

# Risk Spillovers between China's Climate Policy Uncertainty and Green Assets

Yonghui Meng

Shanghai University, Shanghai, 200000, China

## Abstract

This paper uses a TVP-VAR-DY model to examine the dynamic risk spillover effects between China's climate policy uncertainty (CCPU) and green assets. Monthly data from 2017 to 2026 are selected, covering assets such as green power, CSI New Energy, Shanghai Stock Exchange Green Bond, WTI crude oil, and gold ETFs. The spillover effects among these variables are analyzed from both static and dynamic perspectives. The analysis shows that there are significant time-varying and asymmetric spillover effects between green assets and CCPU, especially during major climate events and policy adjustments. WTI crude oil has the most significant impact on CCPU, while gold ETFs have a positive spillover effect on green bonds and CSI New Energy. The results indicate that CCPU has a significant dynamic impact on green assets. Investor and policymakers should closely monitor policy changes to optimize asset allocation and enhance risk management capabilities.

## Keywords

China's Climate Policy Uncertainty; Green Assets; Risk Spillovers.

## 1. Introduction

With the widespread attention of global climate change, sustainable finance has gradually become an important direction for the development of the financial market in recent years. Green finance attaches more importance to environmental, social and governance factors compared with traditional financial markets. With the advancement of global green transformation and carbon neutrality goals, green assets such as green bonds and green stocks are constantly developing, but they are still susceptible to policy adjustments, market sentiment and changes in the macroeconomic environment. Risk fluctuations and risk transfer between assets deserve further study.

Secondly, China's climate policy uncertainty index (CCPU) is an important factor affecting green assets. Policy adjustments may change enterprise investment expectations and project returns, which affects the performance of green assets as green industries are closely related to government subsidies, carbon emission policies and energy transformation targets. Investors' expectations on future policies and green project returns may change and exacerbate asset price fluctuations when policy uncertainty rises. At the same time, risk may also be further transmitted through the association between different assets, forming a more complex risk spillover relationship.

In summary, this study examines the dynamic risk spillovers between climate policy uncertainty and green assets. It further explores the risk transmission structure from a network perspective to identify the roles of different assets and how they change over time. This helps provide a more comprehensive understanding of the risk linkages in green asset markets under climate policy uncertainty and offers useful insights for investors in asset allocation and risk management.

## 2. Literature Review

Existing studies show that climate policy uncertainty (CPU) affects green assets and related markets through spillovers, with effects varying across markets and asset classes. Ding et al. (2023), using the DY and BK spillover indices, found mainly high-frequency spillovers between climate policy uncertainty and energy and metal markets, with clean energy markets generally acting as net transmitters and traditional energy markets as receivers. Liu et al. (2023) found that climate policy uncertainty contributes to extreme risk spillovers across energy markets, with asymmetric effects across market conditions. Zhang et al. (2023) showed that different climate shocks affect broad asset returns, with climate attention shocks having the strongest spillover effects.

Most studies suggest that climate policy uncertainty has significant spillover effects on green assets, characterized by time variation and asymmetry. Ji et al. (2022) found that the impact of climate risk perception on financial markets varies over time, with green asset prices fluctuating more sharply during the early stages of policy adjustment. Ren et al. (2023) showed that the effects of climate policy uncertainty on green and traditional energy markets also vary over time, particularly during key stages of the energy transition. Lei et al. (2024) pointed out that climate policy uncertainty affects clean and fossil energy assets asymmetrically, with clean energy assets being more sensitive to policy uncertainty than traditional energy assets.

This study contributes to the literature by examining the risk spillovers between China's climate policy uncertainty (CCPU), WTI crude oil, gold ETFs, and green assets within a unified framework. By combining static and dynamic analyses and using a longer sample period, it provides a broader view of risk spillovers and interactions across markets, offering insights for policymakers and investors.

## 3. Methodology and Data

### 3.1. Methodology and Model

The TVP-VAR-DY model is a model used to analyze the dynamic spillover effect, proposed by Antonakakis and Gabauer (2020). The model introduces time-variance parameters and time-variance-covariance matrix on the basis of the DY spillover index, which can better capture the risk transfer relationship that changes over time between different markets. Compared with the traditional model, this model does not need to set a rolling window, which avoids the loss of information caused by improper selection of window length, and is suitable for analyzing the risk spillover effect with obvious time-changing characteristics in the financial market.

The specification of the TVP-VAR model:

$$\begin{aligned} y_t &= A_t Z_{t-1} + \varepsilon_t, \varepsilon_t | \Omega_{t-1} \sim N(0, \Sigma_t) \\ \text{vec}(A_t) &= \text{vec}(A_{t-1}) + \zeta_t, \xi_t | \Omega_{t-1} \sim N(0, \Xi_t) \end{aligned} \quad (1)$$

Among these,

$$Z_{t-1} = \begin{pmatrix} y_{t-1} \\ y_{t-2} \\ \vdots \\ y_{t-p} \end{pmatrix} \quad A'_t = \begin{pmatrix} A_{1t} \\ A_{2t} \\ \vdots \\ A_{it} \end{pmatrix}$$

$\Omega_{t-1}$  represents the information set available up to period  $t - 1$ .  $y_t$  and  $Z_{t-1}$  are vectors of dimensions  $m \times 1$  and  $mp \times 1$  respectively.  $A_{it}$  is the time-varying coefficient matrix,  $\varepsilon_t$  is an  $m \times 1$  error vector, and  $\xi_t$  is the vector of innovations in the time-varying coefficients.

The TVP-VAR-DY model builds on the spillover index framework developed by Diebold and Yilmaz (2012), incorporating generalized impulse response functions and generalized forecast error variance decomposition (GFEVD). By allowing the model parameters and the variance-covariance matrix to vary over time, it captures changes in spillover effects across variables. The total spillover effect is calculated using GFEVD as follows:

$$C_t(H) = \frac{\sum_{i,j=1, i \neq j}^m \tilde{\Phi}_{ij,t}(H)}{\sum_{i,j=1}^m \tilde{\Phi}_{ij,t}(H)} \times 100 = \frac{\sum_{i,j=1, i \neq j}^m \tilde{\Phi}_{ij,t}(H)}{m} \times 100 \quad (2)$$

The directional spillover from variable  $i$  to  $j$ , and the total directional spillover from variable  $i$  to all other variables, are defined as follows:

$$C_{i \rightarrow \bullet, t}(H) = \frac{\sum_{i,j=1, i \neq j}^m \tilde{\Phi}_{ji,t}(H)}{\sum_{i,j=1}^m \tilde{\Phi}_{ji,t}(H)} \times 100 \quad (3)$$

The net directional spillover of variable  $i$  is calculated as the difference between its spillover to variable  $j$  and the spillover it receives from variable  $j$ :

$$C_{i,t} = C_{i \rightarrow j, t}(H) - C_{i \leftarrow j, t}(H) \quad (4)$$

## 3.2. Data

### 3.2.1. Data Source

Monthly data from 2017 to 2026 are selected, with green asset data obtained from the Wind database and China's climate policy uncertainty index (CCPU) published by the Energy Finance Network. Green Power and CSI New Energy, an index tracking China's new energy sector, are selected to represent green equity assets, while the Shanghai Green Bond Index represents the green bond market. WTI crude oil prices and the Huaan Gold ETF benchmark are also included for comparison, as crude oil is closely related to global climate risks and economic development. The monthly data from 2017 to 2026 cover periods of heightened uncertainty, as well as growing attention to climate risks.

### 3.2.2. Data Description

**Table 1.** Descriptive statistics

|           | CCPU      | Green Power | CSI New Energy | SSE Green Bond | WTI       | Gold ETF  |
|-----------|-----------|-------------|----------------|----------------|-----------|-----------|
| Mean      | 0.0008    | 0.0012      | 0.0031         | 0.0038         | 0.0050    | 0.0109    |
| Median    | -0.0037   | -0.0026     | -0.0005        | 0.0039         | 0.0213    | 0.0059    |
| Maximum   | 0.6059    | 0.2498      | 0.2250         | 0.0179         | 0.5355    | 0.1772    |
| Minimum   | -0.6164   | -0.1884     | -0.2123        | -0.0105        | -0.6006   | -0.1149   |
| Std. Dev. | 0.2013    | 0.0588      | 0.0871         | 0.0046         | 0.1240    | 0.0403    |
| Kurtosis  | 1.5634    | 3.3480      | -0.0037        | 1.0654         | 9.3054    | 3.0894    |
| Skewness  | 0.3308    | 0.5526      | 0.3290         | -0.0919        | -0.7870   | 0.4311    |
| ADF Test  | -7.285*** | -8.994***   | -8.246***      | -9.008***      | -8.409*** | -9.364*** |

After data collection, the data are preprocessed to obtain the log returns of the assets and the growth rate of the CCPU index. 109 valid observations are retained after eliminating invalid and missing values. The descriptive statistics are presented in Table 1. The asset return series exhibit excess kurtosis and fat tails. The ADF test results indicate that the return series are stationary.

## 4. Empirical Analysis

Using the TVP-VAR-DY model, this study first examines the spillover effects among variables from a static perspective based on the average spillover measures. It then conducts a dynamic analysis using the total spillover index, directional spillovers, net spillovers, and pairwise net spillovers to further examine the relationships among variables within the system.

### 4.1. Static Analysis

First, the average spillover index examines the relationships between variables from a static perspective. Table 2 shows that shocks to each variable remain the main source of its own fluctuations, although risk transmission exists across markets. The links between CCPU, energy and green assets are relatively prominent. The average spillover from CCPU to Green Power is 8.632%, while that from Green Power to CCPU is 5.248%. This suggests that changes in climate policy uncertainty may affect the green electricity market through policy expectations, industrial investment and energy transition. CCPU and WTI also show relatively strong two-way spillovers. The spillover from CCPU to WTI is 5.893%, while that from WTI to CCPU is 6.598%, indicating a degree of mutual transmission between climate policy uncertainty and the traditional energy market. In contrast, spillovers within green assets are relatively weaker.

**Table 2.** Spillover effect between factors

|                | WTI    | Gold ETF | Green Power | CSI New Energy | CCPU   | SSE Green Bond |
|----------------|--------|----------|-------------|----------------|--------|----------------|
| WTI            | 76.591 | 1.425    | 2.394       | 2.874          | 6.598  | 7.429          |
| Gold ETF       | 1.140  | 83.256   | 2.126       | 4.653          | 4.093  | 3.749          |
| Green Power    | 4.692  | 2.599    | 77.518      | 4.759          | 5.248  | 4.084          |
| CSI New Energy | 3.910  | 4.673    | 4.643       | 82.563         | 2.451  | 4.427          |
| CCPU           | 5.893  | 3.040    | 8.632       | 1.665          | 75.313 | 6.809          |
| SSE Green Bond | 7.774  | 5.006    | 4.686       | 3.486          | 6.297  | 73.503         |

### 4.2. Total Spillover Effect Analysis

Figure 1 shows that the average total connectedness index (TCI) of the system is 21.88%, with fluctuations mainly driven by shocks to individual variables. From 2021 to 2022, rising global inflation in the post-pandemic period and the outbreak of the Russia-Ukraine conflict led to severe fluctuations in international energy markets, while overall risk connectedness within the system remained relatively high. Geopolitical tensions and the energy crisis amplified risk transmission across markets, strengthening the links between climate policy uncertainty, crude oil and China's green capital markets. Since reaching a low point in early 2025, the TCI has continued to rise, forming a new peak following the US-Iran military conflict in early 2026. Military tensions in the Middle East disrupted the Strait of Hormuz, increasing uncertainty over global oil supplies. Renewed concerns about energy safety also affected expectations for global climate transition policies, accompanied by rising CCPU volatility.

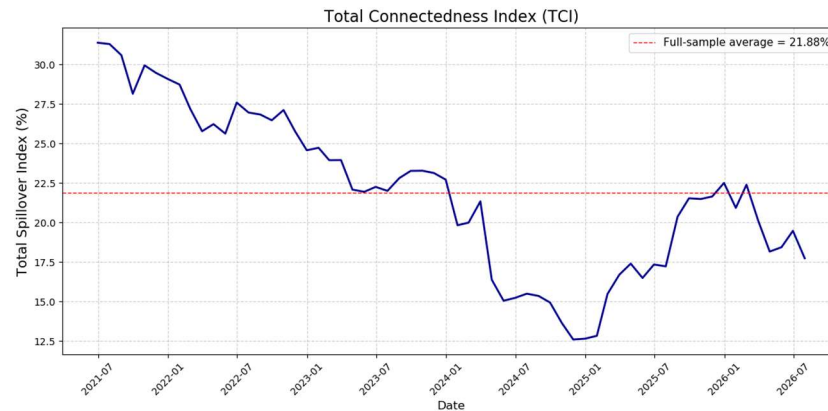


**Figure 1.** Total Connectedness Index

### 4.3. Analysis of the Directional Spillover Effect

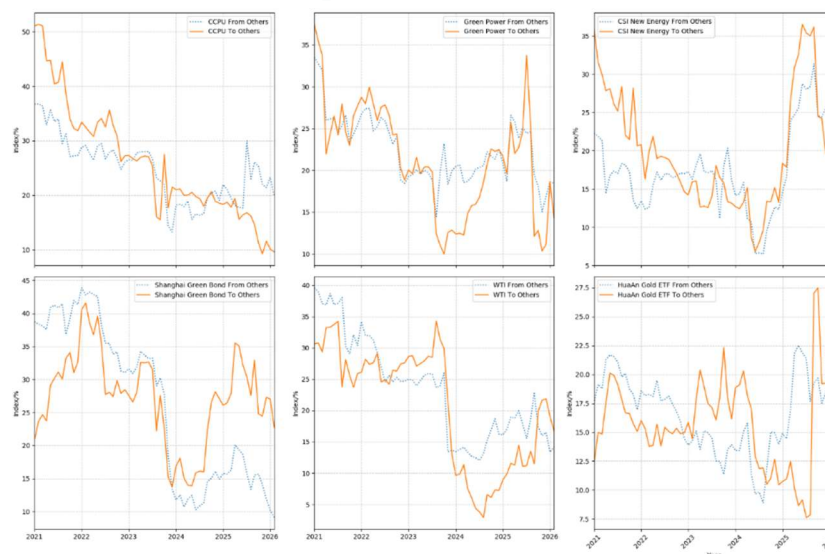


**Figure 2.** Directional spillover effect

Overall, risk transmission and reception across markets show clear time-varying characteristics. Each market can act as either a net transmitter or a net receiver, and these roles change over time.

In 2025, risks across markets increased amid multiple overlapping external shocks. The Red Sea shipping crisis continued to escalate, raising geopolitical risks and increasing oil and gold spillovers. Meanwhile, OPEC began gradually reversing its voluntary production cuts in April 2025, adding uncertainty to oil supply expectations. Overcapacity in China's domestic lithium battery industry also caused sharp fluctuations in lithium carbonate prices, increasing volatility in the A-share new energy sector and risks in green assets. In November, the US did not participate in the COP30 climate conference in Brazil, while countries remained divided over the pace of the transition away from fossil fuels, adding to global climate policy uncertainty. Rising risk aversion and cross-asset capital reallocation further intensified market linkages. Together, these events contributed to a sharp increase in two-way spillover indicators across markets.

### 4.4. Analysis of Net Spillover Effect

Regarding net spillovers, Figure 3 shows that the net spillover effects fluctuate around zero, consistent with the directional spillover results. No variable remains a net transmitter or receiver throughout the sample, reflecting strong time variation. The values fluctuate within a

range of approximately -20% to 20%, with frequent changes in spillover roles. In the early period, CCPU was a major net transmitter, but later became a net receiver amid geopolitical risks and crude oil shocks, as energy markets also affected climate policy expectations. As a fixed-income safe-haven asset, green bonds do not always passively receive risks. When concentrated safe-haven inflows lead to sharp fluctuations in the bond market, green bonds may also become a temporary net risk transmitter within the system. Net spillovers from crude oil and gold fluctuate over time, with geopolitical events serving as a key external factor driving changes in their risk transmission roles.

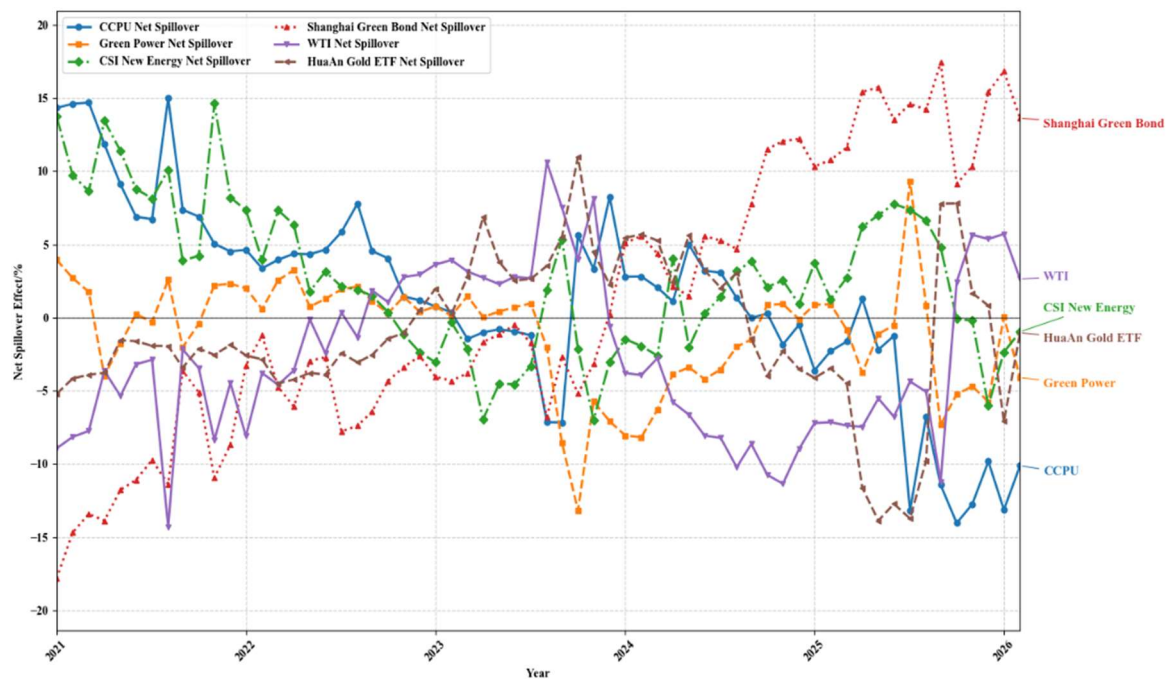


Figure 3. Net spillover effect

#### 4.5. Analysis of Pairwise Net Spillovers

From the analysis of the interactions between pairs of variables, Figure 4 shows that spillovers among Green Power, CSI New Energy, WTI, the Gold ETF, Shanghai Green Bonds and CCPU exhibit clear time variation and asymmetry. The pairwise net spillovers are related to major events occurring at the corresponding times.

From the perspective of CCPU, it acts as a net transmitter to CSI New Energy, Green Power and Shanghai Green Bonds. In the early period, climate policy uncertainty was a source of shocks, and policy changes affected green asset prices. However, in the later period, external pressures shifted towards geopolitical tensions in the Middle East and the oil crisis. Energy market turmoil first changed the actual energy landscape and then influenced climate policy expectations. Green capital markets and crude oil markets began to affect CCPU in the opposite direction, reversing the direction of risk transmission. Green energy markets also affected climate policy uncertainty in turn.

Regarding the impact of WTI on other variables in the system, spillovers increased at certain stages from the second half of 2025 to 2026. When crude oil prices fluctuate at high levels, pressure on energy security increases, forcing countries to reconsider the strength of their carbon neutrality policies. Oil price shocks affect climate policy decisions and disrupt policy expectations. Commodity markets can therefore influence climate policy uncertainty in the opposite direction, creating two-way feedback.

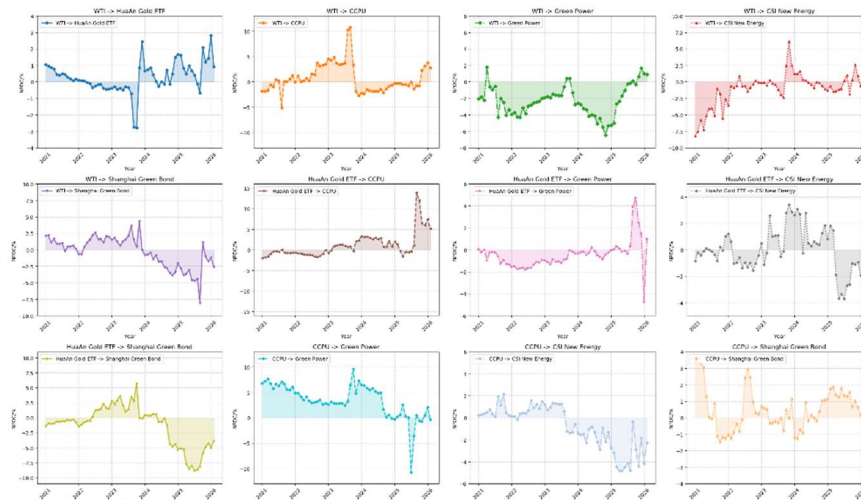


Figure 4. Pairwise net spillover effect

## 5. Conclusion and Suggestions

### 5.1. Conclusion

Through the study from a static perspective, the average spillover effect shows that there is a significant spillover effect between factors. From a dynamic perspective, the TCI index reflects that there is a strong connectedness in the system, with obvious time varying and asymmetric characteristics. The elements in the system are closely linked, and they are not all net spillovers and net receivers in all periods. The transmission effect between asset markets is strong and changes rapidly.

The impact of WTI on CCPU increased in several periods after the second half of 2025. Oil price shocks affected climate policy decisions and expectations, while commodity markets also influenced climate policy uncertainty in the opposite direction, forming a two-way feedback effect. The Gold ETF generally showed positive net spillovers to Shanghai Green Bonds and CSI New Energy. When managing their portfolios, investors' investment decisions regarding green bonds and CSI New Energy may be influenced to a considerable extent by returns. CCPU previously acted as a net transmitter to CSI New Energy, Green Power and Shanghai Green Bonds. However, the geopolitical oil crisis at the end of 2025 caused turmoil in energy markets and affected climate policy expectations. Green capital markets and crude oil markets then began to influence CCPU in the opposite direction, reversing the direction of risk transmission. This suggests that green energy markets can also affect climate policy uncertainty.

The findings provide some insights for policymakers and investors participating in the market.

### 5.2. Suggestions

Investors should pay attention to the dynamic impact of climate policy uncertainty on green assets which is significantly variable. When allocating green assets, investors should pay close attention to the dynamic changes of climate policy, especially the timing and intensity of policy adjustment. In addition, the risk caused by policy uncertainty can be reduced by diversifying the portfolio. For example, during the period of high policy uncertainty, the allocation of risk-averse assets such as gold ETFs should be appropriately increased to hedge the volatility risk of green assets.

Policymakers should strengthen the transparency and stability of climate policies. The impact of climate policy uncertainty on green assets is not only reflected in the direct impact of policy adjustments, but also indirectly affects asset prices through market sentiment and investor expectations. Therefore, policymakers should avoid excessive market fluctuations caused by frequent policy changes.

## References

- [1] Ding, S., Liang, Z., & Chen, J. (2023). Research on the spillover effects among climate policy uncertainty, energy, and metal markets from the time-frequency perspective. *Systems Engineering-Theory & Practice*, 43(8), 2222–2235. <https://doi.org/10.12011/SETP2022-2462>
- [2] Liu, Z., Ding, Z., & Duan, Z. (2023). Does climate policy uncertainty exacerbate extreme risk spillovers across energy markets? *Systems Engineering-Theory & Practice*, 43(6), 1651–1667. <https://doi.org/10.12011/SETP2022-2280>
- [3] Zhang, Y., Guo, K., Ji, Q., & Zhao, W. (2023). Information spillover effect of climate shocks on Chinese asset returns. *China Journal of Econometrics*, 3(2), 426–442. <https://doi.org/10.12012/CJoE2022-0125>
- [4] Ji, Q., Zhao, W., Zhang, D., & Guo, K. (2022). Climate risk perception and its impacts on financial markets: micro-evidence from listed firms in China. *China Journal of Econometrics*, 2(3), 666–680.
- [5] Ren, X., Li, J., He, F., & Lucey, B. (2023). Impact of climate policy uncertainty on traditional energy and green markets: Evidence from time-varying granger tests. *Renewable and Sustainable Energy Reviews*, 173, 113058.
- [6] Lei, H., Xue, M., & Ye, J. (2024). The nexus between ReFi, carbon, fossil energy, and clean energy assets: Quantile time–frequency connectedness and portfolio implications. *Energy Economics*, 132, 107456. <https://doi.org/10.1016/j.eneco.2024.107456>
- [7] Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2020). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management*, 13(4), 84. <https://doi.org/10.3390/jrfm13040084>
- [8] Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1), 57–66. <https://doi.org/10.1016/j.ijforecast.2011.02.006>