Exploring the bidirectional causality between green markets and economic policy: Evidence from the time-varying Granger test

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Abstract: The vigorous development of green markets and the effective mitigation of economic policy fluctuations are current hotspots that intrigue our interest in exploring the causal relationships between green market returns and economic policy uncertainty (EPU). Green bonds, corporate environmental responsibility, green technology investment, and the carbon trading market are our research objects to comprehensively understand the interaction among them, from both macro and micro perspectives. Considering the importance of temporal heterogeneity and spillover direction in causation, we employ the time-varying Granger causality method to obtain bidirectional real-time identification. We find that green market returns exhibit a time-varying bidirectional causality with EPU over most of the sample period. In contrast, green markets are more a risk spillover than a recipient. Notably, this causality is vulnerable to exogenous financial risks, especially structural changes caused by the COVID-19 pandemic. Overall, this paper provides insights into the deep-seated causes of price fluctuations, volatile market uncertainty, and the interaction mechanism between them, as well as implications for market participants and policymakers.

Keywords: Time-varying Granger; Green markets; EPU; bidirectional causality

JEL classification: C32; D81; G15

1. Introduction

Recently, there has been worldwide recognition of the problems associated with effectively addressing climate challenges and promoting a decarbonized economy. Policy documents such as the Paris Agreement and the Sustainable Development Goals (SDGs), launched in 2015, put curbing global temperature rise, building climate resilience and moving towards a sustainable development path on the international agenda (Iacobuţă et al., 2022). Against the backdrop of the global environmental movement's enthusiasm, green markets with core values of promoting the realization of dual carbon goals and sustainable development have received considerable attention. In this context, the transition to the decarbonized investment pattern and green financing channel has become crucial (McCollum et al., 2018).

From a macro perspective, this is based on collective rationality corresponding to the efforts of international governments to mitigate climate risks (Braouezec and Joliet, 2019). On the one hand, as an important guarantee and primary condition for the implementation of sustainable development agendas, green finance funds green technology and enables the implementation of environmental responsibility (Madaleno et al., 2022). On the other hand, the up-and-coming green bond and well-established carbon trading markets share commitments to construct an environmentally friendly society and curb global warming (Ren et al., 2022c). From a micro perspective, this is based on individual rationality corresponding to companies' spontaneous environmental protection behaviors (Braouezec and Joliet, 2019). Considering the externality of carbon emissions (Sajid et al., 2021), only companies with a high sense of social and environmental responsibility are motivated to reduce greenhouse gas emissions through a series of low-carbon and environmentally friendly initiatives, including green technology investments and green bond purchases among others.

Most of the existing research has focused on the nexus of specific green markets and other financial markets (Elsayed et al., 2022; Rannou et al., 2021), the interrelationships between corporate green behavior and economic performance (Algarni et al., 2022; Farza et al., 2021), and green technology innovation (Li et al., 2022; Liao and Li, 2022). However, little literature has examined green markets and sustainable development through the lens of economic policy uncertainty (EPU). Therefore, our study fills the gap in the existing literature by providing a fresh perspective in investigating the bidirectional causality between EPU and green market prices via the time-varying Granger causality test.

The SDGs report claims that increasingly intractable climate problems are to blame for the existing economic development patterns (United Nations Global Compact, 2019). History warns us that if we blindly stick to the traditional development path and promote economic growth at the expense of ecological civilization, not only the efficient operation of the economy will be jeopardized, but also market uncertainty will increase (Gu et al., 2021). The green market is regarded as the main engine of sustainable development due to its huge development potential and economic value. Improving green bonds and carbon trading market mechanisms, establishing corporate environmental responsibility, and increasing investment in green technology may be an effective way to get out of the current economic predicament and help reduce uncertain policy fluctuations. In this pursuit, the means to find the point of convergence and balance between green sustainable development and the EPU is a top priority.

The COVID-19 pandemic is currently eroding the global economy with endless financial turmoil and sudden risks that have exacerbated the volatility of EPU (Rjiba et al., 2020). Moreover, with the deepening of economic globalization and financial integration, the cross-market spillover and contagion effects of EPU have become increasingly prominent (Bai et al., 2019). EPU affects green market returns directly by impacting investors' expectations and behaviors and indirectly through macroeconomic channels. Also, market returns will react on EPU, because the public can accurately perceive the signals released by return fluctuations and respond accordingly, and these corresponding actions are important references for government policy arrangements. Therefore, analyzing the bidirectional causality and interaction mechanism between EPU and green market returns helps understand the deep-seated causes of price fluctuations and volatile market uncertainty, as well as provides implications for investors' risk management and government regulation policies (Bai et al., 2021).

Using the time-varying Granger technique and daily data from February 2012 to March 2022, we clearly illustrate the dynamic interaction mechanism between EPU and the green markets and the trajectory of their causality over time. We find some intriguing results: The causality between the EPU and the green markets is vulnerable to disruption by unexpected events or economic turmoil, especially structural mutations in the causal relationship caused by the COVID-19 pandemic. In addition, as global low-carbon ambitions intensify and green strategic action deepens, green markets play the role of risk spillovers to a greater extent, and have permeated significantly into the realm of economic policy. When we consider the spillover effect of EPU, this significant causal effect exists only in specific periods, not generally. And the impact on corporate behavior is more pronounced, while the impact on the green bonds is minimal. Our conclusions provide reasonable explanations for abnormal market price fluctuations and substantial changes in EPU during the crisis period.

With this research article, we contribute to the existing literature as follows. First, we provide the first systematic consideration of how green finance, corporate environmental responsibility, green technology investment, and carbon trading systems respond to the challenges of economic policy volatility and affect market uncertainty. In the context of carbon-neutral sustainable development, it is of practical significance to weigh the interactive spillovers of green ecological benefits and economic policy fluctuations, and will open up new avenues for the examination of the interrelationship between green markets and uncertainty in the future. Second, the nexus of financial market prices and economic policy changes is fragile and sensitive to different periods, making real-time detection of causal relationships an imperative. Here, the time-varying Granger approach was adopted to allow a deep insight into the time-varying characteristics in the case of dynamic changes in the economic environment and market conditions. This constitutes a novel attempt in EPU and market price research. Third, the superiority of the time-varying Granger technique proposed by Shi et al. (2018, 2020) is that it adopts robust econometric methods and can accurately identify the onset and collapse dates of causality, which has been widely practiced in the macroeconomic field (Dogan et al., 2022; Hammoudeh et al., 2020). Therefore, the conclusions of this paper can provide policymakers and market participants with a powerful dynamic analysis tool, especially in risk mitigation, strategic planning and asset management. Fourth, our study provides rounded, detailed illustrations of the bidirectional interaction mechanism between EPU and green market prices and captures abnormal fluctuations in market prices and economic policy simultaneously, making it a useful complement to the existing literature.

The study is presented as follows. Section 2 reviews the relevant literature. Section 3 describes the methods and data. Section 4 analyzes and discusses the empirical results. The last section summarizes the manuscript.

2. Literature review

To unravel some of the mysteries surrounding the interrelationship between the EPU and green markets, we briefly review the existing literature concerning the green bond and carbon trading markets, corporate environmental responsibility, green technology, the bidirectional spillover relationships between EPU and specific financial markets, and the connections between EPU and the aforementioned individual market.

The first category of literature is a review of green bonds, carbon market, corporate environmental responsibility and green technology. As a powerful platform for implementing carbon peaking and carbon neutralization, the green bond and carbon trading markets jointly play a crucial role in improving green financing channels and optimizing the green market system (Rannou et al., 2021), and have stimulated the research interest of a large number of scholars. With the advantages of low financing costs and effective allocation of excessive costs, green bonds are a momentous financial tool for the transformation to a low carbon energy structure (Sartzetakis, 2021). Consequently, as a nonnegligible fresh force in the financial derivatives market, attention has recently focused on the provision of its connections with other markets (Pham, 2021; Tiwari et al., 2022) or macro and micro factors (Boutabba and Rannou, 2021; Simeth, 2021). In the same vein, as a mature capital market with a complete trading system, the carbon market plays a pivotal role in curbing carbon emissions and optimizing investment portfolios (Ren et al., 2022a), triggering a surge of interest in the carbon market and its connection with the fossil energy (Gong et al., 2021; Kartal, 2022) and carbon price prediction (Ren et al., 2022b; Zhang and Xia, 2022).

In addition to policy guidance at the macro level, the enterprise level is also a crucial relationship in enhancing green and sustainable development. On one hand, companies that consciously fulfill their social responsibility contribute to enhancing their competitiveness and continuous superiority (Yuan et al., 2022). Supporting this view, Han and Cao (2021) demonstrate that corporate environmental responsibility promotes energy conservation, emission reduction, and sustainable development. Likewise, Garel and Petit-Romec's (2021) comprehensive review concludes that enterprises adopting environmental responsibility strategies during crises boost equity returns. Not only that, given the innovation-driven development strategy, green technology has also played an important role in the balanced development of environmental governance and economic growth (Lin and Ma, 2022), attracting the research interest of scholars on green technology innovation (Deng et al., 2022; Li et al., 2022).

The second category of literature is a review of the bidirectional spillover relationship between EPU and specific financial markets. There has been extensive literature confirming the strong links between EPU and macro markets (Gu et al., 2021; Hu et al., 2020). In addition, instability amid global economic turmoil has led to prolific research on the spillover relationships between EPU and special financial markets. Considering EPU as the spiller and financial markets as the receiver, Stolbov and Shchepeleva (2020) emphasized that EPU transmits uncertainty to specific financial markets or the real economy through macro-fundamental channels, thereby, affecting commodity prices and the market structure (Ermoliev et al., 2015). Ma et al. (2019), using the GARCH-MIDAS method, suggested that EPU significantly and positively affects oil return fluctuations. They also confirm the EPU's predictability of oil price volatility, a view that is also supported by Wang et al. (2022). Xu et al. (2021) examine the interaction between the EPU index and the Chinese stock markets, corroborating that EPU decreased the expected return on stocks. As for the global stock markets, Gong et al. (2022) demonstrate a similar result. Moreover, there is abundant published literature (e.g., Huynh, 2020; Zhang et al., 2021) that describes the nexus of EPU and the gold market.

Considering the opposite direction, relevant studies mainly focused on the spillover effect of crude oil on EPU. For example, Su et al. (2021) indicate the asymmetrical causality of oil price on EPU in BRICS countries by applying the quantile

Granger causality approach. Aimer and Lusta (2022) complement this conclusion by arguing that oil price shocks do not impact EPU in the long run and the spillover effects are only observed in the short term. On the contrary, Dash and Maitra (2021) argue that oil's future and spot prices have a negligible impact on EPU. Other scholars have provided evidence on spillovers from gold prices (Chai et al., 2019) and climate risks (Ye, 2022) to EPU.

The third category of literature is a review of the relationship between EPU and the four green markets analyzed in this paper. Undoubtedly, there is abundant literature on the link between EPU and the aforementioned markets. Using the MSDR model, Pham and Nguyen (2022) explore the time-varying correlations and asymmetric dependencies between EPU and green bond returns. Hou et al. (2022) examine the nexus of EPU and corporate green behaviors, showing that this relationship is heterogeneous and negative. Li et al. (2022) claim a positive impact of EPU on carbon allowances via the nonlinear ARDL model. However, Tiwari et al. (2021) hold the opposite stance, arguing that EPU negatively affects carbon prices.

Regarding the research on green technology, only a few articles focus on its relationship with EPU, especially, on how to drive green technology innovation (Hu et al., 2022; Tang et al., 2021). To sum up, the literature on incorporating green bonds, environmental responsibility, green technology, and carbon markets into an empirical analysis framework, simultaneously considering the bidirectional spillover relationships between EPU and market prices, remains scant. Here, we address this issue with in-depth research.

3. Methodology and data

Here, we introduce the applied methodology and dataset. First, the time-varying Granger approach based on three algorithmic frameworks, which is used to figure out the bidirectional causality between green market prices and EPU, is described. Then, the statistical description and preliminary analysis of the variables are presented.

3.1. The time-varying Granger causality test

The conventional Granger causality test following the predictability framework is widely used in the field of econometrics owing to its relaxed model setting and randomness to variables (Shi et al., 2018). However, this approach is sensitive to sample periods and lacks clarity in capturing the causal relationships over time (Psaradakis et al., 2005). In view of this, we adopt a novel time-varying Granger technology reported by Shi et al. (2018, 2020) to delve deeper into the causal relationships between green market returns and EPU. The method is based on the lag-augmented VAR (LA-VAR) specification (Yamada and Toda, 1998) and considers three algorithms used in generating test statistics, namely, the forward expanding (FE), rolling (RO), and recursive evolving (RE) windows, and their schematic diagrams are shown in Fig. 1. Since this procedure leverages past information, it enables the real-time identification of causal relationships.

The cardinal advantages of the time-varying Granger test are the following. First, it is data-driven, thus, it allows for accessing in-depth information on the changes of causality in different periods or directions and mines the temporal heterogeneity of causal relationships. Second, the estimation adopts a recursive algorithm that yields robust results even without pre-trending the data or precise prior information on the existence of a unit root. Third, it accurately identifies the switch-on and switch-off dates of the Granger causation in the time dimension and data-stamps the timing of changes. Thus, we chose the time-varying Granger test to achieve our research objectives.

Consider a time series $\{x_t\}$ defined as:

$$x_t = \beta_0 + \beta_1 t + \mu_t, \tag{1}$$

where μ_t follows a VAR(q) progress:

$$\mu_t = \gamma_1 \mu_{t-1} + \cdots + \gamma_q \mu_{t-q} + \varepsilon_t, \tag{2}$$

with an error term ε_t. Integrating Eq. (2) into Eq. (1) results in:

$$x_t = \alpha_0 + \alpha_1 t + \gamma_1 x_{t-1} + \cdots + \gamma_q x_{t-q} + \varepsilon_t, \tag{3}$$

where α_i denotes the function of β_i and γ_j with $i = 0,1$ and $j = 1, ..., q$.

Following the specification of the LA-VAR model developed by Dolado and Lütkepohl (1996) and Toda and Yamamoto (1995), the Granger test for the possible integrated variable x_t is as follows:

$$\begin{aligned} x_t &= \alpha_0 + \alpha_1 t + \sum_{i=1}^{q} \gamma_i x_{t-i} + \sum_{q+1}^{q+d} \gamma_j x_{t-j} + \varepsilon_t \\ &= \mathrm{A}\tau_t + \Theta y_t + \Psi z_t + \varepsilon_t, \end{aligned} \tag{4}$$

where $\gamma_{q+1} = \cdots = \gamma_{q+d} = 0$, $A = (\alpha_0, \alpha_1)_{n\times 2}$, $\tau_t = (1, t)'_{2\times 1}$, $y_t = (x'_{t-1}, \cdots, x'_{t-q})'_{nq\times 1}$, $z_t = (x'_{t-q-1}, \cdots, x'_{t-q-d})'_{nd\times 1}$, $\Theta = (\gamma_1, \cdots, \gamma_q)_{n\times nq}$, $\Psi = (\gamma_{q+1}, \cdots, \gamma_{q+d})_{n\times nd}$, where d denotes the maximum order of integration in x_t. It can be expressed in a more compact form:

$$X = \tau \mathrm{A}' + \mathrm{Y}\Theta' + \mathrm{Z}\Psi' + \varepsilon, \quad (5)$$

where $X = (x_1, \cdots, x_T)'_{T\times n}$, $\tau = (\tau_1, \cdots, \tau_T)'_{T\times 2}$, $Y = (y_1, \cdots, y_T)'_{T\times nq}$, $Z = (z_1, \cdots, z_T)'_{T\times nd}$, and $\varepsilon = (\varepsilon_1, \cdots, \varepsilon_T)_{T\times n}$.

The null hypothesis for Granger non-causality is based on the restriction, such that:

$$H_0: \boldsymbol{R}\theta = 0, \quad (6)$$

considering the row vectorization for the parameter $\theta = vec(\Theta)$. $\boldsymbol{R}$ denotes the $m \times n^2 q$ matrix, and *m* denotes the number of restrictions. Since the last *d*-order lag elements in the matrix Ψ equal zero, they can be ignored. Following the Shi et al. (2018), the OLS estimators are given by:

$$\widehat{\Theta} = X'QY(Y'QY)^{-1}, \quad (7)$$

where $Q = Q_\tau - Q_\tau Z(Z'Q_\tau Z)^{-1} Z' Q_\tau$ and $Q_\tau = I_T - \tau(\tau'\tau)^{-1}\ \tau'$. In addition, let $\hat{\theta} = vec(\widehat{\Theta})$ and $\widehat{\Omega}_\varepsilon = \frac{1}{T}\hat{\varepsilon}'\hat{\varepsilon}$, and then the Wald statistics with asymptotically χ^2_m can be defined as:

$$W = (\boldsymbol{R}\hat{\theta})'[\boldsymbol{R}\left\{\widehat{\Omega}_\varepsilon \otimes \left(Y'QY\right)^{-1}\right\}\boldsymbol{R}\,]^{-1}\boldsymbol{R}\hat{\theta}. \quad (8)$$

The real-time causality approach is based on the modified Wald (MWald) statistics from subsamples. Consider f_1 and f_2 as the (fractional) beginning and ending points of estimated samples. Assume that $\tau_1 = [f_1 T]$ and $\tau_2 = [f_2 T]$ are the integer parts of the product with *T* representing the number of observations. Likewise, $\tau_0 = [f_0 T]$ represents the minimum observation numbers required for the estimation procedure. Based on the observations over $[f_1, f_2]$ with a sample size fraction of $f_w = f_2 - f_1 \geq f_0$ represented by $W_{f_2}(f_1)$, the supremum (sup) Wald statistics are given by:

$$SW_f(f_0) = \sup_{(f_1, f_2)\in\Pi_0, f_2 = f}\left\{W_{f_2}(f_1)\right\}, \quad (9)$$

where $\Pi_0 = \{(f_1, f_2): 0 < f_0 + f_1 \leq f_2 \leq 1, and\ \ 0 \leq f_1 \leq 1 - f_0\}$ for some minimal sample size $f_0 \in (0,1)$ in the regression[1].

[Insert Fig. 1 here]

3.2. Data and preliminary analysis

To examine the bidirectional causality between green markets and economic policies, we choose the S&P's Green Bond Select Index, Environmental and Social Responsibility Index, Renewable Energy & Clean Technology Index, and GSCI Carbon Emission Allowances as proxies for the green markets. The sample time started on February 29, 2012, and ended on March 29, 2022, with a total of 2,486 observations from S&P Dow Jones Indices LLC[2]. The paper adopts logarithmic preprocessing for the original price series to improve data stability and reduce the estimation error.

The trajectory of the analyzed price series shown in Fig. 2 reveals that all of them are trending. Specifically, green bonds show a volatile upward trend, while environmental responsibility, green technology, and carbon allowance present a continuing upward trend throughout the sample period. The four graphs demonstrate that green markets have undergone severe turbulence during the COVID-19 pandemic, leading to a marked surge or sudden drop in prices in 2020. A brief pullback in green bonds and green technology prices is noted after 2021. Overall, the frequently changing price series reaffirms the necessity of using time-varying techniques.

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[1] Due to space limitations, we put the introduction of the specific differences between the three algorithms and the formulas for generating Wald statistics in the appendix.

[2] The data is obtained from the official website of S&P Dow Jones Indices: http://www.spglobal.com/spdji/en/.

[Insert Fig. 2 here]

Table 1 shows the results of the descriptive statistics analysis. As it can be seen, the carbon price has the largest fluctuation degree (0.820), contrary to green bond prices (0.065). This may be closely related to the fact that green bonds act as the fixed income financing instrument, while carbon allowances are continually traded and auctioned by market participants (Ren et al., 2022c). The right skewness and positive kurtosis suggest that prices in green markets are characterized by a fat-tailed and asymmetric distribution, which is also authenticated by the Jarque-Bera test, meaning that they are significant at the 1% level.

[Insert Table 1 here]

We measured changes in policy-related market uncertainty using the EPU Index developed by Baker et al. (2016) based on newspaper coverage frequency, which has the advantages of reliability and consistency and shows strong links with other indices that measure economic uncertainties. The time-series diagram of EPU is depicted in Fig. 3. Extensive literature has demonstrated that peaks in the EPU index correspond to "black swan" incidents and serves as a strong predictor of financial market volatility (Wang et al., 2020), such as the Fed's "Fiscal Cliff" crisis in late 2012, the stagflation in some emerging countries, the stock market crash in China in 2015, the Brexit referendum and the Paris Agreement signed in 2016, as well as the Crude Oil War and the COVID-19 Outbreak in 2020.

[Insert Fig.2 here]

4. Empirical results

In this section, we first present the performance of a unit root test on all variables to identify the integration or cointegration properties of the time series. Then, we delve into the bidirectional time-varying causality between EPU and green market returns. Based on the empirical results, we answer two questions of interest from the perspective of dynamical framing and temporal heterogeneity: whether the policy fluctuations cause exogenous shocks to green markets and whether the rise and fall of market prices affect the level of economic uncertainty.

4.1. The unit root test

To identify the integration order for the selected variables, since it is considered necessary for the time-varying Granger method and a core parameter required for the estimation process, we first employ two unit root tests, namely Augmented Dickey-Fuller (Cheung and Lai, 1995) and Phillips-Perron (Phillips and Perron, 1988). As shown in Table 2, we find a unit root in green bonds, environmental responsibility, green technology, and carbon allowance, as well as the stationarity of EPU. In other words, the four green market prices are stationary at their respective first differences, i.e., an I(1) process, while EPU is stationary at its level. Thus, choosing $d = 1$ as the lag parameter of the LA-VAR model is optimal.

As pointed out by Shi et al. (2018), the most accurate performance for detecting time-varying features of causality is obtained when the Granger frame contains an integrated variable and a stationary variable, which lay a solid theoretical foundation for our follow-up empirical research. Following the principle of minimizing the information criterion and the practice of Shahzad et al. (2021), we set the lag order of the VAR model as $p = 4$ and use a robust heteroskedasticity estimation.

[Insert Table 2 here]

4.2. One direction: From EPU to green markets

EPU stems from the governmental policies to adjust the allocation of market resources. Hence, the mismatch and time lag between policies and economic variability are linked to the distortion and fluctuation of relevant market prices. Green markets are the support and foundation of the development of a green economy, acquiring a nature of "public goods". As an institutional arrangement, the operation of green markets is affected by the macro-policy regulation of an authoritative government. Based on this, we discuss the first issue of concern of this paper: the directional time-varying Granger causality of EPU on green markets in the view of maintaining the smooth functioning of green markets.

Table 3 reports the Wald tests of Granger causality, indicating that the FE method provides only some evidence of non or weak Granger relations. Additionally, economic policy fluctuation does not significantly put pressure on green bond pricing. The graphic representation of time-varying Granger causation between the four pairs (i.e., EPU-green bond, EPU-environment responsibility, EPU-green technology, EPU-carbon allowance) and the corresponding bootstrapped critical values are displayed in the left panel of Fig. 4–7. What stands out in these figures is the vivid time-varying features of causality.

As shown in Fig. 4a, the EPU causality over green bonds is less obvious; only the RE algorithm shows a brief significant causal relationship in early 2020, which is consistent with the conclusions of Table 3. This may be related to the large-scale social shutdown and the blocking of short-term capital flows in the initial stage of the pandemic when market participants are not optimistic about the issuance of green bonds due to credit risks (Yi et al., 2021). The view is also supported by Ren et al. (2022c), who claims that green bonds are more vulnerable to EPU during downturns. In addition, the insignificant Granger causality can be explained by the nature and characteristics of green bonds, such as over-reliance on private governance mechanisms and lack of unified public supervision, making the link between green bond markets and macro EPU alienated.

The causal link between EPU and environmental responsibility is quite different (Fig. 5a). Under the RO and RE windows, causality exhibits high volatility. The diagram of the RE method shows that EPU continuously caused exogenous impacts on corporate environmental responsibility for most of the period 2016–2020, possibly attributed to the inhibitory impact of high EPU on environmental responsibility in the context of insufficient market confidence, financing constraints, and policy alienation (Hou et al., 2022). The causation seemingly has declined after 2020, suggesting that the COVID-19 pandemic likely plays a long-term catalytic role on environmental responsibility, rather than having an instantaneous effect (Garel and Petit-Romec, 2021). Another alternative explanation is that companies with high environmental responsibility hold more social trust capital that helps them withstand external shocks caused by public emergencies (Zhang et al., 2022).

The results of the FE window exceed the critical value only at individual points, while the RO window is above the critical line for rejecting the null hypothesis for a slightly longer period, and the RE window exhibits a significant Granger causality of EPU on green technology at a larger scale (Fig. 6a). As argued by Shi et al. (2018), the RE algorithm has the best performance in the case of limited samples compared with the FE and RO algorithms. Thus, we focus on the conclusions drawn from the RE algorithm. The figure indicates that from mid-2016 to early 2020, economic uncertainty and policy volatility had significant predictive power on green technology prices. A possible explanation for this is that the immaturity of green technology makes it vulnerable to market risk interference (Feng et al., 2022). Therefore, when faced with the shock of policy uncertainty, the development of green technology encounters strong financial constraints and insufficient supply in the financing markets (Feng et al., 2020). It is somewhat surprising that the causality of EPU on green technology has plummeted during the pandemic, which indicates that the predictive power of EPU has declined due to the sudden health crisis.

In Fig.7 a, the FE algorithm provides no evidence for a significant cause-and-effect link between EPU and the carbon market. However, the RO and RE algorithms demonstrate a consistent time-varying causal relationship between them. Considering that the carbon market is built based on a market-oriented trading mechanism (Dou et al., 2022), it is frequently affected by external economic turmoil and financial pressure. We also note that this causal effect has been sharply exacerbated by the outbreak of

COVID-19, which has seen carbon market transactions across the globe experience price declines and large swings. However, with the economic recovery after 2021, the EU has also proactively launched a series of green support programs, which have played a role in mitigating carbon price fluctuations. Overall, this dynamic evidence and comprehensive information stemming from EPU are beneficial for market participants and policymakers to accurately predict the carbon price fluctuations.

In conclusion, we can draw the following inferences: The green bond market, due to its lack of unified regulation and reliance on private governance, is shielded from economic policy fluctuations. The environmental awareness and strategic actions of enterprises are easily dominated by the entire economic policy environment; the innovative development of green technology benefits from the incentives and support of government economic policies (Shen et al., 2021); and the price mechanism of frequent trading in the carbon market and the sensitivity to financial markets, these factors make them vulnerable to EPU.

[Insert Table 3 here]

4.3. Another direction: From green markets to EPU

Market price acts as an indicator of changes in supply and demand. Therefore, its excessive volatility not only leads to market disorder and flooding of speculation but also the fragility of the financial system and high uncertainty of economic policies. Furthermore, the green market is an emerging financial derivative market, and various operating mechanisms and regulations are still imperfect. Thus, relevant policy interventions occur from time to time, with external effects on the macroeconomy that exacerbate the increase of EPU levels. For this, we further discuss the second focus of this article: exploring the retroaction of changes in green market prices to the EPU index from a fresh perspective.

Table 4 presents the summary statistics of the Wald test. Almost all green market prices are significant Granger causes of EPU except for green bond markets based on FE algorithms. To gain a more comprehensive and explicit understanding of the time-varying causality from green markets to EPU, the graph of the evolution of the Granger relationship between the four pairs (i.e., green bond-EPU, environment responsibility-EPU, green technology–EPU, carbon allowance-EPU) over time is shown in the right panel of Fig. 4–7. We still distinctly capture the dynamics of this causality.

The results based on the FE window are below the critical value, and the predictability of green bond prices for EPU is not detected, as seen in Fig. 4b. This might be due to green bond markets having a late start and immature development, thus, acting as a receiver of financial information or external shocks in most cases (Reboredo, 2018). In contrast, the RO and RE algorithms depict situations different from that of an unambiguous failure of no causality, with green bond causality over EPU changes being significant after the beginning of 2020. A possible explanation for this is that the investors' active participation in the green bond market has contributed to increasing capital flows and exacerbating risk spillovers from green bond price volatility to the macroeconomic and other financial markets. This, coupled with the resilience of the green finance market, has resulted in record issuance of green bonds, and a sustained rebound is expected. In addition, this contagion effect has been amplified in the context of public security emergencies (Gao et al., 2021).

As shown in Fig. 5b, the three algorithms give causal relationship curves with a consistent trend. From 2014 to 2016, the causality gradually declines and changes from significant to insignificant. Then, from 2016 to 2019, there is a slightly undulating insignificant transition period. Finally, at the beginning of 2020, there is an extreme jump in causality that subsequently remains constant with a high level of significance. This underscores the forward-looking predictive power of corporate environmental responsibility during the pandemic crisis. Notably, the COVID-19 pandemic is also acting as an important medium for changing the environmental awareness and social responsibility of investors and enterprises (Severo et al., 2021). In this scenario, they may increase their investments in green finance, creating a situation where related price fluctuations increase the levels of economic uncertainty.

In Fig 6b, the causal relationship based on RO windows reveals more obvious fluctuation characteristics compared with the FE and RE algorithms. Nonetheless, all three procedures provide us with strong evidence that the predictability of green technology for EPU reached an extreme peak during the COVID-19 crisis, which is related to the global shift of strategic focus to green areas in 2020 and an emphasis on promoting energy security and sustainability through green technologies. Feng et al. (2021) point out that the development of green technology plays an intermediary role between environmental information disclosure and economic operation. In view of this, we believe that the stock price fluctuations of companies that develop green technologies and sustainable construction will lead to the introduction of relevant environmental regulations and policy systems, thereby, affecting the EPU level. These conclusions also agree with our findings that the green technology causality over EPU is significant during most sample periods (Wang et al., 2022).

From Fig. 7b, it can be inferred that although the results of the RO algorithm show more frequent and erratic changes in causality, all three estimation processes support a significant causal impact of carbon markets on EPU. This performance could be attributed to the frequent trading patterns and abnormal price volatility in the carbon market and its synchronization with macroeconomic fluctuations (Jiao et al., 2018). Unsurprisingly, the causality rose sharply in the early stages of the COVID-19 pandemic, probably due to the production stagnation that curbed carbon emission. This impact has further spread to the carbon trading market, thereby, jointly increasing EPU levels.

To sum up, the green markets are in most cases spillovers of price risk to the economic policy arena. The operating mechanism of the green bond market is not yet mature, and its risk contagion effect is amplified only in times of crisis due to increased capital flows. Whether a company has a sense of environmental responsibility will have a disparate impact on its development path and spread to the economic society; green technology plays an intermediary role in economic operation and environmental information disclosure; carbon markets profoundly affect energy structure and synchronize with macroeconomic fluctuations, which cause them to significantly affect EPU in most periods.

[Insert Table 4 here]

[Insert Fig. 4 here]

[Insert Fig. 5 here]

[Insert Fig. 6 here]

[Insert Fig. 7 here]

5. Conclusion

In the context of a low-carbon sustainable economy and dual-carbon goals, governments and enterprises around the world are actively guiding and nurturing the development of green markets. Coupled with the continuous turmoil in the global financial market, the levels of EPU rise constantly, resulting in obvious spillover shocks. Inspired by this, this study detects the real-time bidirectional causal relationship between green market returns and EPU via the fresh time-varying Granger causality approach. We chose the green bond market, corporate environmental responsibility, green technology investment, and the carbon trading market as proxies for green markets to comprehensively understand the interaction mechanism between and spillover effect of the green market and economic policy fluctuations from a macro and micro perspective. Notably, the RE algorithm provides the best estimation performance based on finite samples.

The major findings that emerged from this study are summarized as follows. First, time-varying bidirectional causal effects between green market returns and EPU are present for most of the sample period. In this vein, we need to pay extra attention to the vulnerability of this causal relationship to external turbulent events. Particularly, structural changes that arise from the COVID-19 pandemic may be attributable to changes in the behavior and preferences of market participants and the introduction of a series of policy measures triggered by crises or health events. Second, looking at the direction of spillover from EPU to green markets, economic policy fluctuation does not appear to significantly put pressure on green bond pricing. Besides, corporate environmental responsibility, the green technology market, and the carbon trading market are all significant recipients of risk spillovers during special periods. In particular, whether a company adopts green behavior largely depends on the level of EPU. Third, looking at the direction of spillover from green markets to EPU, nearly all green markets are price risk spillovers, especially in the wake of the COVID-19 crisis, warning us of the spillover risks of abnormal market price fluctuations during public emergencies.

Our results have meaningful implications for investors, companies, and governments. They can inspire market participants to reduce irrational investments during periods of extreme volatility and help them timely optimize their portfolios. They can also alleviate the adverse impact of market uncertainty on the implementation of corporate green strategies and help governments effectively predict future economic fluctuations, therefore, achieving the win-win goal of green and low-carbon development and stable economic operation.

To sum up, although we examine time heterogeneity and bidirectional spillovers in the causality between green markets and EPU, these are limited to qualitative analysis. The magnitude of this causal effect and whether it is positive or negative cannot be understood and requires further investigation in the future. Moreover, the role of developing countries, such as China, in green economic development and low-carbon transformation should not be underestimated and needs further research.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and materials

Most of the basic data are publicly available, mainly from the Wind and IFind financial databases. Other data are calculated by authors, and the calculation method is shown in the text of this paper.

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Authors' contributions

Xiong Wang: Conceptualization, Supervision, Funding Acquisition

Jingyao Li: Data Collection, Data Analysis, Software, Writing – Original draft preparation

Xiaohang Ren: Conceptualization, Methodology, Writing - Editing and Writing – Reviewing

Zudi Lu: Writing – Reviewing

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Appendix

As mentioned earlier, three algorithms are used to generate Wald statistics. With respect to the FE methodology (Thoma, 1994), the Wald test statistic first computes the minimum window size, $\tau_0 = T_{r0}$, and successively expands the length of the observations until all samples are used (Fig. 1a). The RO procedure (Arora and Shi, 2016; Swanson, 1998) moves forward by a fixed window length at a time and calculates the Wald statistics for each subsample separately (Fig. 1b). The RE approach (Phillips et al., 2015) provides common endpoints for each subsample given a specific observation interval; then, the algorithm calculates the Wald statistics for each subsample with the window length of τ_0 or greater when repeating the process (Fig. 1c). Notably, the three algorithms may generate different conclusions in practical causal tests due to their performance differences in limited samples. In a single switch procedure, the dating rule is giving by the crossing times, specifically, for each algorithm we have:

FE: $\hat{f}_e = \underset{f\in[f_0,1]}{inf}\{f: W_f(0) > cv\}$ *and* $\hat{f}_f = \underset{f\in[\hat{f}_e,1]}{inf}\{f: W_f(0) < cv\}$, (1)

RO: $\hat{f}_e = \underset{f\in[f_0,1]}{inf}\{f: W_f(f-f_0) > cv\}$ *and* $\hat{f}_f = \underset{f\in[\hat{f}_e,1]}{inf}\{f: W_f(f-f_0) < cv\}$, (2)

RE: $\hat{f}_e = \underset{f\in[f_0,1]}{inf}\{f: SW_f(f_0) > scv\}$ *and* $\hat{f}_f = \underset{f\in[\hat{f}_e,1]}{inf}\{f: SW_f(f-f_0) < scv\}$, (3)

where *cv* denotes the critical value of W_f and *scv* denotes the critical value of SW_f. $\hat{f}_e$ and $\hat{f}_f$ denote the start and end points of the causal relationship, respectively. They are identified as the first observation that exceeds or falls below the causal test threshold.

We search the start and end points of episode i in the sample ranges of $[\hat{f}_{i-1f}, 1]$ and $[\hat{f}_{ie}, 1]$ respectively.

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Tables

Table 1. Descriptive statistics of price series.

Table 2. Results from unit root tests.

Table 3. Wald tests of Granger causality: From EPU to green markets.

Table 4. Wald tests of Granger causality: From green markets to EPU.

Table 1

Descriptive statistics of price series.

	BOND	RESP	TECH	EUA
Minimum	4.916	7.056	4.670	2.403
Maximum	5.204	8.623	6.119	5.820
25th Quartile	4.991	7.523	4.875	3.082
75th Quartile	5.068	8.057	5.274	4.467
Mean	5.037	7.798	5.151	3.759
Stdev	0.065	0.402	0.339	0.820
Skewness	0.620	0.224	0.786	0.688
Kurtosis	2.805	2.252	2.776	2.313
JB test	496.747***	183.157***	582.694***	374.697***

Note: (i) The sample period is from February 29, 2012 to March 29, 2022. (ii) The Jarque-Bera (JB) statistics test for the null hypothesis of normality of target series. (iii) * denotes the 10% significance level; ** denotes the 5% significance level; *** denotes the 1% significance level. (iv) BOND denotes the S&P's Green Bond Select Index, RESP denotes the Environmental and Social Responsibility Index, TECH denotes the Renewable Energy & Clean Technology Index, and EUA denotes the Carbon Emission Allowances.

Table 2

Results from unit root tests.

	Levels		First-differences		Outcome
	ADF	PP	ADF	PP	
BOND	-1.639	-1.612	-33.420***	-48.402***	I(1)
RESP	-2.881	-3.134*	-35.317***	-58.494***	I(1)
TECH	-2.574	-2.560	-33.404***	-51.049***	I(1)
EUA	-2.263	-2.232	-37.478***	-51.288***	I(1)
EPU	-11.050***	-15.324***	/	/	I(0)

Note: (i)The Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test report unit root test results with the null hypothesis of non-stationarity. (ii) * denotes the 10% significance level; ** denotes the 5% significance level; *** denotes the 1% significance level.

Table 3

Wald tests of Granger causality: From EPU to green markets.

Causality	Forward			Rolling			Recursive		
	Wald	95th	99th	Wald	95th	99th	Wald	95th	99th
$EPU \xrightarrow{GC?} BOND$	4.661	9.33	14.10	9.630**	9.07	12.37	12.594**	9.50	14.09
$EPU \xrightarrow{GC?} RESP$	10.472**	8.52	14.48	17.538***	8.46	14.87	19.360***	9.14	14.87
$EPU \xrightarrow{GC?} TECH$	10.535**	8.74	12.65	14.899***	8.84	11.67	19.877***	9.20	12.65
$EPU \xrightarrow{GC?} EUA$	4.338	7.90	14.06	18.458***	8.17	14.06	18.615***	8.60	14.06

Note: (i) The table reports the robust Wald test statistics of Granger causality and the 95^{th} and 99^{th} quantiles of the empirical distributions of the bootstrap statistics. (ii) * denotes the 10% significance level; ** denotes the 5% significance level; *** denotes the 1% significance level.

Table 4

Wald tests of Granger causality: From green markets to EPU.

Causality	Forward			Rolling			Recursive		
	Wald	95th	99th	Wald	95th	99th	Wald	95th	99th
$EPU \overset{GC?}{\longrightarrow} BOND$	7.434*	9.03	11.92	21.234***	8.89	11.76	22.775***	9.31	11.97
$EPU \overset{GC?}{\longrightarrow} RESP$	28.735***	8.03	11.10	32.579***	8.13	11.10	35.355***	8.29	11.10
$EPU \overset{GC?}{\longrightarrow} TECH$	32.649***	9.31	17.30	29.667***	8.71	19.02	41.810***	9.31	19.02
$EPU \overset{GC?}{\longrightarrow} EUA$	15.920***	9.22	13.29	23.039***	9.41	13.22	23.063***	9.68	13.55

Note: (i) The table reports the robust Wald test statistics of Granger causality and the 95^{th} and 99^{th} quantiles of the empirical distributions of the bootstrap statistics. (ii) * denotes the 10% significance level; ** denotes the 5% significance level; *** denotes the 1% significance level.

Figures

Fig. 1. The three algorithms used in generating test statistics of time-varying Granger causality.

Fig. 2. Time plots of green bond, environmental responsibility, green technology, and carbon allowance from February 29, 2012 to March 29, 2022.

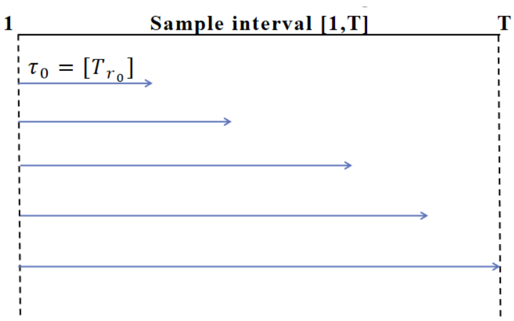
Fig. 3. Time plots of daily EPU Index in the US from February 2012 to March 2022.

Fig. 4. Time-varying Granger causality tests between green bond with EPU.

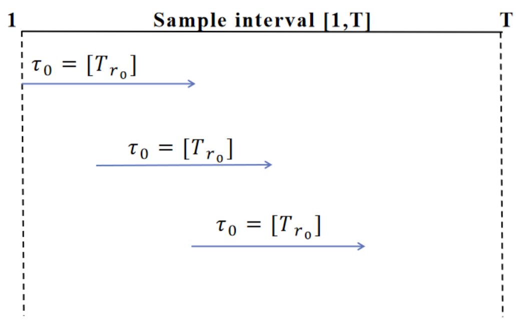
Fig. 5. Time-varying Granger causality tests between environmental responsibility with EPU.

Fig. 6. Time-varying Granger causality tests between green technology with EPU.

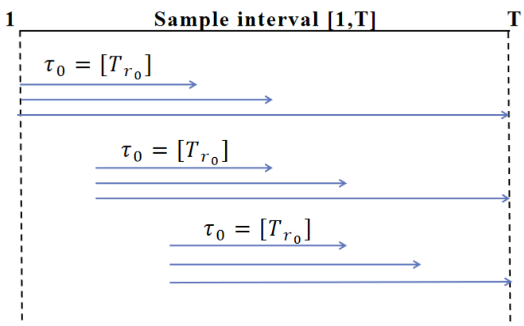
Fig. 7. Time-varying Granger causality tests between carbon allowance with EPU.



(a) Forward expanding window



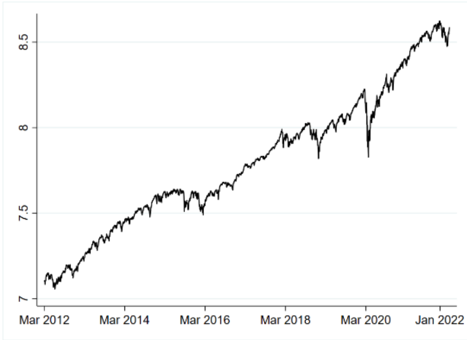
(b) Rolling window



(c) Recursive evolving window

Fig. 1. The three algorithms used in generating test statistics of time-varying Granger causality.

(a) green bond



(b) environmental responsibility

(c) green technology

(d) carbon allowance

Fig. 2. Time plots of green bond, environmental responsibility, green technology, and carbon allowance from February 29, 2012 to March 29, 2022.

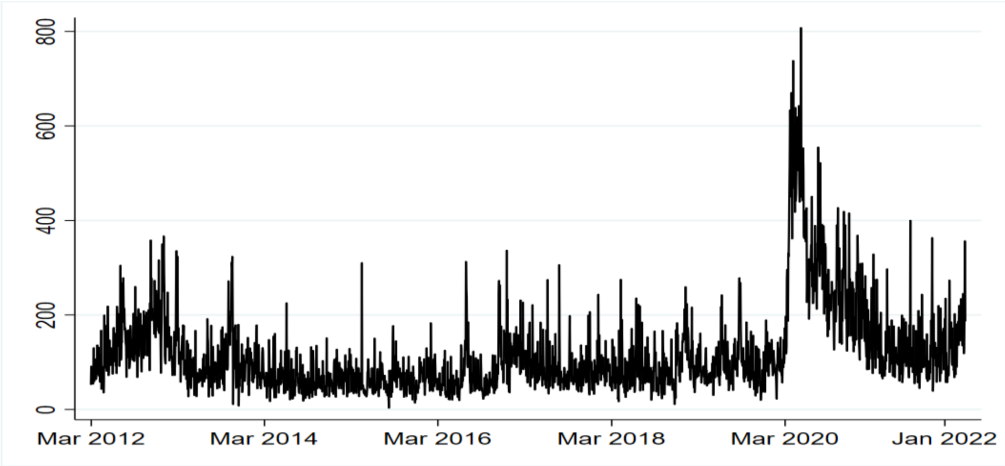
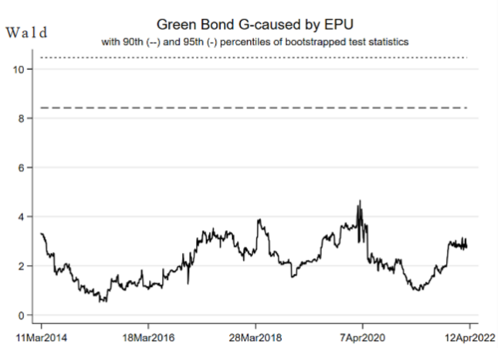
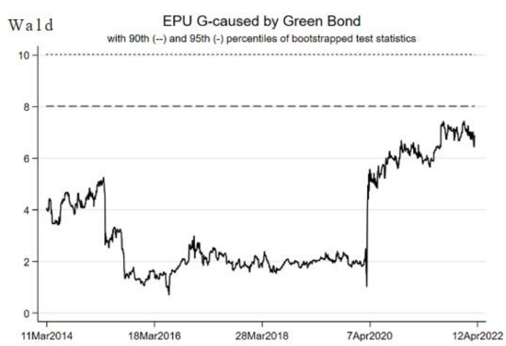


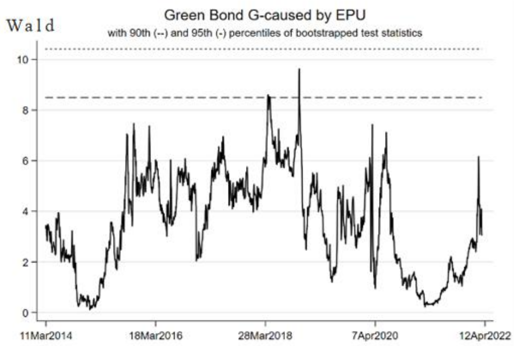
Fig. 3. Time plots of daily EPU Index in the US from February 2012 to March 2022.

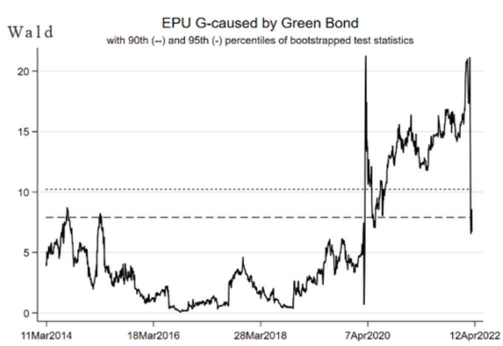
Forward Expanding



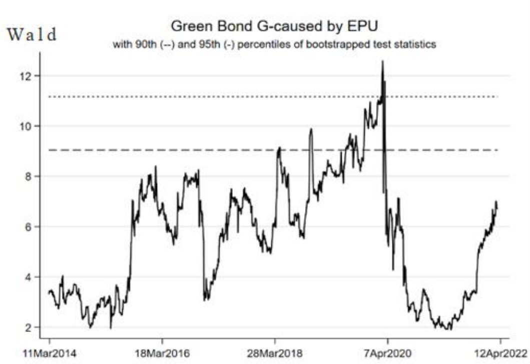


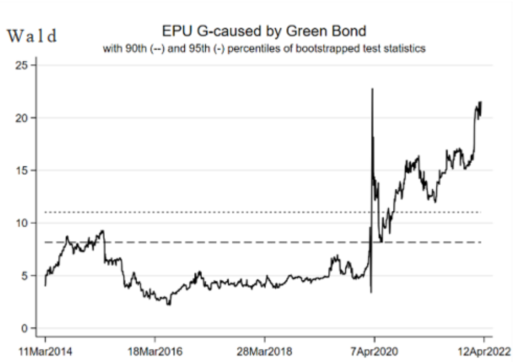
Rolling Window





Recursive Evolving

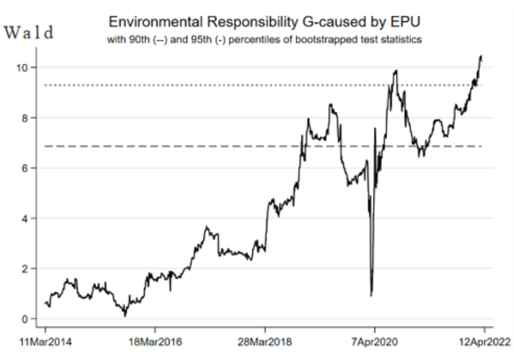


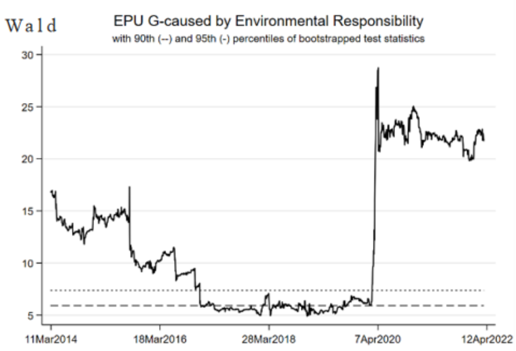


(a) $EPU \overset{GC}{\rightarrow} BOND$ (b) $BOND \overset{GC}{\rightarrow} EPU$

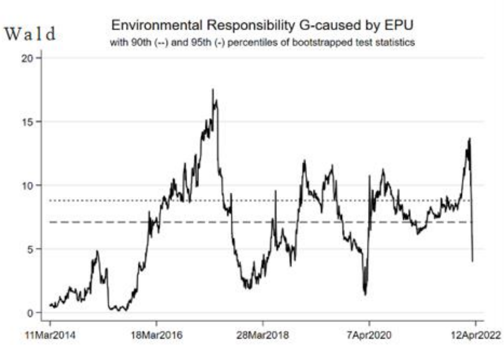
Fig. 4. Time-varying Granger causality tests between green bond with EPU.

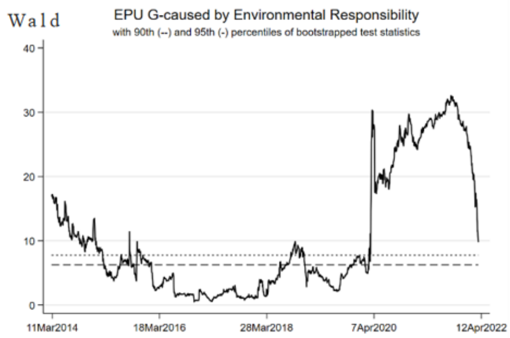
Forward Expanding



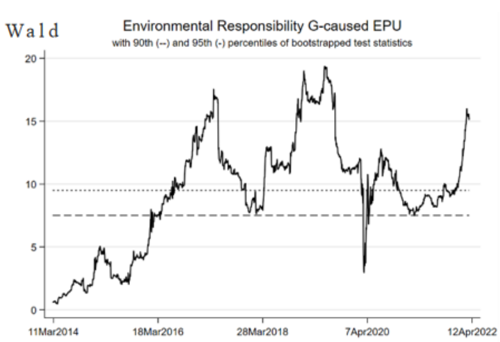


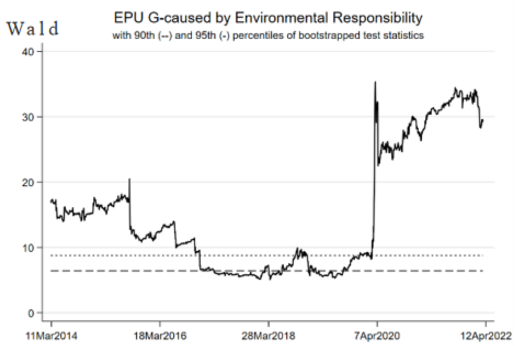
Rolling Window





Recursive Evolving

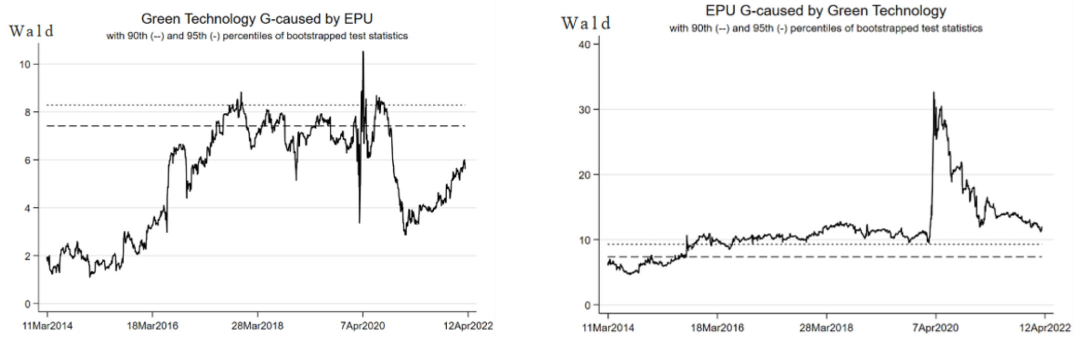




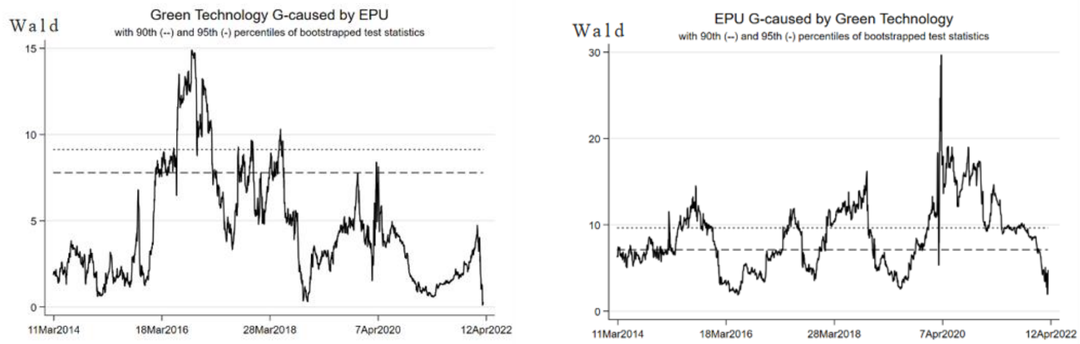
(a) $EPU \overset{GC}{\rightarrow} RESP$ (b) $RESP \overset{GC}{\rightarrow} EPU$

Fig. 5. Time-varying Granger causality tests between environmental responsibility with EPU.

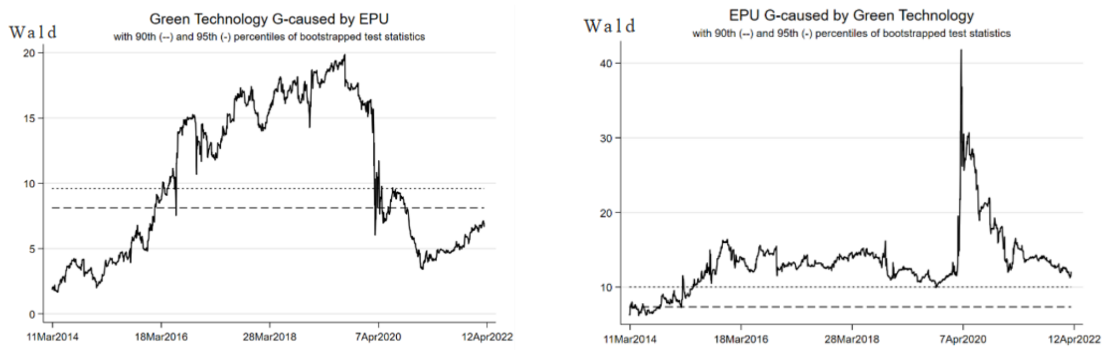
Forward Expanding



Rolling Window



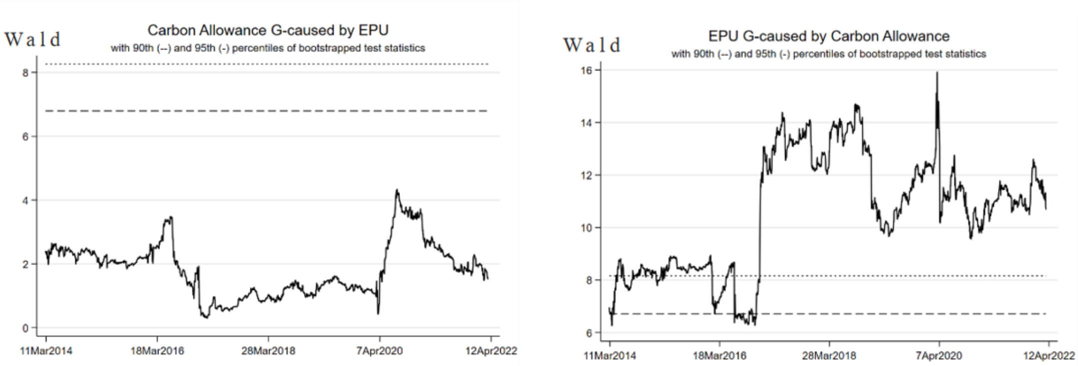
Recursive Evolving



(a) $EPU \xrightarrow{GC} TECH$ (b) $TECH \xrightarrow{GC} EPU$

Fig. 6. Time-varying Granger causality tests between green technology with EPU.

Forward Expanding



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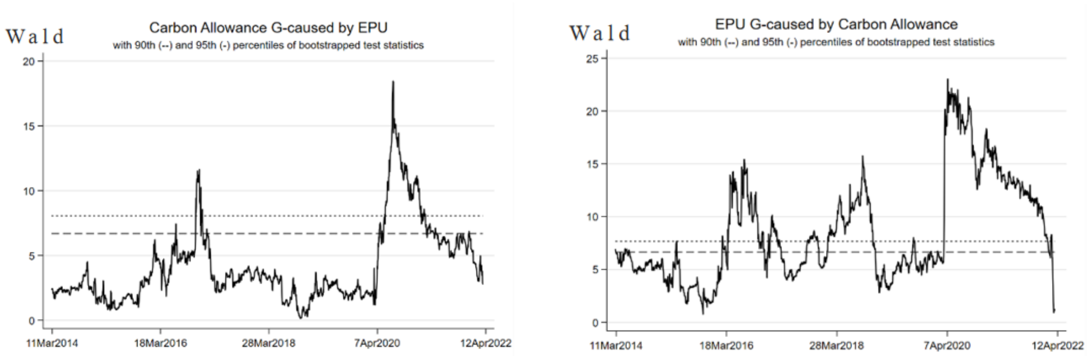
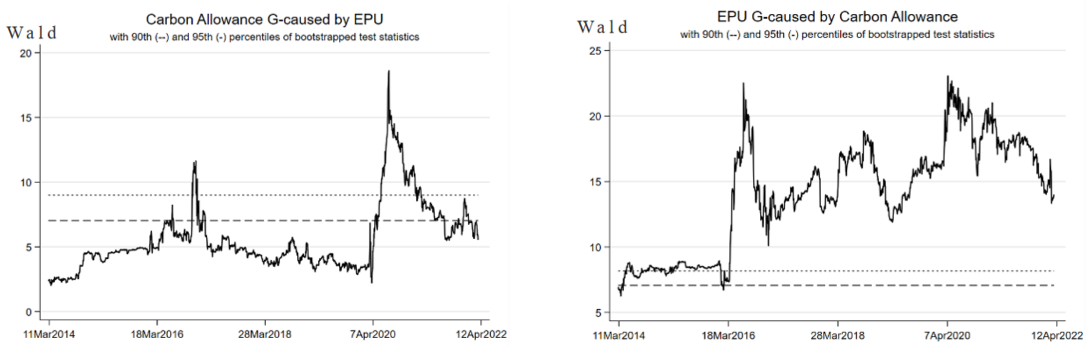


Recursive Evolving



(c) $EPU \overset{GC}{\rightarrow} EUA$ (d) $EUA \overset{GC}{\rightarrow} EPU$

Fig. 7. Time-varying Granger causality tests between carbon allowance with EPU.