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# VOLATILITY SPILLOVER BETWEEN HUBEI CARBON MARKET AND GREEN FINANCIAL MARKET: EVIDENCE FROM TVP-VAR-DY MODEL

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**Abstracts:** In the context of the global climate crisis and China's dual-carbon target, a Time-Varying Parameter Vector Autoregression-Diebold-Yilmaz (TVP-VAR-DY) model is employed to examine risk spillovers between Hubei carbon and green financial market from January 5th, 2016 to January 6th, 2025. According to the findings, Hubei's carbon-green finance system exhibits moderate and time-varying volatility spillover. Green equities predominantly function as information transmitters, whereas green bonds act as receivers, showing risk concentration within the green stock-bond nexus rather than carbon-finance linkages. Then, exogenous shocks such as trade conflict, the COVID-19 pandemic and carbon policy adjustments amplify cross-market spillover intensity. These findings elucidate risk transmission mechanisms in climate-aligned markets, provide investors with portfolio rebalancing insights and enhance regulators' systemic risk monitoring capabilities.

**Keywords:** Hubei carbon market; Green bond market; Green stock market; Volatility spillover effects; TVP-VAR-DY model

# 1 INTRODUCTION

Carbon market and green financial market are key market-based solutions designed to reduce greenhouse gas emissions, operating as complementary mechanisms in facilitating low-carbon economic transitions. As a designated pilot region for both carbon emission trading and green financial innovation in China, Hubei Province presents a critical case for examining the interplay between these two markets. Analysing their intrinsic linkages and spillover effects could not only foster synergistic development through policy interoperability but also inform risk mitigation strategies against cross-market contagion. Current academic investigations mainly concentrate on the following aspects.

# 1.1 Interdependence between Carbon and Green Financial Markets

Carbon assets exhibit inherent financial attributes, demonstrating time-varying correlations with energy, traditional financial, and commodity markets [1-3]. As green finance matures globally, international studies have focused on the EU Emissions Trading System (ETS), revealing significant bidirectional spillover effects among carbon allowances, green bonds and green stocks, with green financial products serving as effective hedges against carbon price volatility [4-5]. Emerging studies in China suggest time-varying spillovers between domestic carbon markets and green financial instruments [6-7]. Carbon-green bond market linkages surpass those with green equities [8], while short-term risk spillovers dominate long-term interactions [9].

# 1.2 Policy Synergy in Hubei's Carbon-Green Financial Ecosystem

As China's pioneering carbon market pilot, Hubei Province has institutionalized a distinctive "carbon market–green finance" coupling mechanism. Its tripartite "Carbon Market + Carbon Finance + Inclusive Carbon System" framework leverages innovative instruments like carbon asset pledged loans to amplify green industrial investments, establishing replicable policy templates for regional decarbonization [10]. Academic consensus highlights Hubei's evolving governance model. Lin and Cao conceptualize a "core-dual wings" strategy, positioning the carbon market as the nexus while expanding green bonds and low-carbon industry funds to optimize capital allocation to realize green transformation [11]. Since May 2024, Hubei's "Electricity- Carbon-Finance" tri-market synergy mechanism represents a groundbreaking advancement in carbon finance, enabling cross-market pricing signals and risk-sharing [12].

Current research results have three limitations. First, predominant unilateral analysis of carbon or green financial markets neglect bidirectional interaction mechanisms and coordinated governance strategies. Second, excessive focus on the EU carbon market, overshadows empirical investigations into China's regional pilot systems, particularly Hubei's institutional innovations. Third, static spillover models inadequately capture nonlinear, time-changing interdependencies in emerging markets. Thus, we construct a TVP-VAR-DY model to quantify real-time risk transmission between Hubei carbon market and green financial market by utilizing high-frequency trading data, and explore risk monitoring strategies for both investors and regulators.

#### 2 METHODOLOGY AND DATA

#### 2.1 Construction of TVP-VAR-DY Spillover Index Model

Diebold and Yilmaz introduced the spillover index methodology (DY model), which employs the forecast error variance decomposition (FEVD) within a vector autoregressive (VAR) framework [13-15]. This approach quantifies spillover mechanisms across markets through both static spillover index tables and dynamic spillover index graphs. Compared to traditional spillover analysis methods, the DY framework offers three key advantages. First, it eliminates the dependence of results on subjective selection of VAR lag orders. Second, it quantifies both the intensity and directional pathways of information spillovers among multiple variables, enabling the identification of net spillover transmitters and the roles of different assets in market information transmission. Third, when integrated with a rolling window technique, the model generates a time-varying spillover index, capturing evolving spillover effects in response to market shocks or structural changes.

The construction of a TVP-VAR-DY model can be divided into three steps as follows.

First, construct the VAR model.

Construct the following p-th order VAR model for the returns of N markets.

$$Y_t = \sum_{i=1}^p \varphi_i Y_{t-i} + \varepsilon_t \tag{1}$$

 $Y_{t} = \sum_{i=1}^{p} \varphi_{i} Y_{t-i} + \varepsilon_{t}$ Where Y<sub>t</sub> is the N-dimensional column vector of market returns,  $\varphi_{i}$  is the N×N dimensional coefficient matrix and  $\varepsilon_{t}$  is the N-dimensional column vector of random disturbances, satisfying the basic assumptions of no serial correlation, zero mean, and independent and identical distribution.  $\Sigma$  is the matrix of autoregressive coefficients at time t=1, ..., T. Then, the moving average form of VAR(p) is obtained as follows.

$$Y_t = \sum_{i=1}^{\infty} A_i \, \varepsilon_{t-i} \tag{2}$$

$$A_{i} = \phi_{1} A_{i-1} + \phi_{2} A_{i-2} + \cdots + \phi_{p} A_{i-p}$$
(3)

where Equation (2) is the moving average form of VAR(p) and A<sub>0</sub> is the N×N unit matrix. When i<0, A<sub>i</sub>=0, when i>0, A<sub>i</sub> obeys the recursive form of Equation (3).

Second, the generalised variance decomposition is used to deal with the shocks in the predicted residual terms.

In order to make the variance decomposition unaffected by the ordering of variables, the forward H-step FEVD is considered, and the FEVD matrix can be obtained as follows.

$$\theta_{i \leftarrow j}^{H} = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H} \left( \dot{e_i} A_h \sum e_j \right)^2}{\sum_{h=0}^{H} \left( \dot{e_i} A_h \sum A_h e_j \right)}$$
 (4) where Equation (4) represents the proportion of forecast error of the ith market return that comes from the jth market

return,  $\Sigma$  is the covariance matrix of the error  $\varepsilon$  vector, and  $\sigma_{ii}$  is the sequence of standard errors of  $\varepsilon$ .  $e_i$  is an N-dimensional selection vector whose ith element is 1, and the rest of the elements are 0. For the variable  $\theta_{i\leftarrow j}^H$ , the sum of the contributions of the other variables to its prediction error variance is not equal to 1. Thus, it is standardized as follows.

$$\theta_{i\leftarrow j}^{H} = \frac{\theta_{i\leftarrow j}^{H}}{\sum_{j=1}^{N} \theta_{i\leftarrow j}^{H}}$$

$$\sum_{i,j=1}^{N} \theta_{i\leftarrow j}^{H} = N, \quad \sum_{j=1}^{N} \theta_{i\leftarrow j}^{H} = 1$$

$$(5)$$

$$\sum_{i,j=1}^{N} \theta_{i \leftarrow j}^{H} = N, \quad \sum_{j=1}^{N} \theta_{i \leftarrow j}^{H} = 1$$
 (6)

Thus, the pairwise spillover relationship of market I to market j can be obtained under step H.

Third, the total connectedness index (TCI), directional connectedness index, net spillover index, and net pairwise directional connectedness (NPDC) are calculated.

The TCI, which represents the contribution of mutual spillovers among N variables to the total forecast error variance, is averaged by summing the off-diagonal elements of the forecast error variance decomposition matrix as follows.

$$S^{*}(H) = 100 \times \frac{\sum_{i,j=1,i\neq j}^{N} \hat{\theta}_{ij}^{*H}(H)}{\sum_{i,j}^{N} \tilde{\theta}_{ij}^{*H}(H)}$$

$$= 100 \times \frac{1}{N} \times \sum_{i,j=1,i\neq j}^{N} \tilde{\theta}_{ij}^{*H}(H)$$
(7)

The directional spillover index is decomposed into spill-out index and spill-in index. The spill-out index measures the directional spillover from market i to all other variables, reflecting its outward influence, while the spill-in index quantifies the directional spillover into market i from all other variables, capturing its susceptibility to external shocks. They are as follows.

$$S_{to} = 100 \times \frac{\sum_{j=1, i\neq j}^{N} \hat{\theta}_{ij}^{* H}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{* H}(H)}$$

$$= 100 \times \frac{1}{N} \times \sum_{j=1, i\neq j}^{N} \hat{\theta}_{ij}^{* H}(H)$$

$$S_{from} = 100 \times \frac{\sum_{j=1, i\neq j}^{N} \hat{\theta}_{ji}^{* H}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^{* H}(H)}$$

$$(8)$$

$$S_{from} = 100 \times \frac{\sum_{j=1, i \neq j}^{N} \hat{\theta}_{ji}^{* H}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^{* H}(H)}$$

$$= 100 \times \frac{1}{N} \times \sum_{j=1, i \neq j}^{N} \tilde{\theta}_{ji}^{* H}(H)$$
(9)

The net spillover index, which measures the size of market's net spillover to all other markets, is as follows.

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$$S_{net} = S_{to} - S_{from} \tag{10}$$

The net pairwise directional connectedness (NPDC) is given by:

$$NPDC_{ij}(H) = 100 \times (\tilde{\theta}_{ji}^{*H}(H) - \tilde{\theta}_{ij}^{*H}(H))$$

$$(11)$$

# 2.2 Data Selection and Pre-Processing

As the largest and most actively traded pilot carbon market in China, Hubei ETS provides an exemplary case for investigating the interplay between regional carbon market and green financial instruments. This study employs the closing price of Hubei carbon allowance (hbea) as the primary indicator for Hubei carbon market. For analyzing green finance components, it distinguishes between green bonds and green equities markets. While provincial-level price data for green instruments remains limited, this study utilizes two national proxies of China Bond-China Green Bond Wealth Index (gb) and CSI 300 Green Leading Stock Index (gs). This methodological choice aligns with the assumption of uniformity in green financial policies, given that national indices comprehensively encompass major Hubei-based green enterprises and reflect policy coordination effects.

The dataset for each market was sourced from the Wind database, spanning the period from January 5th, 2016 to January 6th, 2025. All variables utilize daily closing prices, with non-synchronous trading days across markets excluded, yielding a total of 2,126 observations. This sample period strategically covers the maturation of Hubei carbon market pilots (2016–2020) and the institutional consolidation following the national carbon market's formal launch (2021–2025). It can comprehensively reflect the market linkage dynamics under "dual-carbon" objectives.

In this paper, we calculate the logarithmic returns for each market using daily closing prices, defined as  $r_t = 100 \times ln$  ( $p_{i,t}/p_{i,t-1}$ ), where  $p_t$  denotes the closing price at time t. Table 1 summarizes the descriptive statistics of the market returns.

Table 1 Results of Descriptive Statistics

Yield variable	Mean (%)	Maximum value (%)	Minimum value (%)	Standard deviation	ADF
hbea	0.0262916	11.08045	-19.72102	2.828749	-44.486***
gb	0.0187945	0.8008372	-0.8183246	0.0794773	-29.159***
gs	-0.0044412	10.32083	-10.32339	1.656642	-46.319***

Note: \*\*\*, \*\*, \* represent statistical significance at the 1%, 5% and 10% level respectively.

First, the mean value of the carbon yield is higher and the standard deviation are larger than other markets, which indicates that Hubei carbon market is characterized by higher yield and high volatility. This volatility pattern highlights the practical significance of studying cross-market spillover effects for carbon market risk management. Second, the green bond market exhibits remarkably low volatility, with its standard deviation approaching zero. This characteristic suggests the green bond has the nature of a hedge asset. Finally, the time series of market yields are found to be stable by Augmented Dickey-Fuller (ADF) test, and can be studied by DY spillover index model for this study.

# 3 EMPIRICAL ANALYSIS ON MODEL ESTIMATION RESULTS

# 3.1 Static Time-Domain Spillover Analysis

The TVP-VAR-DY model is used to examine total spillover effects in the static time-domain. Following the Akaike Information Criterion (AIC) and Schwarz Criterion (SC) criteria, the optimal lag order for the autoregressive process is identified as 4, and the Generalized Forecast Error Variance Decomposition (GFEVD) horizon is standardized to 10 periods. Using Equations (7)-(10), total connectedness index (TCI), directional spillover indices (FROM, TO), and net spillover index (NET) are calculated, as shown in Table 2.

The results show a TCI of 4.24% across the integrated system, revealing intricate systemic spillover relationships among Hubei carbon market, green bond market, and green stock market. Directional spillover analysis indicates that Hubei Carbon Emission Allowance (hbea) market receives 1.88% spillovers from external markets, while green bonds (gb) and green stocks (gs) absorb 3.76% and 2.84% respectively. Conversely, these markets transmit spillover effects of 2.06%, 2.52%, and 3.89% to other markets respectively. Significantly, the green stock market emerges as the dominant net transmitter of information flows, primarily driven by their sensitivity to climate policy changes such as subsidies, carbon taxes and to market sentiment fluctuations. It is the first to capture market expectations toward the green economy and transmit signals to other markets. Carbon market exhibits a low-level positive net spillover, where price fluctuations directly impact high-carbon firms' emission costs and profit expectations. Rising carbon prices may force these firms to increase investments in emission reduction or accelerate green technology adoption, thereby influencing both green stock and green bond markets. Green bond market demonstrates a negative net spillover index, functioning mainly as information receivers. This reflects their fixed-income characteristics, pricing mechanisms anchored to traditional bond markets, lower liquidity, and reduced sensitivity to short-term policy and stock market volatility. During risk events, investors often reallocate capital from volatile carbon or equity markets to relatively stable green bonds, resulting in passive spillover reception.

Table 2 Total Static Spillover Indices								
Variable	hbea	gb	gs	Direnctional spillover index (FROM)				
hbea	98.12	0.89	0.98	1.88				
gb	0.85	96.24	2.90	3.76				
gs	1.21	1.63	97.16	2.84				
Directional spillover index (TO)	2.06	2.52	3.89	8.47				
Net spillover index (NET)	0.19	-1.24	1.05					
Gross connectedness index (TCI)				4.24				

Table 2 Total Static Spillover Indices

#### 3.2 Dynamic Spillover Analysis

Since the static spillover indices fail to capture time-varying interactions, the rolling-window approach with a 200-day window, 10-step forecast horizon reveals evolving spillover dynamics between Hubei carbon market and green financial market. Figures 1 and 2 present the dynamic total spillover index and dynamic net spillover index, respectively.

# 3.2.1 Dynamic total spillover analysis

Figure 1 illustrates significant time-varying spillover effects between Hubei carbon market and green financial market over the sample period. From 2018 to 2019, heightened systemic risks driven by macroeconomic shocks such as U.S.-China trade tensions, continuous RMB depreciation, and stock market volatility propelled the TCI upward, sustaining it at high levels. In 2020, the outbreak and rapid spread of COVID-19 in Wuhan triggered widespread market panic, amplifying cross-market spillovers and driving the TCI to its peak. In early 2021, the index began to decline, benefiting from China's effective pandemic containment, coupled with economic stabilization and improved investor confidence. In July 2021, the launch of China's national carbon emissions trading market (NCETM) catalyzed low-carbon transition investments. This structural shift intensified carbon-green financial market linkages, driving up the TCI. In January 2024, Chinese Certified Emission Reduction (CCER) was restarted, complementing the carbon pricing mechanism. In April, the State Council formally approved the inclusion of the steel, cement, and aluminium smelting industries into NCETM. In May, implementation of the Interim Regulations on Carbon Emissions Trading bolstered market confidence, diversified participants and financial instruments, and improved cross-market liquidity and price discovery. These reforms accelerated carbon-green financial market integration, elevating spillover levels to new highs. Through the above analysis, it is found that special events such as trade frictions, the COVID-19 pandemic, and intensive implementation of carbon market systems have strengthened the correlation between Hubei carbon market and the green financial market.

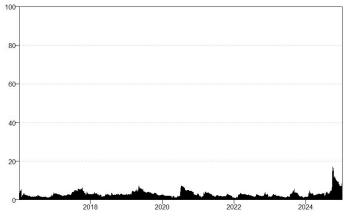


Figure 1 Dynamic Total Connectedness Index

#### 3.2.2 Dynamic net spillover analysis

In Figure 2, during the sample period, the dynamic net spillover indices of Hubei carbon market, green bond and green stock markets exhibited significant time-varying features, fluctuating within a 10% range. First, the absolute value of net spillover index in Hubei carbon market exhibits limited variations, indicating a generally low net spillover level. However, distinct cyclical patterns emerge as compliance deadlines approach. During these periods, trading activity surges, driving a sharp rise in transaction volumes and transforming the carbon market into a net transmitter. The outbreak of COVID-19 pandemic in early 2020 triggered a marked decline in carbon market activity, showing its high sensitivity to external shocks. Second, green bond market function as net recipients of spillover effects, absorbing shocks from interconnected markets, while green stock market act as net transmitter. Both have higher net spillover

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levels than the carbon market. The spillover fluctuations in green bond and stock market intensified under major events including US-China trade tensions, the COVID-19 pandemic and intensive rollouts of carbon market regulations.

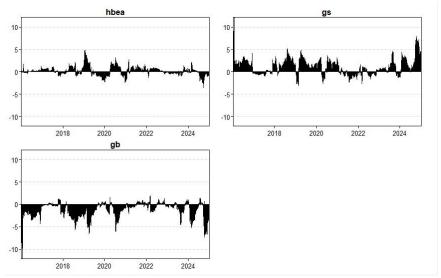


Figure 2 Dynamic Net Spillover Indices of Various Markets

# 3.3 Volatility Spillover Network Analysis

Understanding spillover network paths enables investors, enterprises and policymakers to better anticipate market fluctuations and optimize decision-making. Based on Equation (11) of the TVP-VAR-DY model, we derive the NPDC indices and employ complex network analysis to construct a spillover network. Figure 3 shows the dynamic NPDC indices across markets, while Figure 4 illustrates the time-domain spillover network for the "carbon-green bond-green stock" system, revealing transmission pathways between markets. The direction and thickness of connecting lines respectively signify spillover directions and intensities. Risk transmission follows a closed-loop spillover pathway of "green stocks → green bonds → carbon market → green stocks", reflecting a transmission mechanism where the stock market reflects corporate expectations for green technologies, which subsequently affects green bond issuance costs, and ultimately transmits to carbon allowance demand via green financing projects. The green stock market predominantly acts as an information transmitter, while the green bond market serves as a net receiver. The volatility spillover level between the green stock and green bond markets is significantly high, whereas the carbon market exhibits weaker interconnectivity with both green financial markets (Figures 3 and 4). This disparity stems from the nascent stage of the Hubei carbon market, which currently lacks derivative instruments such as carbon futures. Consequently, its price discovery mechanism remains underdeveloped, and its pricing efficiency requires enhancement. Looking ahead, as carbon financial derivatives develop and the green financial system becomes more integrated, the connectedness among Hubei carbon market, green bond and green stock markets is expected to strengthen over time.

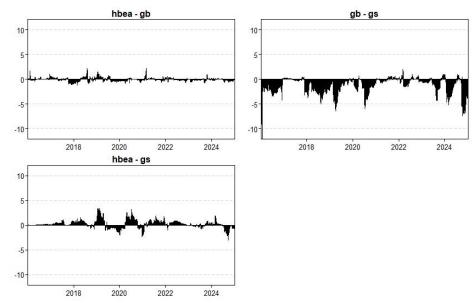


Figure 3 Dynamic NPDC Indices of Various Markets

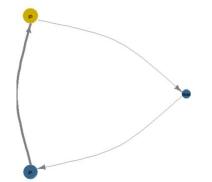


Figure 4 Time-Domain Spillover Network

# 4 CONCLUSIONS

Based on a TVP-VAR-DY model, this study has examined the dynamic spillover effects between Hubei carbon market and green financial markets. The findings reveal the following conclusions.

First, there is a complex systematic spillover relationship among Hubei carbon market, green bond and green stock markets, with an average total spillover index of 4.24% across the sample period. This indicates moderate but persistent interconnectedness within the "Carbon-Green Bond-Green Stock" system.

Second, both gross and net spillover indices exhibit significant time-varying characteristics. Gross spillover analysis reveals the green stock market predominantly acts as an information transmitter, while the green bond market serves as an information receiver. Net spillover analysis shows the green stock and carbon markets as persistent net spillover transmitters, contrasted with the green bond market as a net receiver. Therefore, investors should adapt portfolio allocations dynamically based on differentiated green asset-carbon market linkages, policy adjustments and external shocks.

Third, external shocks including trade conflicts, the COVID-19 pandemic, and regulatory reforms in carbon market systems substantially amplified cross-market correlations. Therefore, Hubei government should develop cross-market risk warning mechanisms to avoid systemic spillovers and adopt forward-looking policies to reduce market uncertainties. In addition, carbon-linked financial instruments such as carbon futures and carbon options should be innovated to stabilize market expectations under policy shocks.

Finally, the risk contagion follows a closed-loop pathway of "green stocks  $\rightarrow$  green bonds  $\rightarrow$  carbon market  $\rightarrow$  green stocks". Green stocks act as the risk source, while the carbon market serves as a feedback amplifier. Notably, spillover effects concentrate between green bonds and stocks, with weaker direct linkages to the carbon market. As low-carbon transition policies intensify, interconnectivity between carbon market and green finance strengthens. Thus, policy design should prioritize leveraging the differentiated linkages between Hubei carbon market and green financial market to maximize their synergy and complementarity.

#### **COMPETING INTERESTS**

The authors have no relevant financial or non-financial interests to disclose.

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