventional financial markets during the COVID-19 pandemic.

The changing geopolitical situation due to the outbreak of the Russian-Ukrainian war undoubtedly causes uncertainty. Literature review revealed that there is a lack of studies related to the connectedness between the green bond market and conventional financial markets and the impact of uncertainties on this connectedness during the Russian-Ukrainian war. Thus, our research is dedicated to closing this gap.

The study contributes to the literature on the connectedness between the green bond market and conventional financial markets, the impact of uncertainties on the connectedness, and their changes during crisis periods. Moreover, we apply Dynamic Model Averaging (DMA) to capture not only the change of coefficients over time but also the change of the forecasting model over time. This enables us to assess the significance, direction, and forecasting precision of uncertainty indices during turbulent periods, such as the start of the war in Ukraine.

The article consists of four sections. In Section 2, we introduce a research design. In Section 3, we provide empirical results. In Section 4, we summarize the major findings.

2. Research design

2.1. Models

In this section, we outline the research design in a structured manner. First, we introduce the two core econometric models employed in the empirical analysis and discuss their alignment with the research objectives. The Diebold and Yilmaz spillover index is applied to capture the time-varying connectedness between the green bond market and conventional financial markets. To examine the role of uncertainty, we employ the Dynamic Model Averaging (DMA) approach, which enables the evaluation of the evolving impact of uncertainty indices on the level of spillovers. Following the model discussion, we define the variables used in both stages of the analysis, justify their selection based on prior literature, and explain how they are measured. Last, we describe the dataset, including information on data sources, the sampling period, the number of observations, and key descriptive statistics.

Connectedness of financial markets is assessed in the first stage of the study. It can be measured using various research methods, such as the wavelet approach, copulas, and generalized autoregressive conditional heteroskedasticity (GARCH). One of the most common methods used is the Diebold and Yilmaz spillover index (Elsayed et al., 2022; Ferrer et al., 2021) since it provides insights about static and dynamic connectedness and network channels between markets. In addition, the spillover index determines average-based connectedness between the markets, ignoring the size and direction of return changes. This spillover analysis offers greater utility than traditional two-dimensional methods such as GARCH, Granger causality, and wavelet, as it allows for identifying the direction of spillovers and assessing net pairwise spillover effects (Caporin et al., 2023; Ngoepe and Bonga-Bonga, 2024). We choose the methodology of Diebold and Yilmaz (2012, 2014) to assess the time-varying connectedness between the green bond market and other financial markets during the Russian-Ukrainian war. The rolling-window approach is employed to estimate the Diebold and Yilmaz spillover index because it is a widely used and transparent method for capturing the time-varying connectedness of financial markets. While TVP-VAR models have the advantage of not requiring a pre-specified window size, the rolling-window method provides intuitive interpretability of the evolution of spillovers over fixed periods and enables straightforward comparisons with previous studies (e.g., Ferrer et al., 2021; Xia et al., 2020). The spillover index enables us to determine the degree to which shocks in one market affect other markets. This index is based on Koop et al. (1996) and Pesaran and Shin's (1998) methodology. In this methodology, the generalized forecast error variance decomposition (GFEVD) is employed for the vector autoregression model (VAR).

For the assessment of spillover, the VAR model is constructed following the formula below:

$$Y_t = v + \sum_{i=1}^{n} \phi_i Y_{t-i} + \varepsilon_t \tag{1}$$

where Y_t – vector of endogenous variable at time t; v – vector of intercepts; Φ(Y) – matrix of lagged coefficients; and ε_t – vector of error terms.

Following Koop et al. (1996) and Pesaran and Shin (1998), GFEVD enables the elimination of the dependence of results on variable ordering, also known as the Cholesky ordering issue. This decomposition implies that each variance of the forecast error for an asset depends on two components: Its own contribution to shocks and the effect of other assets that are correlated with an asset.

The formula of GFEVD to H-step-ahead is presented below:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} e_i' \, h_h \sum e_j}{\sum_{h=0}^{H-1} e_i' \, h_h \sum e_j} \tag{2}$$

where $\theta_{ij}^{g}(H)$ – contribution of the jth variable to the variance of forecast error of the variable ith at horizon H; $\sum e_j$ – variance matrix of the error vector ε_t; σ_{jj} – diagonal element of matrix Σ; and e_i – vector of the i^{th} element which is equal to one or zero otherwise.

To make the results of the spillover decomposition easier to interpret and to reduce the risk of misleading interpretation that may arise due to different scales of data or exceptions, the GFEVD matrix is normalized according to Formula 3:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{3}$$

where $\tilde{\theta}_{ij}^{g}(H)$ – direction spillover from variable j to i at forecast horizon H.

The use of GFEVD enables us to focus on two mutually reinforcing aspects in the analysis. On one hand, the total spillover index is useful for measuring systematic risk and enables us to assess the overall health of financial systems. Furthermore, this method enables us to assess the impact of individual variables or asset classes on the total spillover index and measure net spillovers. On the other hand, the asset classes are linked to each other and form the network. Therefore, the assessment of the specific impact or weight of each asset class on the rest of the variables and its directions is also important for highlighting the links between the markets.

The "from", "to", and "net" spillover measures are defined in Equations (4)–(6). Equation (4) calculates the spillover received by variable i from all other variables, while Equation (5) measures the spillover transmitted from variable i to the rest. The net spillover for variable i is then obtained in Equation (6) as the difference between its outgoing and incoming spillovers, summarizing the overall directional impact of that variable within the system.

$$S_{i\leftarrow\odot}(H) = \sum_{j\neq i} \tilde{\theta}_{ij}^{g}(H) \tag{4}$$

where $S_{i\leftarrow\odot}(H)$ is the direction spillover from other variables to i at forecast horizon H.

$$S_{i\rightarrow\odot}(H) = \sum_{j\neq i} \tilde{\theta}_{ji}^{g}(H) \tag{5}$$

where $S_{i\rightarrow\odot}(H)$ is the direction spillover from i to other variables at forecast horizon H.

$$S_{i}^{net}(H) = S_{i\rightarrow\odot}(H) - S_{i\leftarrow\odot}(H) \tag{6}$$

where $S_{i}^{net}(H)$ is the net spillover of variable i at forecast horizon H.

In the first stage, we test two hypotheses:

H1: Total spillover increases during the Russian-Ukrainian war.

H2: The green bond market is a net receiver among the selected markets during the pre-war and war periods.

H1 is based on the empirical findings of many scientists who proved that total spillovers usually increase during periods of economic and financial turmoil (Chen et al., 2024; Mensi et al., 2024; Xu et al., 2024; Zhao and Park, 2024; Oliyide et al., 2023). H2 is based on the statement that the green bond market experiences significant price spillovers from conventional markets (Elsayed et al. 2022; Reboredo and Ugolini, 2020; Pham, 2016). This is because it is relatively smaller, policy-driven, and dominated by niche investors.

The impact of uncertainty factors on the connectedness between the green bond market and other major financial markets is analyzed in the context of the Russian-Ukrainian war in the second stage of the study. DMA proposed by Koop and Korobilis (2012) is applied for this purpose. Based on the studies of Drachal (2018) and Wan et al. (2023), a set of dynamic linear models (DLMs) is generated for the estimation of DMA. The specification of the DLM is estimated using a Kalman filter with smoothing. Probabilities of the DLM are based on relative explanatory powers.

In the second stage, we test the H3 and H4 hypotheses:

H3: Total spillover is positively affected by EPU and TEU, and negatively by VIX and GPR.

H4: Uncertainty indices have a greater impact on total spillover during the Russian-Ukrainian war.

H3 is based on the findings of Zhao and Park (2024), Tang et al. (2023), Wan et al. (2023), Benlagha and Hemrit (2022), and Mokni et al. (2020). These findings proved that VIX and GPR weaken the connectedness, while EPU and TEU strengthen. H4 is based on the statement of Wan et al. (2023) that shocks and risks were more readily and rapidly transmitted across markets during the crisis periods.

The set of the DLM is based on combinations of all possible explanatory variables. The kth model in the DLM set consists of an observation equation (Formula 7) and a state equation (Formula 8):

$$y_t = x_t^{(k)}\theta_t^{(k)} + \varepsilon_t^{(k)} \tag{7}$$

$$\theta_t^{(k)} = \theta_{t-1}^{(k)} + \delta_t^{(k)} \tag{8}$$

where y_t – dependent variable, in our case, spillover level; $x_t^{(k)}$ – independent variables (drivers) in the k^th^ model; $\theta_t^{(k)}$ – regression parameters of the k^th^ model; $\varepsilon_t^{(k)}$, $\delta_t^{(k)}$ – error vectors for the observation and state equations corresponding to a normal distribution; and t – time index.

At the starting point (when the first-period t is equal to zero), all K models are assumed to be equally "good", i.e., assigned the same conditional state distribution (Formula 9):

$$\pi_{0|0,k} = \frac{1}{K} \tag{9}$$

Retrospective analysis consists of an estimation of the probability of the predicted model (Formula 10) and the probability of the updated model (Formula 11). The estimated probability of the predicted model should always be above 0.20 to keep variables within the model (Catania and Nonejad, 2018).

$$\pi_{t|t-1,k} = \frac{(\pi_{t-1|t-1,k})^{\alpha} + c}{\sum_{i=1}^{K}[(\pi_{t-1|t-1,k})^{\alpha} + c]} \tag{10}$$

$$\pi_{t|t,k} = \frac{\pi_{t|t-1,k} f_k(y_t|Y^{t-1})}{\sum_{i=1}^{K} \pi_{t|t-1,i} f_i(y_t|Y^{t-1})} \tag{11}$$

where $\pi_{t|t-1,k}$ – probability of predicted model (posteriori inclusion probabilities); $\pi_{t|t,k}$ – probability of updated model (posteriori predictive probabilities); a – decay factor (forgetting factor) fixed from (0,1); c – small number, which avoid the model probabilities being brought to zero; and $f_k(y_t|Y^{t-1})$ – predictive density of the k^th^ model at y_t, given the data from previous periods.

Then, the forecast is obtained from the following equation (Formula 12):

$$y_t^{DMA} = \sum_{i=1}^{K} \pi_{t|t-1,i} \widehat{y_t^{(k)}} \tag{12}$$

where y_t^{DMA} – forecast of the spillover at time t; $\pi_{t|t-1,i}$ – predicted probability assigned to the i-th model at time t; and $\widehat{y_t^{(k)}}$ – prediction given by the k-th regression model.

According to Catania and Nonejad (2018), it takes around 30 to 50 iterations for DMA to adapt to the time series given the prior. Thus, we remove the first 30 days when estimating the coefficient and inclusion probabilities for the DMA. According to Drachal (2018), DMA enables the uncertainty in the model and the parameters of each model to change over time. In other words, the final DMA forecast is calculated as a weighted average of the forecasts of all possible K models. Still, the weights change over time according to the predictive power of each regression model at a given point in time. DMA forecasting results are then compared to dynamic model selection (DMS), where a single (potentially different) model is used as the forecasting model at each point in time (Koop and Korobilis, 2012).

2.2. Variables

Scholars choose green bond indices to investigate the connectedness of the green bond market with other financial markets: The Bloomberg Barclays MSCI Euro Green Bond (BBGB-EU) index for the EU market and the Bloomberg Barclays MSCI US Green Bond (BBGB-US) index for the US market (Martiradonna et al., 2023; Xu et al., 2023; Elsayed et al., 2022; Reboredo et al., 2020). All bonds included in these indices comply with the green bond principles. Considering the previous research practice, we choose the Bloomberg MSCI Global Green Bond Index for the green bond market and use the abbreviation GREEN.

The most popular financial markets included in the investigation of connectedness are treasury, corporate bond, stock, crude oil, dollar, and gold markets. We choose the following indices as the proxies of other financial markets: The S&P 500 (SPX) index – for the stock market; S&P GSCI precious metals (SPGSPMTR) index – for the gold market; US Fed Trade Weighted Nominal Broad Dollar (USTWBGD) index – for the dollar market; and S&P Global Oil (SPGOGUP) index – for the crude oil market. These indices, except for the USTWBGD index, were included by Zhang et al. (2023) in examining the time-varying causal relationship between green finance and geopolitical risk. Further, we use the following abbreviations: SPX – for the stock market, SPM – for the gold market, SPG – for the crude oil market, and UST – for the dollar market.

Table 2. Summary of variables used in the analysis.

Variable	Abbrevation	Market type	Source	Measurement / Description
Bloomberg MSCI Global Green Bond Index	GREEN	Green Bonds	Bloomberg	Market value-weighted index including only bonds that meet the Green Bond Principles
S&P 500 Index	SPX	Stock Market	Bloomberg	Capitalization-weighted index tracking the performance of 500 large-cap US companies
S&P GSCI Precious Metals Index	SPM	Gold Market	Bloomberg	Commodity index tracking the performance of precious metals (mainly gold and silver)
US Trade Weighted Broad Dollar Index	UST	FX Market	Bloomberg	The weighted average of the US dollar's exchange rate against major trading partners
S&P Global Oil Index	SPG	Oil Market	Bloomberg	Market-cap weighted index reflecting the performance of global oil and gas companies
Global Geopolitical Risk Index	GPR	Uncertainty	The Caldara and Iacoviello construct	Index based on the frequency of newspaper articles related to geopolitical tensions
Volatility Index	VIX	Uncertainty	Chicago Board Options Exchange (CBOE)	Derived from S&P 500 option prices; measures expected 30-day market volatility
Economic Policy Uncertainty Index	EPU	Uncertainty	Economic Policy Uncertainty	Computed from the newspaper coverage frequency of economic policy uncertainty terms
Twitter Economic Uncertainty Index	TEU	Uncertainty	Economic Policy Uncertainty	Index constructed using algorithmic analysis of tweets related to economic uncertainty

Uncertainty indices help assess market sentiment, investor confidence, and the level of risk that may arise in extreme market conditions. Among the most popular uncertainty indices used by scholars (Xu et al., 2023; Wan et al., 2023; Zhang et al., 2023; Elsayed et al., 2022) are the VIX index, EPU index, GPR index, and TEU index. VIX is known as the “fear index”, which shows the expected volatility of the S&P 500 stock index over the next 30 days and helps measure the level of risk, fear, or stress in the market. The EPU index captures policy-related economic uncertainty as reported by prominent newspapers. The GPR index measures global geopolitical risk through the number of articles related to adverse geopolitical events. The TEU index reflects economic uncertainty based on information published on the Twitter platform.

Table 2 outlines the variables employed in the study, detailing their sources, market categories, and how each is measured.

These variables provide a comprehensive and well-established representation of financial markets and uncertainty measures, supporting a thorough analysis of market connectedness and its drivers.

2.3. Research data

The sample of daily data covers the period from the 1st of March, 2021 to the 23rd of February, 2023. The number of total observations is 520. The sample is divided into two approximately equal one-year sub-samples: The pre-war period (01-03-2021–23-02-2022) and the war period (24-02-2022–23-02-2023). We choose no more than a one-year sub-sample to avoid the influence of the COVID-19 pandemic on the data. Equal pre-war and war periods were also used by Jiang and Chen (2024), Derindere Köseoğlu et al. (2024), and Yousaf et al. (2023).

Figure 1 represents the time-series plots of the original data.

The data shows greater or lesser fluctuations of indices and reduced stability at the beginning of 2022. This can be related to the start of the Russian-Ukrainian war, resulting in uncertainty in financial markets, rising inflation, interest rates, deterioration of the global trade supply chain, etc. It is confirmed by the extremely high growth and volatility of the GPR index, fluctuations in the global stock VIX index, and changes in the TEU index. During the analyzed period, the most stable is the index of precious metals, which is considered a safe haven during periods of turmoil (Wan et al., 2023; Zhang et al., 2023). The green bond index, which is also considered a safe haven, is relatively stable. However, greater volatility is evident during the period of the Russian-Ukrainian war. Similar trends are observed in Figure 2, which represents time-series plots of returns. Particularly high volatility is observed in crude oil, stocks, green bonds, and US dollar markets, while the precious metals index remains the most stable.

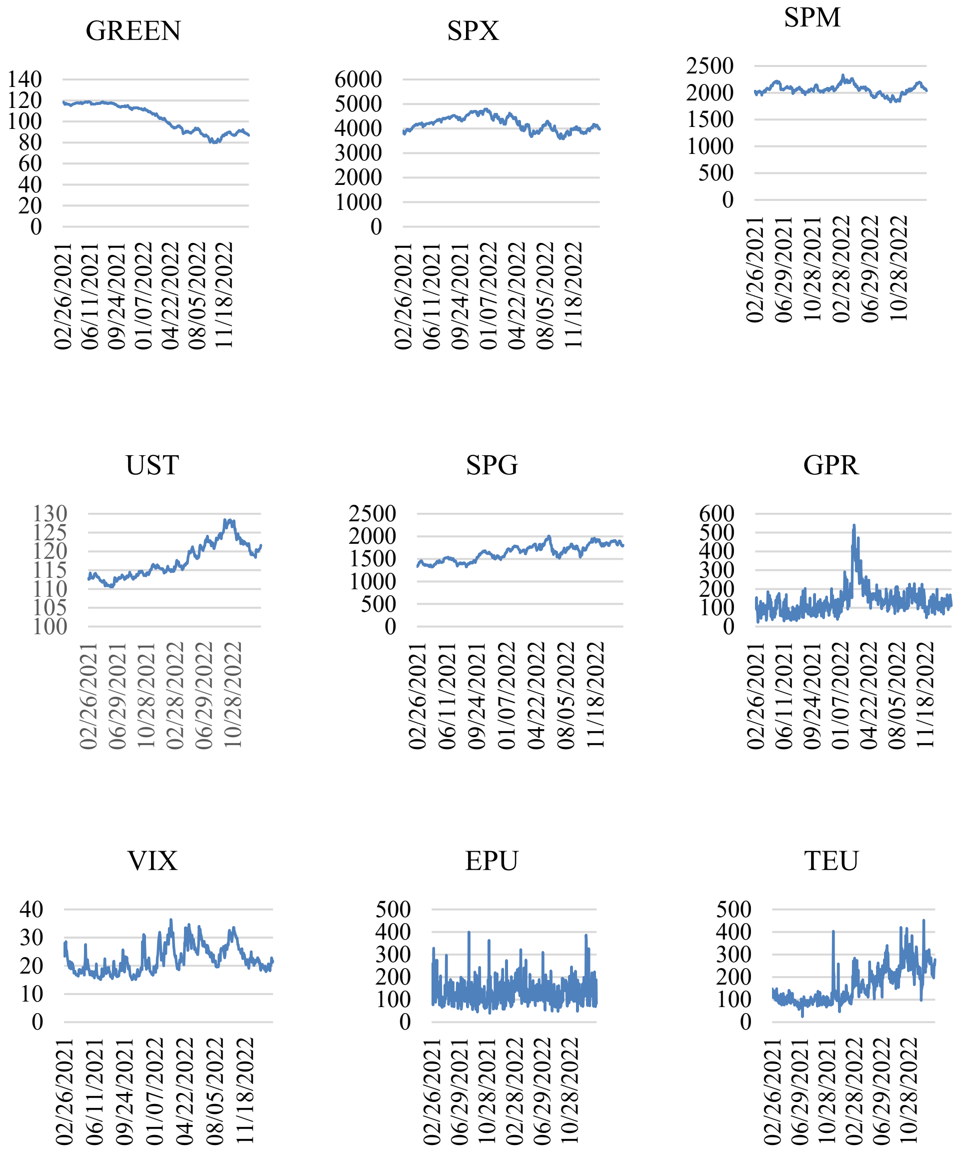

Figure 1. Time-series plots of original data.

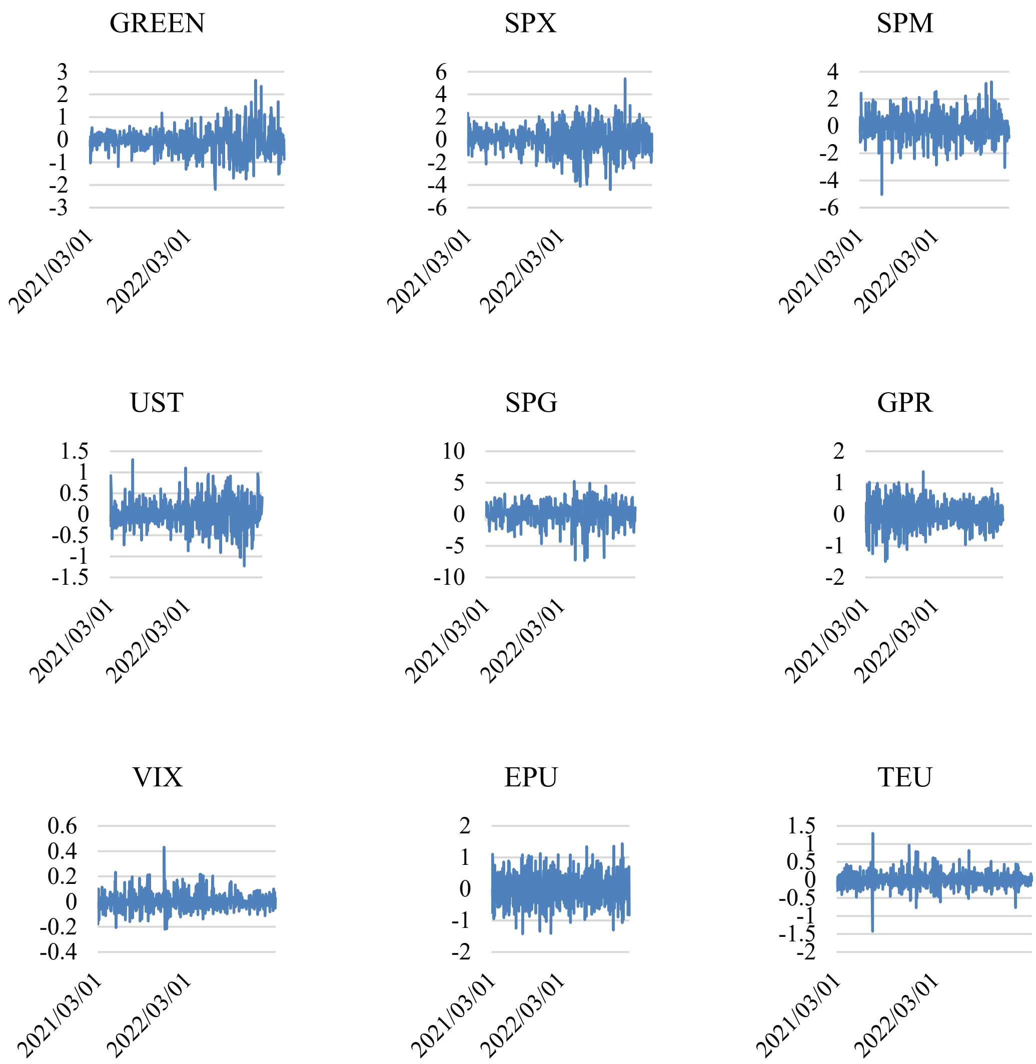

Figure 2. Time-series plots of returns.

Descriptive statistics of variables are presented in Table 3.

The results show that the stock market is the most volatile (standard deviation equals 1.210), while the US dollar market is the least volatile (0.338). Among uncertainty indices, the volatility of EPU and GPR is the highest (standard deviation equals 0.479 and 0.403, respectively) while the volatility of VIX is the lowest (0.073). An important observation is that the green bond index and the EPU have negative means. This indicates that the absolute values of indices decreased during the period analyzed.

The correlation matrix of indices' returns is presented in Table 4. To assess potential multicollinearity in the VAR model, Variance Inflation Factors (VIF) are calculated for the four explanatory variables. The results are: SPX = 1.26, SPM = 1.37, UST = 1.60, and SPG = 1.13. All values are well below the conventional threshold of 5, indicating that multicollinearity is not a concern and that the VAR model estimates are robust.

Table 3. Descriptive statistics.

Variable	Mean	Median	Minimum	Maximum	Standard deviation
Indices included in the total spillover index:					
GREEN	−0.060	−0.047	−2.201	2.630	0.583
SPX	0.008	0.000	−4.420	5.395	1.210
SPM	0.001	0.000	−5.047	3.268	0.956
UST	0.014	0.000	−1.232	1.305	0.338
SPG	0.059	0.000	−7.355	5.247	1.615
Uncertainty indices:					
GPR	0.000	−0.001	−1.499	1.357	0.403
VIX	0.000	−0.009	−0.220	0.432	0.073
EPU	−0.002	−0.007	−1.426	1.440	0.479
TEU	0.001	−0.011	−1.427	1.297	0.234

Table 4. Correlation matrix.

Variable	GREEN	SPX	SPM	UST	SPG	GPR	VIX	EPU	TEU
GREEN	1	0.31***	0.45***	−0.68***	0.07	−0.08	−0.14**	−0.08	−0.06
SPX	0.31***	1	0.13**	−0.37***	0.30***	−0.04	−0.73***	0.03	−0.08
SPM	0.45***	0.13**	1	−0.52***	0.16***	0.03	−0.09*	0.00	0.00
UST	−0.68***	−0.37***	−0.52***	1	−0.28***	0.03	0.27***	0.07	0.11*
SPG	0.07	0.30***	0.16***	−0.28***	1	0.02	−0.31***	0.05	−0.06
GPR	−0.08	−0.04	0.03	0.03	0.02	1	0.02	0.01	0.05
VIX	−0.14**	−0.73***	−0.09*	0.27***	−0.31***	0.02	1	−0.06	0.15**
EPU	−0.08	0.03	0.00	0.07	0.05	0.01	0.00	1	−0.02
TEU	−0.06	−0.08	0.00	0.11*	−0.06	0.05	0.15***	−0.02	1

Note: significance level: *** 1%; ** 5%; * 10%.

The data revealed that returns of the green bond index are strongly negatively (-0.68) correlated with US dollar (UST) index returns, weakly negatively (-0.14) – with the returns of VIX, semi-strongly positively (0.45) – with S&P precious metals (SPM) index returns, and weakly positively (0.31) – with global stock (SPX) index returns. Correlations between the returns of the green bond index and other indices' returns are not statistically significant. In addition, only one statistically significant correlation between the returns of uncertainty indices is observed: Weakly positive (0.15) between VIX and TEU.

3. Empirical results

3.1. Connectedness analysis

We start the results section with the testing of time series for stationarity and normality (Table 5). According to the ADF test results, variables do not have a unit root as all p-values are below 0.05. The Jarque-Bera test showed that the data do not follow a normal distribution except for EPU. For the construction of the VAR model, the number of lags is determined using Akaike, Hannan-Quinn, and

Schwarz information criteria. Based on Xia et al. (2020), we use a rolling window of one-third of the total observations to test the robustness of the model and the results obtained. As the total observations in our study are approximately 500 days, we apply a rolling window of 150 days. Following Diebold and Yilmaz (2012, 2014) and Mensi et al. (2023), we use a 10-step forecast horizon in GFEVD for the assessment of dynamic spillover indexes.

Table 5. Results of the test for normality and unit root.

Variable	Skewness	Ex. Kurtosis	Jarque−Bera	ADF
Indices included in the total spillover index:				
GREEN	0.143	1.849	75.845***	−20.1646***
SPX	−0.153	1.416	45.478***	−22.9172***
SPM	−0.289	2.087	101.592***	−10.7355***
UST	0.108	1.149	29.632***	−21.2429***
SPG	−0.679	2.900	222.207***	−22.3251***
Uncertainty indices:				
GPR	−0.145	0.730	13.372***	−14.107***
VIX	0.761	2.931	236.289***	−13.7062***
EPU	0.025	0.109	0.315	−13.2257***
TEU	0.206	5.217	593.265***	−11.4106***

Note. Confidence level: *** 1%; ** 5%; * 10%.

The total spillover index and uncertainty indices are presented in Figure 3.

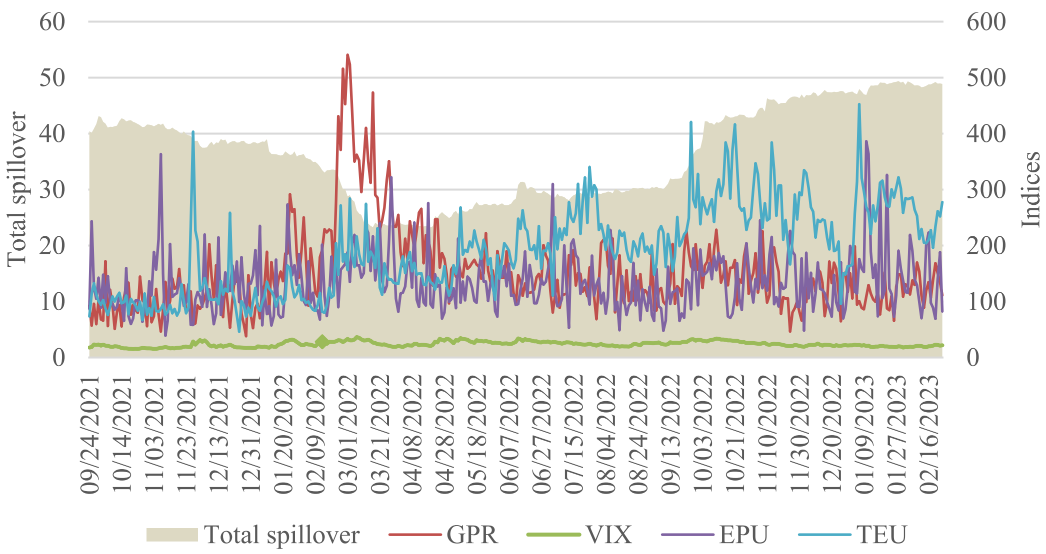

Figure 3. Total spillover and uncertainty indices.

The curve indicates that the total spillover index was at its lowest point before the Russian-Ukrainian war. The GPR index peaked as the war started. Other indices remained relatively stable at the moment of the Russian invasion of Ukraine. Around October 2022, the total spillover index increased. Furthermore, the TEU index also greatly increased. The EPU index also peaked on January 20, 2023. However, this was not followed by a significant change in the total spillover index.

Figure 4 represents the dynamics of net spillover for all indices representing different financial markets.

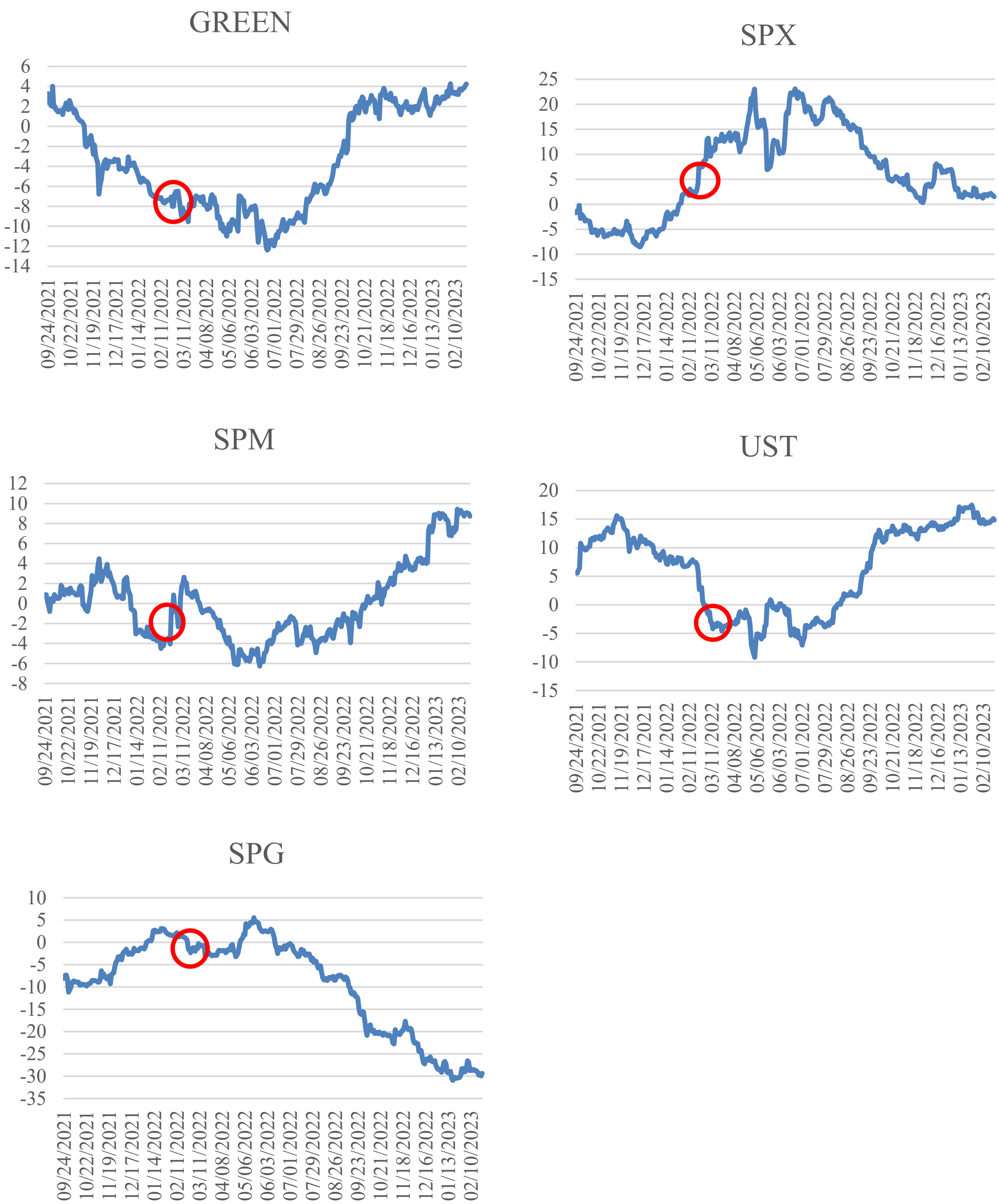

Figure 4. Net spillovers of selected indices.

Note: The red mark indicates the start of the Russian-Ukrainian war (24-02-2022).

We observe that the returns of the green bond market are mostly explained by other markets' returns, as net spillovers have negative values. However, they became positive in the final months of the analyzed period. SPX had a high net spillover value after the start of the war in Ukraine. SPM net spillover used to have a negative value but became positive at the end of 2022 and was rapidly growing. UST net spillover greatly decreased after the start of the war in Ukraine. SPG net spillover started to decrease after the Russian invasion of Ukraine and continuously decreased until the end of the study period. To summarize, the start of the Russian-Ukrainian war had the most effect on stocks, precious metals, and the US dollar markets.

Next, we provide aggregate matrices to explain pair-wise relationships between financial markets within the total spillover index. We begin with the pre-war period matrix (Table 6, Panel A). Here, we can see that the total spillover used to be smaller (32.36%), and the green bond market used to have a negative net spillover (−7.37%). This market receives 35.77% and transmits 28.40%. It was also heavily influenced by the US dollar market. S&P 500 and US Fed dollar indices used to be the main net spillover transmitters. The diagonal values in Table 4 represent the contribution of each market's own shocks to its forecast error variance, indicating the extent to which a variable is influenced by its own past. The off-diagonal values show the contribution of shocks from and to other markets, reflecting the spillovers transmitted between markets.

Table 6. Matrix of spillovers from, to, and net between financial markets.

Panel A. The pre-war period						
Variable	GREEN	SPX	SPM	UST	SPG	From
GREEN	64.23	2.07	11.04	22.24	0.42	35.77
SPX	0.14	77.56	1.27	3.54	17.49	22.44
SPM	10.61	1.79	68.72	17.91	0.97	31.28
UST	17.42	7.33	15.01	53.01	7.22	46.98
SPG	0.23	15.35	0.55	9.17	74.70	25.30
TO	28.40	26.54	27.87	52.86	26.10	32.36
Net	−7.37	4.10	−3.41	5.88	0.80	
Panel B. The war period						
Variable	GREEN	SPX	SPM	UST	SPG	From
GREEN	45.64	12.08	17.26	24.95	0.07	54.36
SPX	12.97	57.88	12.64	12.50	4.02	42.13
SPM	17.45	10.02	46.86	23.81	1.86	53.14
UST	23.13	10.03	22.18	42.61	2.05	57.39
SPG	5.04	11.52	9.81	10.99	62.65	37.36
To	58.59	43.65	61.89	72.25	8.00	48.87
Net	4.23	1.52	8.75	14.86	−29.36	

Table 5, Panel B represents pair-wise relationships between financial markets within the total spillover index in the war period. The data show that the green bond market is a net transmitter: It transmits shocks to other financial markets. A comparable pattern is evident in the precious metals index, which, similarly to the green bond market, is considered a safe haven asset. However, the net spillover index of GREEN is quite small (4.23%). The green bond market receives 54.36% and transmits 58.59%. We observe a strong relationship between the green bond and the US dollar markets.

However, the US dollar index explains the green bond index better than vice versa. There is also a strong relationship between the green bond and precious metals markets, and the green bond index has a slightly stronger effect. Other notable observations are that the US dollar market explains other markets best, while the crude oil market is mostly explained by others. The total spillover index is estimated to be 48.87%. Moreover, the net spillover index of SPG reached negative 29.36% during the war period, compared to a slightly positive 0.80% beforehand, indicating a clear transition from a transmitter to a significant receiver of shocks. This reversal likely reflects the market's heightened sensitivity to geopolitical tensions, supply chain disruptions, and global demand uncertainty triggered by the war.

We accept H1: Total spillover increases during the Russian-Ukrainian war, and partly accept H2 because the green bond market is a net receiver of shocks during the pre-war period but a net transmitter during the war period.

3.2. Impact analysis

DMA modeling results are provided in Table 7.

Table 7. Estimates of DMA parameters.

Variables	E[theta_t]	SD[theta_t]	E[P(theta_t)]	SD[P(theta_t)]
Intercept	2.87	6.17	1.00	0.00
Lag(Total Spillovers, 1)	0.76	0.27	0.75	0.25
Lag(Total Spillovers, 2)	0.12	0.11	0.32	0.05
Lag(Total Spillovers, 3)	0.04	0.07	0.25	0.03
Lag(GPR, 1)	−0.03	0.02	0.25	0.06
Lag(VIX, 1)	−0.12	0.32	0.34	0.03
Lag(EPU, 1)	0.02	0.02	0.23	0.06
Lag(TEU, 1)	0.02	0.07	0.27	0.05
Residuals				
Min	1Q	Median	3Q	Max
−1.9048	−0.3015	−0.0481	0.2106	2.7506

The model results exclude the first 32 days, in which the model's estimates become more stable. Here, we observe that the average values of model coefficients differ in their sign. The GPR and VIX have negative coefficients, showing that they, on average, have more negative than positive impacts on total spillover. On the other hand, EPU and TEU have positive coefficients, showing that they increase the total spillover index. Even though the VIX has a negative coefficient value (−0.12), it has a high standard deviation (0.32). Estimated posterior p-values of all variables are above 0.20, indicating that all variables are significant within the model. Among uncertainty indices, the VIX has the most significant impact, as estimated by the average p-value (0.34), whereas EPU has the smallest (0.23).

The expected number of predictors within the reduced models with the highest model probabilities and their dynamics are provided in Figure 5. Statistical estimates for forecasting results are presented in Table 8. Mean squared error (MSE) is larger in the DMS; mean absolute deviation (MAD) is also larger in the DMS; and log-predictive likelihood is also larger in the DMS. Therefore, the DMA is estimated to have a lower MSE, thus producing more precise predictions.

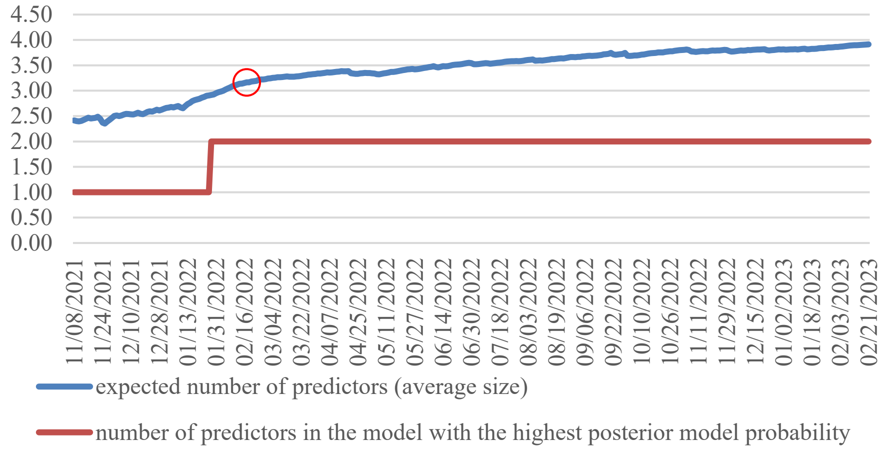

Figure 5. Number of predictors in DMA.

Note: The red mark indicates the start of the Russian-Ukrainian war (24-02-2022).

Table 8. Evaluation of forecast results using DMA and DMS approaches.

Model	DMA	DMS
MSE	0.341	0.537
MAD	0.399	0.478
Log-predictive Likelihood	−722.93	−717.10

Graphical depictions of forecast results compared to actual values of the total spillover index are provided in Figure 6. We compare the DMA model and the DMA with the highest posterior model probability. Here, we can see that forecasted values closely follow the actual values of the total spillover index. The difference between the two models is mostly seen in the first months of the time frame.

Further, we analyze the dynamics of estimated model coefficients and posterior inclusion p-values and how they differ over time. We begin by analyzing posterior inclusion p-values (Figure 7). GPR and TEU indices increase in posterior inclusion p-value from about 0.20 to above 0.30 throughout the period. The VIX remains steady at about 0.30. The EPU rises from 0.10 to about 0.30. There are no significant fluctuations in the parameters' posterior inclusion p-values, except for the GRP index in August 2022 and the VIX in April 2022, where p-values slightly decrease.

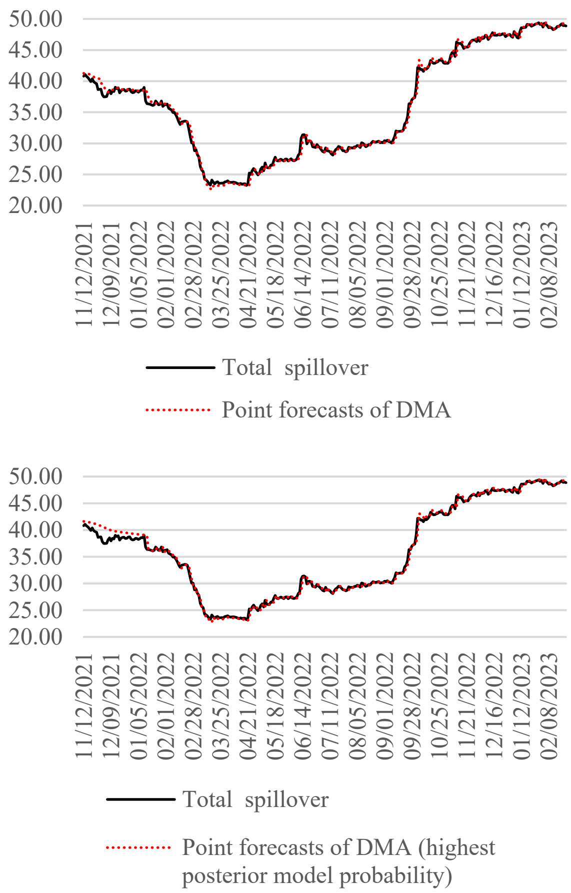

Figure 6. Comparison of actual vs. fitted values of the forecast.

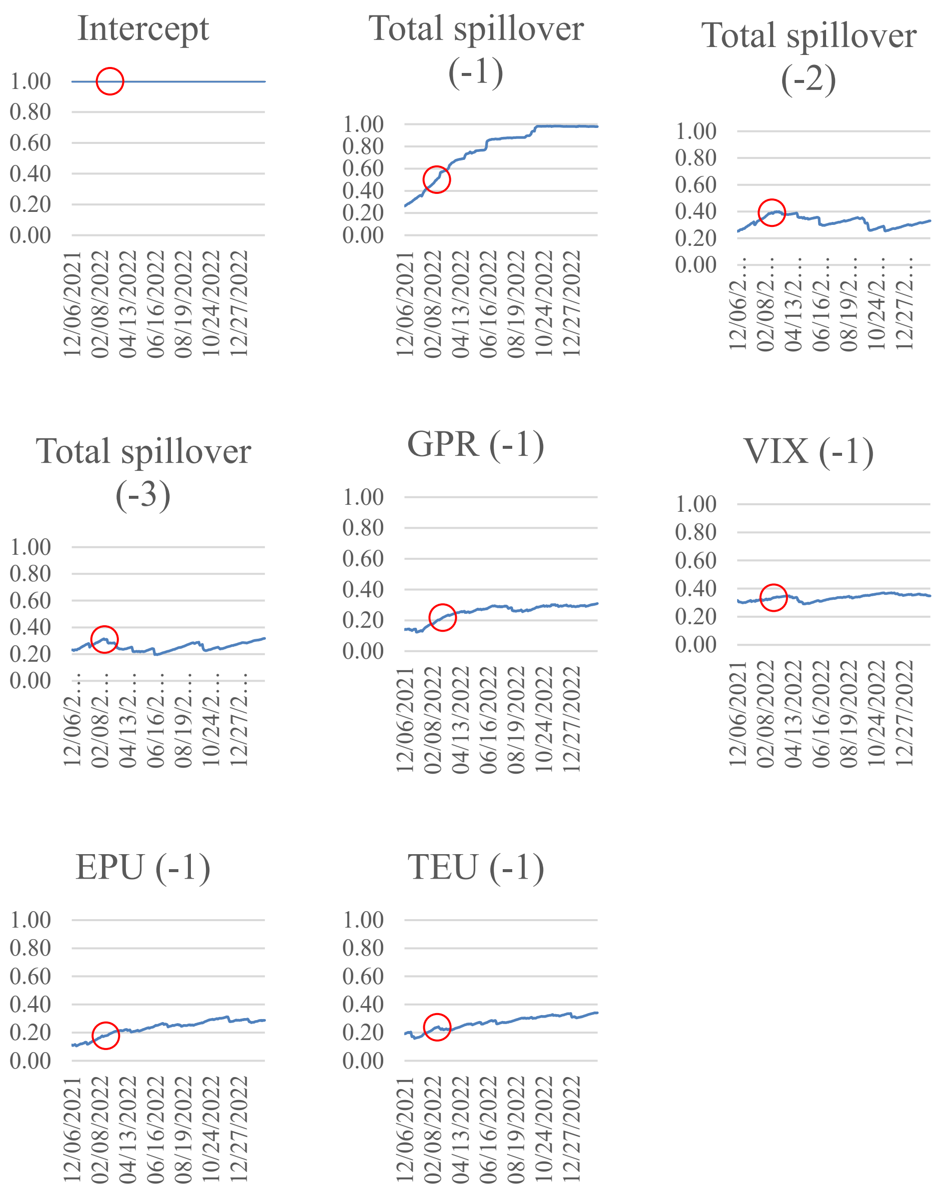

Figure 7. Posterior inclusion probabilities of the predictors.

The dynamics of estimated model coefficients are provided in Figure 8. The GPR coefficient is mostly negative and decreases further in November 2022. The VIX fluctuates among time samples and remains negative. The value greatly decreased after the war in Ukraine started. EPU and TEU have predominantly positive coefficients: Both grow in their values throughout the period analyzed. However, the coefficient values of EPU and TEU peaked in December 2022.

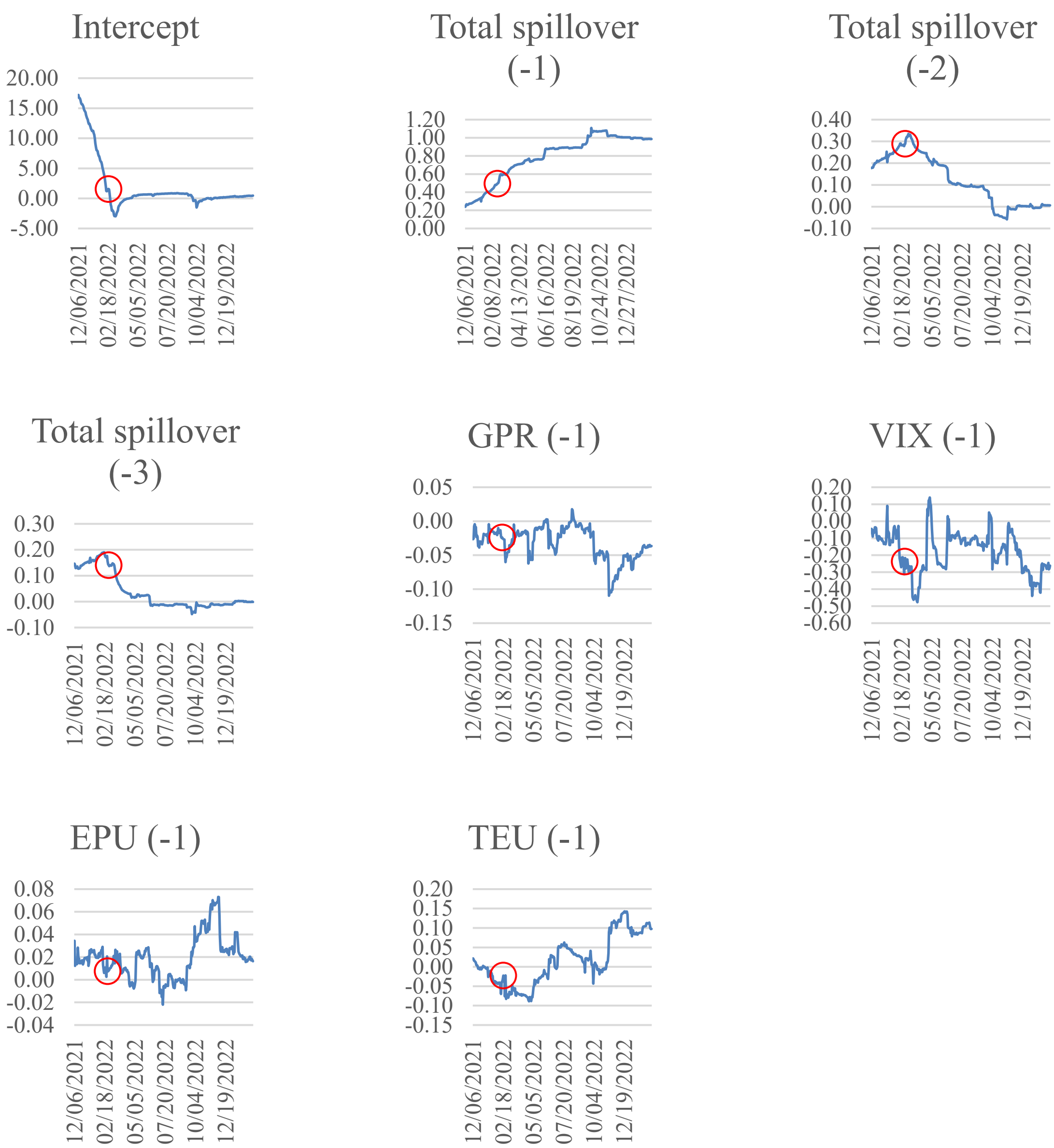

Figure 8. Filtered estimates of the regression coefficients.

Note: The red mark indicates the start of the Russian-Ukrainian war (24-02-2022).

The assessment of the impact of uncertainties on total spillover enable us to accept H3 because EPU and TEU increase total spillover, while GPR and VIX decrease it. The findings reveal that all four uncertainty indices have a greater impact (higher posterior inclusion p-values) on total spillover during the Russian-Ukrainian war. These findings prove H4.

4. Conclusions and discussion

Even though there is plenty of research related to the connectedness of the green bond market with conventional financial markets during crises, we closed the gap by answering two questions. First, we revealed the specifics of markets' connectedness during the Russian-Ukrainian war. Second, we determined the impact of uncertainties on the connectedness for total observations and the change of this impact in the context of the Russian-Ukrainian war.

The study revealed that total spillover increased during the Russian-Ukrainian war. The change of total spillover is a phenomenon of contagion effect characteristic for financial markets during economic and financial crises. The rise in connectedness can be explained by growing and elevated uncertainty caused by social, economic, or political factors, which often trigger exaggerated market reactions, disrupt the decision-making processes of market participants, increase their perception of risk, and cause market inefficiencies (Naeem et al., 2021). Our findings agree with the results of scholars who studied spillover effects in financial markets during the crisis periods. According to Chen et al. (2024), total spillover effects increase notably during extreme market conditions. Mensi et al. (2024) pointed out that periods of major crises are associated with unusually high connectedness. Arif et al. (2021) found enhanced connectedness during the COVID-19 period. War-caused uncertainty significantly increases the connectedness among the volatilities of global financial markets (Yousaf et al., 2023). There is some evidence that, after the war, total connectedness rose twice (Jang and Chen, 2024). In addition, we revealed the specific behavior of the green bond market in the context of the Russian-Ukrainian war: The green bond market was a net receiver of shocks during the pre-war period but a net transmitter during the war period. This means that the net spillover effect and direction depend on the specifics of the studied crisis. Moreover, the net spillover of the green bond market was relatively small in both sub-periods. A weaker effect is typical for shorter periods. Total spillover is affected by all factors of uncertainty. The study revealed that EPU and TEU increase total spillover while GPR and VIX decrease it. All four uncertainty indices had a greater impact on total spillover during the Russian-Ukrainian war.

Usually, the green bond market is a net receiver of shocks due to the relatively low quantity of green bonds in the market. However, the connectedness is dynamic: It changes over time (Elsayed et al., 2022). We provide some insights into the connectedness between the green bond and conventional financial markets. First, we found that the connectedness between the green bond market and conventional financial markets increased during the war period. The increased connectedness between green and other financial markets during the COVID-19 crisis was also observed by Arif et al. (2021). In addition, they stated that a smooth transition to a green economy depends on the overall financial stability of financial markets. Second, the net spillover of green bonds was relatively small in both sub-periods, while in other studies it was larger (Chen et al., 2024; Lu et al., 2023). Mensi et al. (2023) found a net spillover of green bonds in the short term. Third, the green bond market was a receiver of shocks during the pre-war period but a transmitter during the war period. The green bond market is a niche, relatively small, and less integrated market. That is why it was a receiver of shocks during the pre-war period. During crisis periods, investors often shift to safer, ESG-aligned assets. Sudden demand spikes in green bonds create volatility that spills back into other conventional markets. Furthermore, these results suggest that the safe haven role of green bonds may be weakened during times of crisis. In other words, if the green bond market becomes a transmitter of shocks to other markets, this may indicate that it has become a less predictable and more sensitive market. Sheenan (2023) reached similar conclusions, finding that green bonds may be more sensitive to geopolitical risk and contagion than traditional bonds. Moreover, the green bond market is less liquid. During stress, price swings are amplified, and these fluctuations transmit risks outward to related markets. Moreover, Lu et al. (2023) identified that during both periods, the pre-COVID-19 and the post-COVID-19, the green bond market was a receiver and a larger receiver in the post-COVID-19 period. Mensi et al.

(2023) found that the green bond market is a net receiver in the long term and a net transmitter in the short term. In summary, we expanded the evidence on the behavior of the green bond market during crisis periods. One important insight is that the net green bond spillover effect and direction depend on the specifics of the crisis period. For example, crises caused by the COVID-19 pandemic and the Russian-Ukrainian war had different consequences and impacts on financial markets.

The strongest connectedness is observed between the green bond market and the US dollar market in both sub-periods. The green bond market receives more shocks from the US dollar market; however, the gap between "from" and "to" is smaller in the pre-war period. Moreover, the US dollar has the largest outward and inward spillovers in both sub-periods, as was identified in the short term by Wan et al. (2023). Similarly, Saeed et al. (2021) found that the US dollar is usually a shock transmitter to other markets, such as stocks and crude oil. This is consistent with the dominance of the US dollar, which is the most frequently used currency in global trade and a key unit in international financial transactions. Moreover, fluctuations in the US dollar exchange rate are an indicator of shocks in the foreign exchange market (Wan et al., 2023). The pattern of green bond market connectedness with other financial markets is similar in both sub-periods, with the exception that the green bond market transmits a bit more to equity than to the crude oil market during the war period. This can be explained by the findings of Yousaf et al. (2024), who found that connectedness between crude oil futures and green bonds is weak across all periods, making green bonds suitable for diversification. Similarly, Elsayed et al. (2022) state that due to the low integration of green bonds with energy markets, they provide a safe haven against price fluctuations.

Total spillover is affected by all the analyzed uncertainty indices. However, the study indicates that EPU and TEU increase total spillover while GPR and VIX decrease it. These findings are consistent with those of Zhao and Park (2024), who observed that the financial stress index and TEU strengthen connectedness, whereas VIX and GPR weaken. Tang et al. (2023) also observed similar results. The impact of EPU and TEU can be explained by their functioning through different market mechanisms, strengthening the transmission of uncertainty. During the war, EPU may have increased due to sanctions and supply chain disruptions. They made market participants more sensitive to new information, leading them to adjust investments and increase market connectedness. The TEU, based on social media, also stimulated investor activity and portfolio changes due to the rapid spread of information and emotions. Moreover, GPR and VIX reduced the intensity of market connectedness, as market participants moved to safer assets, avoiding risk. The high level of GPR promoted stability and reduced activity, while VIX reflected risk aversion and the shift of investments to less risky assets. VIX spikes mean heightened volatility in equities and risky assets. Investors look for stable, less volatile, fixed-income assets. Green bonds, like conventional high-grade bonds, benefit from this capital inflow. Moreover, green bonds are closer to conventional bonds than to stocks. So when stock market fear rises, they move differently, offering diversification and safe haven qualities. Unlike VIX, which is largely financial-market specific, EPU and TEU capture uncertainty in fiscal policy, regulation, trade wars, etc. These affect all sectors, including the green economy and sustainable finance. Instead of being a shield like under VIX shocks, under EPU/TEU shocks, green bonds become a transmitter because their fundamental value is policy-sensitive. Our findings demonstrated that uncertainties influence spillovers across the analyzed financial markets during the Russian-Ukrainian war. We found that all studied uncertainty indices are significant throughout the conflict, despite variations in their sign. The stronger impact can be explained by increased market sensitivity, rising levels of financial stress, shifts in investor behavior, and the accelerated dissemination of information during times of crisis. Similar results were obtained by Wan et al. (2023) and Wei et al. (2024), who stated that shocks and risks were more readily and rapidly transmitted across markets during this period.

The findings are valuable from a scientific point of view. They support the contagion theory, stating that correlation across markets appears to increase under extreme economic events. We revealed that the green bond market changes the direction of net spillover from the receiver to the transmitter, and a net spillover is relatively large in the pre-war period but small in the war period. Our study contributes to the literature on the connectedness between green and conventional financial markets during crisis periods. These results support the modern portfolio theory: Green bonds, as a safe haven investment, play an important hedging role in investors' portfolios. We assessed the impact of uncertainties and captured their dynamics by applying DMA. These findings give some insights into the context of risk theory focused on risk mitigation and uncertainty reduction.

The findings are useful for portfolio managers, policymakers, and environmentally friendly investors. A negative correlation between the US dollar and the green bond markets shows the possibilities for risk diversification. Green bonds transmit and receive very few shocks from the crude oil market in both sub-periods. Moreover, green bonds have the lowest net spillovers among the analyzed financial markets. This reflects the strong save haven features of green bonds. The VIX is the most significant among uncertainty indices, so it is a good prediction tool to forecast the spillover effect among the analyzed financial markets. This provides portfolio managers with insights for changing risk management strategies. Policymakers can make decisions to safeguard the stability of financial markets and increase the awareness of investors. This would increase the attractiveness of green bonds and contribute to climate change mitigation and other environmental issues.

The limitations of the study are caused by the applied research methods and scope. DMA requires continuous updates and combines multiple models. Its performance depends on the initial pool of candidate models and the specification of various parameters. This model can also overfit the risk. More advanced models can be applied, such as the construction of DMA models consisting of different variables and a comparison of their results. Research may be accompanied by causality tests. We included a limited set of market and uncertainty indices, which could be expanded. We restricted our analysis to several implications for investors. In future studies, researchers could quantify the diversification and hedging benefits of green bonds against conventional assets. Social bonds can also be incorporated into the assessment of connectedness.

Author contributions

Vilija Aleknevičienė. Conceptualization. Writing: original draft, review and editing.
Algirdas Justinas Staugaitis. Methodology. Investigation. Software. Validation. Visualization.
Rugilė Gudaitienė. Conceptualization. Formal Analysis. Providing material. Visualization.
Asta Bendoraitytė. Data Curation.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

The authors declare no conflicts of interest.

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