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GREEN BOND VS GREEN STOCK: WHICH ONE CAN RESIST CLIMATE POLICY UNCERTAINTY IN CHINA?

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Abstract. This paper applies the time-varying parameter-stochastic volatility-vector auto-regression (TVP-SV-VAR) method to explore the correlations among China's climate policy uncertainty (CPU), green stock (GS), and green bond (GB). The findings evidence dynamic impacts from CPU to the green assets, indicating that the hedging ability of green assets varies over time. In the short and medium term, the GS may hedge the rising CPU risks effectively while the GB is not. However, in the long term, both the GS and GB may resist the CPU risks, although the GS is found to perform better. Furthermore, the results also suggest that the GS is more reliable when the unexpected shocks happen. Thus, compared to the GB, the GS may possess higher uncertainty risks hedging ability. Nevertheless, the results also suggest that the hedging ability of the GS decreases in recent years. The findings may help investors construct portfolios to hedge CPU risks. Moreover, the results suggest that the government should further promote the standardisation of green investment and reduce the information asymmetry of climate policy, which is critical to improve the performance of green assets.

Keywords: climate policy uncertainty, China, green stock, green bond, hedging-ability, time-varying.

JEL Classification: C32, D81, G12, I2.

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1. Introduction

This research aims to check whether Green Stock (GS) and Green Bond (GB) are still trustworthy when facing the rising Climate Policy Uncertainty (CPU) in China. The GS and GB are becoming increasing popular as the climate issues have attracted great attention in recent years (Razzaq et al., 2023). Due to the frequent climate disasters, China's government has taken great effort to tackle climate change issues, including the promulgation of various climate policies and the encouragement of green investment (Wu & Liu, 2023; Qin et al., 2024a; X. Q. Wang et al., 2025c). On the one hand, China announced in 2020 that it plans to achieve carbon peak and carbon neutrality by 2030 and 2060, respectively (K.-H. Wang et al., 2025b). On the other hand, China's GS and GB market have experienced unprecedented developments. According to the China Finance, China issued 685 billion yuan of GB in 2024, and the GS index has increased from 1000 to 2113[1] between June 2012 and May 2025. However, new challenges emerged, that is, the rising uncertainty of China's climate policy. The existing literature explained the rising CPU in the following two perspectives: First, the promulgation of China's dual carbon plan implies that the government will accomplish the goal within the shortest period. To ensure the realisation of the sustainable development goal, the government frequently revises its policies designed to combat climate threats, which increases CPU greatly (Ren et al., 2022a). Second, many factors in China, including market sentiment, technological innovation, and social stability, may also lead to a dramatic change in CPU (X. Q. Wang et al., 2025a).

Meanwhile, the rising uncertainty of climate policy may strike investors' optimistic expectations for green investments. This may be explained by two reasons: First, some research find green investments may be risker during the uncertainty period (Ziadat et al., 2024). Thus, whether the green investments can resist CPU risks is still uncertain. Second, China's green industry relies on climate policies support heavily, while GS and GB are both critical financing channels, which implies that green assets are intimately connected with CPU. Thus, the rising CPU may strike investors' expectations and influence the prices of GS and GB. For instance, an increase in carbon tax would increase investors' confidence in green industry, while a cancellation of subsidies for new energy vehicles may strike the enthusiasm for green investment (Liu et al., 2024). Therefore, whether GS and GB can resist CPU risks is still uncertain. Furthermore, considering that China's climate policy will remain highly uncertain over a long period (Qin et al., 2024b), it is necessary to check whether GS and GB are still trustworthy when facing the rising CPU.

The investigation may provide the following three contributions: First, the existing literature has investigated the hedging function of green investments under different uncertainty risks comprehensively, such as geopolitical risks (Doğan et al., 2023) and economic policy uncertainty (Igeland et al., 2024), while few focuses on whether GS and GB can resist CPU risks. Besides, the divergent opinions regarding the hedging function of GS and GB imply that the performance of green assets may differ when facing different uncertain risks. Thus, this investigation may fill this gap by investigating the inter-relationship among CPU, GS, and GB. Second, the inter-relationship among the variables may be unstable during the uncertainty period, which implies that the inter-relationship is time-dependent. Thus, this paper applies the time-varying parameter-stochastic volatility-vector auto-regression (TVP-SV-VAR) model to investigate the variables' dynamic correlations. Third, a comprehensive study of CPU and green assets may offer valid suggestions for both investors and governments. Green investors could construct green asset al.ocations based on the deep understanding of the relationship among CPU, GS, and GB. Meanwhile, the investigation results may help the government not only understand the influences of the climate policy, but also promote the development of green finance market.

2. Literature review

The existing research has explored the hedging abilities of the green assets comprehensively, while no conclusions have been reached. Some research proposes that the green assets

[1] The GS index is CSI Green Investing Index, code 930956.CSI, and the data is derived from Wind Database.

may resist uncertainty risks effectively. For the uncertainty risks of financial assets, Kanamura (2020) finds that compared to traditional bonds, GB performs better when the uncertainties increase, although the performance declines over time. Chopra and Mehta (2022) evidence that GB is a reliable asset to hedge stock sectors risks when unexpected shocks occur. Henriques and Sadorsky (2024) emphasize the diversification benefits of GS in hedging the uncertainty risks in the FinTech markets. For the uncertainty risks of global pandemic, Wan et al. (2021) prove the hedging performance of GS during the pandemic period. Guo and Zhou (2021) find no significant changes in GB's tail risk when COVID-19 happens, emphasising GB's safe-haven property. For the policy uncertainty risks, Bouri et al. (2022) propose that compared to traditional energy stocks, GS performs better when CPU increases. Doğan et al. (2023) emphasize the prominence of GB as safe assets to hedge policy uncertainty risks. Igeland et al. (2024) also holds a similar opinion when investigating the impact mechanism between GS and economic policy uncertainty.

While other literature holds the opposite view, indicating that green investment may be riskier when the uncertainty risk increases. Kocaarslan and Soytas (2021) find the rising economic policy uncertainty may exacerbate the volatility in GS markets. Duan et al. (2023) find that GB is a net recipient during the pandemic period. Ziadat et al. (2024) confirm this view by evidencing that GS and GB play the role of net spillover receiver when the uncertainty risks increase. The existing literature explains the adverse impact of the uncertainty risks on green assets based on three reasons: The first reason is the rising uncertainty risk may reduce green companies' profit. For example, Ivanovski and Marinucci (2021) evidence that the increasing uncertainty would reduce residents' willingness to consume renewable energy. The second reason is the rising uncertainty would strike investors' confidence in green investment. J. Wang et al. (2024) demonstrate that the rising uncertainty has undermined investors' confidence in investing in green projects, which will be reflected in the GS price. The third reason is the higher risks of green projects. For instance, Huo et al. (2023) evidence green project regulation risks, making GB more vulnerable when unexpected shocks happen.

Another strand of the literature proposes that the uncertainty risks hedging ability of green assets is unstable. Saeed et al. (2020) propose that investors should apply dynamic green investments strategy to hedge uncertainty risks, and emphasize the better performance of GS compared to GB. Yang et al. (2021) evidence obvious uncertainty spillovers from geopolitical risks to GS, while the direction of the impact is still uncertain. Pham and Nguyen (2022) find that the inter-relationship between uncertainty risks and GB is unstable, they propose GB can be treated as safe-haven asset during low uncertainty period rather than the high uncertainty period. Ren et al. (2022b) find positive relationship between uncertainty risks and GB in the medium to long term, while the relationship becomes erratic in the short term.

In Summary, although the existing literature has investigated the performance of GS and GB comprehensively, whether they can hedge uncertainty risks is still uncertain. Therefore, this paper aims to enrich the existing literature in the following aspects: First, the research mainly focuses on the performance of green assets when facing the rising economic policy uncertainty, geopolitical risks, and the unexpected shocks, while few investigates the impact of CPU. Thus, this paper tries to fill this gap through investigating the relationship among CPU, GS, and GB, checking whether they are reliable assets to hedge CPU risks. Second, although different studies have proposed their conclusions on the hedging abilities of green assets, including positive and negative judgment, the correlation may be unstable due to the unexpected shocks. Thus, this paper tries to enrich the existing literature through investigating the dynamic correlations between CPU and green assets. Third, some studies choose to exclude the sample period with high instability to ensure the robustness of experimental results, however, it may also lose the chance of checking whether the green assets can resist the uncertainty risks effectively. Thus, this paper applies the TVP-SV-VAR model to overcome this shortcoming by investigating the correlations among the variables under different uncertainty periods.

3. Methodology

The Structural Vector Autoregression (SVAR) model may check whether there are correlations among time series variables. However, the model assumes that the coefficients and the variance of the residuals should be constant (Sims, 1986), which implies the system could only obtain one fixed sequence inter-relationship during the full sample period. The model of SVAR is displayed as the Eq. (1):

$$Ay_t = F_1 y_{t-1} + \ \ldots + F_s y_{t-s} + \mu_t \quad t = s+1, \ldots, n, \tag{1}$$

where y_t represents the observable vector, and $y_{t-1}, \ldots, y_{t-s}$ delegate the lag vectors of y_t. $F_1, \ldots, F_s$ stand for the parameter matrices. μ_t represents the structural shocks, according with $\mu_t \sim N(0, \Sigma\Sigma)$. In addition, matrices A and Σ delegate the lower triangular matrix, which may be displayed as the Eq. (2):

$$A = \begin{bmatrix} 1 & 0 & L & 0 \\ a_{21} & 0 & 0 & M \\ M & 0 & 0 & 0 \\ a_{k1} & L & a_{k,k-1} & 1 \end{bmatrix} \qquad \Sigma = \begin{bmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_k \end{bmatrix}, \tag{2}$$

where σ_i $(i = 1, \ldots, k)$ represents the standard deviation of the systemic changes. We multiply A^{-1} on the right and left side of Eq. (1) and assume $B_i = A^{-1}F_i$ $(i$ = 1, ..., $s)$. Then, the Eq. (2) could be restated as follows:

$$y_t = B_1 y_{t-1} + \ldots B_s y_{t-s} + A^{-1} + \Sigma \varepsilon_t \qquad \varepsilon_t \sim N(0, I_k). \tag{3}$$

Eq. (3) is a SVAR model whose coefficients are stable. On the one hand, we combine the components in B_i into a $K^2 s \times 1$ dimensional vector β. On the other hand, we assume $X_t = I_s \otimes (Y'_{t-1}, \ldots, Y'_{t-s})$ and $\otimes$ represents the Kronecker product. After that, the Eq. (3) may be displayed as the Eq. (4):

$$y_t = X_t \beta + A^{-1} \Sigma \varepsilon_t. \tag{4}$$

Considering the time series variables may be vulnerable to the unexpected shocks, the inter-relationship among the variables may display time-varying features. Thus, we introduce the TVP-SV-VAR model. The model may convert the constant coefficients in Eq. (4) into time-varying coefficients, which is shown in the Eq. (5):

$$y_t = X_t \beta_t + A_t^{-1} \Sigma_t \varepsilon_t, \tag{5}$$

where β_t, A_t^{-1} and Σ_t delegate the non-stable coefficients. Furthermore, the non-zero and-one components in A_t^{-1} can be denoted as $a_t = (a_{21,t}, a_{31,t}, a_{32,t}, \ldots, a_{kk-1,t})'$. h_t delegates the stochastic volatility matrix in the logarithmic form, which could be demonstrated as $h_t = (h_{1t}, \ldots, h_{kt})'$. Specifically, $h_{kt} = \log(\sigma_{kt}^2)$. Besides, we assume the parameter matrices β_t,

A_t^{-1} and Σ_t follow the random walk process and are independent of each other. The Eq. (6) shows the dynamic changes of the coefficients.

$$\begin{aligned}\beta_t &= \beta_{t-1}+\mu_{\beta t}\\ a_t &= a_{t-1}+\mu_{\alpha t}\\ h_t &= h_{t-1}+\mu_{ht}\end{aligned} \quad \begin{pmatrix}\varepsilon_t\\ \mu_t\\ \nu_t\\ \vartheta_t\end{pmatrix} \sim N\left(0, \begin{pmatrix} I & 0 & 0 & 0\\ 0 & \Sigma_\beta & 0 & 0\\ 0 & 0 & \Sigma_a & 0\\ 0 & 0 & 0 & \Sigma_h\end{pmatrix}\right), \tag{6}$$

where I delegates an identity matrix, $\beta_{s+1} \sim N(\mu_0, \Sigma_{\beta_0})$, $a_{s+1} \sim N(\nu_0, \Sigma_{a_0})$, $h_{s+1} \sim N(\vartheta_0, \Sigma_{h_0})$. In addition, since investors' confidence not only influences the price of greens assets but also the inter-relationship between them, we treat green investors' confidence as a control variable. Then, the y_t in Eq. (5) could be rewritten as $y_t = (CPU_t, GS_t, GB_t)'$. The TVP-SV-VAR model may offer two advantages. On the one hand, since the inter-relationship among the CPU, GS, and GB may be vulnerable to the unexpected shocks, the correlation may be time-varying. Thus, the traditional VAR model is not suitable, while the TVP-SV-VAR model can overcome this shortcoming by capturing the dynamic changes. On the other hand, the model can display the impulse response of green assets when facing the rising CPU at different events point, which testifies the hedging abilities of GS and GB under different context. Finally, to improve the empirical accuracy, when considering the likelihood function under experimental conditions with random fluctuations, we apply the Markov chain Monte Carlo simulation (MCMC) method to simulate sampling and check whether the results of the TVP-SV-VAR model are reliable.

3. Data

This paper applies the Twitter-based Chinese climate policy uncertainty[2] proposed by Lee and Cho (2023) to trace the changes of CPU. The index is constructed as scaled frequency counts of social media that discusses the uncertainty of climate policy, and traces the fluctuations of CPU from March 2010 to January 2023. Then, this paper applies the CSI Green Investing Index and the China Bond Index (Tian et al., 2022) to delegate the performance of GS and GB, respectively. Specifically, the CSI Green Investing Index selects 60 representative China's green stocks with a high proportion of green revenue as sample stocks, reflecting the overall performance of green stocks from June 2012. Meanwhile, the China Bond Green Bond Index starts in January 2010 and covers a wide range of GB traded in the market. Since the data set of the variables is different, to obtain the maximum sample interval, this paper chooses monthly data between June 2012 and December 2022 to investigate the correlations among CPU, GS, and GB. The data of GS and GB is derived from the Wind Database.

Figure 1 depicts the trend of the CPU, GS, and GB, and we can find three trend characteristics. Firstly, the uncertainty of climate policy is basically at low level between 2012 and 2020, while it rises significantly in recent years, which emphasizes the importance and the urgence of investigating CPU. Secondly, the GS and GB show an overall upward trend in the sample period, indicating that China's green investment has made great progress in the past decade. Thirdly, compared to the changes of GB, it can be found that the GS is much volatile, which suggests that GB may be a more stable asset to hedge against CPU than GS.

[2] The data is derived from https://twitterchnepu.github.io/

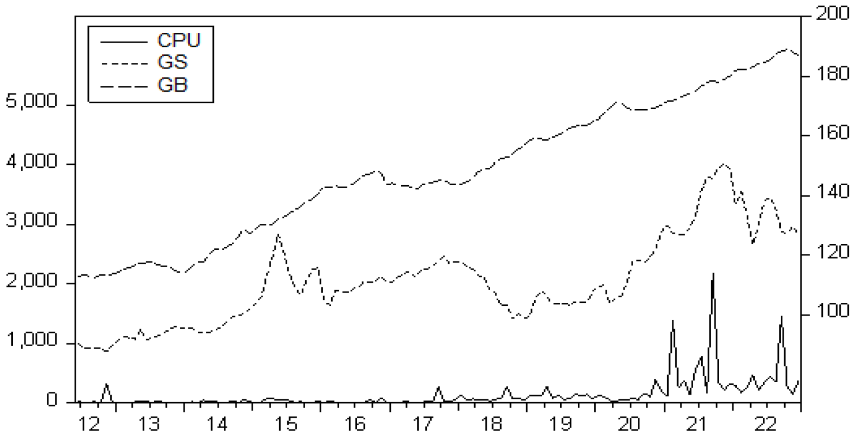


Figure 1. The trends of CPU, GS, and GB

Meanwhile, we select several prominent periods to describe the performance of green assets when CPU experiences great changes. During the period between 2018: M2-2018: M9, the uncertainty of climate policy increases from 40.296 to 274.567. while the reaction of GS and GB is opposite. This suggests that the hedging ability of GS and GB is different. After that, China's first water pollution prevention plan is released in October 2018, and the Central Economic Work Conference in December reaffirms the importance of environmental protection (Razzaq et al., 2023). Although the environmental governance plan becomes gradually clear, the details of policy implementation remain unclear. Therefore, the uncertainty of China's climate policy fluctuates greatly between 2018: M10-2019: M12, with the highest and lowest values being 268.204 and 45.338, respectively. Nevertheless, the green assets still show an overall upward trend. This implies that green investment may posse good resilience to CPU risks.

Then, in the early stage of the COVID-19 outbreak (Wei et al., 2023; Song et al., 2025a), the CPU declines from 127.002 to 14.761, one of reasons is that the sudden stagnation of economic activities reduces the discussion of climate policy. After that, the CPU starts to rise from 14.761 to 384.387 during the period 2020: M4-2020: M11, while the GS rises from 1761.201 to 2584.506, and the GB declines from 171.294 to 169.533. This indicates that when facing CPU risks during the COVID-19, compared with GB, the GS is more synchronized with the changes in CPU. Subsequently, during the period of 2020: M10-2022: M10, the CPU experiences an obvious rise, it reaches a new high point in September 2021, and continues to oscillate in the range of 200 and 300, which may be explained by the worsening contradiction between downward pressure on the economy and the environmental protection (Li & Su, 2024; Song et al., 2025b). Nevertheless, both GS and GB experience an upward trend during the period, which implies that the green assets may resist the increasing CPU risks.

Table 1 displays descriptive statistics of China's CPU, GS, and GB. The mean values of the variables are 132.581, 2037.118, and 148.177, respectively. This indicates that the uncertainty of the climate policy in China is generally at high level. All the variables have positive skewness, indicating that the time series follow the right-skewed distributions. In addition, the kurtosis of CPU is 30.303, implying CPU follows leptokurtic distributions. Meanwhile, GS and GB are complied with the platykurtic distributions since their kurtosis is less than 3. Finally, the Jarque-Bera statistics suggest that all the variables do not follow the normal distribution significantly, implying that the traditional VAR method is not applicable.

Table 1. Descriptive statistics

	CPU	GS	GB
Observations	127	127	127
Mean	132.581	2037.118	148.177
Median	45.339	1942.331	145.246
Maximum	2176.396	4021.749	189.006
Minimum	0	850.765	112.609
Standard Deviation	279.803	749.639	22.967
Skewness	4.801	0.652	0.031
Kurtosis	30.303	2.918	1.874
Jarque-Bera	4432.504***	9.036**	6.731**

Note: *** denotes the significance of 1%.

4. Empirical results

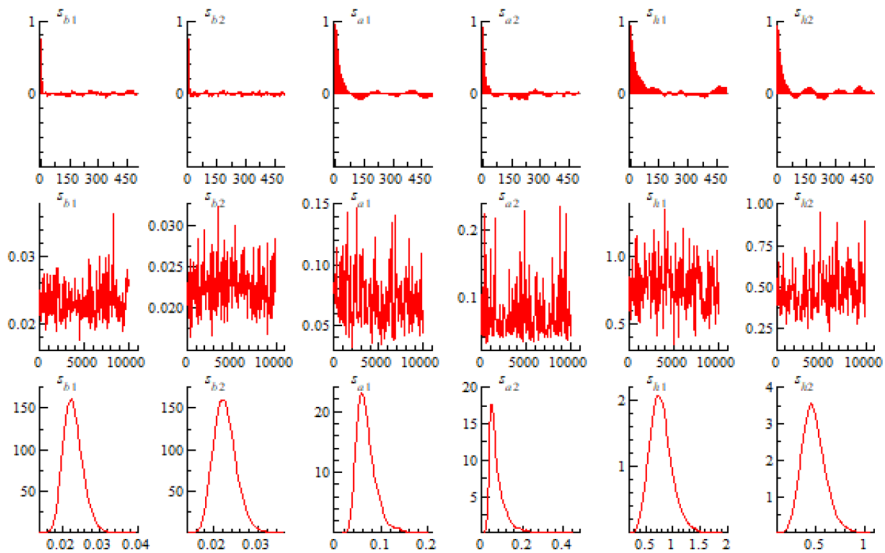
According to the unit root test results, this paper applies the variables after the difference of the first order. Besides, based on the Schwarz information criterion (SIC), this paper chooses 6 as the optimal lag order. Table 2 suggests the mean values for all variables are within 95% confidence intervals. Meanwhile, the Geweke statistics imply that the coefficient estimations conform to the posterior distribution. The variables' inefficiency factors are smaller than 100, which suggests the investigation has utilised enough uncorrelated samples and the estimated coefficient values are valid.

Table 2. The estimation results of parameters in the TVP-SV-VAR model

Parameters	Mean	Standard deviation	95% confidence interval	Geweke	Inefficiency factors
$(\Sigma_\beta)_1$	0.023	0.003	[0.019, 0.029]	0.956	5.43
$(\Sigma_\beta)_2$	0.023	0.003	[0.018, 0.028]	0.431	5.81
$(\Sigma_a)_1$	0.069	0.021	[0.039, 0.122]	0.002	35.31
$(\Sigma_a)_2$	0.075	0.040	[0.034, 0.187]	0.795	12.96
$(\Sigma_h)_1$	0.785	0.200	[0.445, 1.238]	0.528	60.12
$(\Sigma_h)_2$	0.480	0.119	[0.276, 0.747]	0.155	37.21

Note: The parameters are the posterior estimation of the first two diagonal elements of Σ_β, Σ_a and Σ_h, and the results of the remaining elements also achieve the statistical requirements. The 5% critical value of Geweke is 1.96.

Figure 2 further checks the reliability of applying TVP-SV-VAR model, and the first line describes the results of sample autocorrelation. The red part gradually reduces to zero, indicating that sample autocorrelation does not disturb the experimental results. The second line shows the trajectory of the samples. It suggests the data fluctuates around the mean values, implying that the variables have no obvious trends. The third line displays the density of the posterior sample, indicating that the sample data is convergent. Therefore, we can conclude that the TVP-SV-VAR model composed of CPU, GS, and GB is reliable.



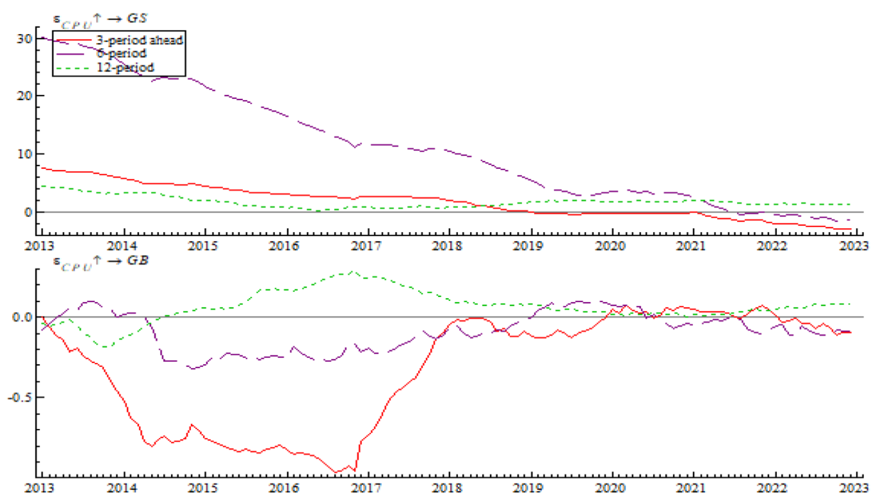
Note: The six columns from left to right are $(\Sigma_\beta)_1$, $(\Sigma_\beta)_2$, $(\Sigma_a)_1$, $(\Sigma_a)_2$, $(\Sigma_h)_1$ and $(\Sigma_h)_2$, respectively.

Figure 2. Sample auto-correlation, path and posterior density of MCMC estimations

Figure 3 demonstrates the impulse responses at different ahead periods (3-, 6-, and 9-periods ahead) in the TVP-SV-VAR model. The results at 3- and 6-periods ahead suggest that the GS may hedge the CPU risks effectively at the beginning, while the hedging ability of the GS gradually decreased over time. This finding is consistent with Kanamura (2020). Furthermore, the impact of CPU on GS has turned from positive to negative after 2021, which is consistent with the finding of Kocaarslan and Soytas (2021). This suggests that the correlation between CPU and GS in the short term and medium term is time-varying, and the hedging ability of GS decreases over time. The positive impact from CPU to GS at the beginning may be explained by the public attention. Specifically, although the green assets have not been widely accepted in the early stage, the increasing discussion of CPU may attract public attention in the green assets. Due to the herd effect, the increasing attention may push the price of the GS. However, the negative impact from CPU to GS in recent years implies that the hedging ability of GS is not stable, which may be explained by the following two reasons: On the one hand, the rapidly rising CPU has exacerbated panic in markets, which strikes investors' confidence in GS (Su et al., 2024b; Huang et al., 2025; Dou et al., 2025). On the other hand, the downturn in China's stock market has also decreased the hedging ability of GS. Due to the finance attributes of GS, the overall decline in the stock market has undermined investors' confidence in investing in GS.

Meanwhile, the negative impact from CPU to GB at 3- and 6-periods ahead suggest that the GB cannot hedge the CPU risks effectively in the short-term and medium-term. The negative impact of CPU on GB may be interpreted by two reasons. First, the substitution effect among green finance markets implies the hedging ability of GB is influenced by other green assets (Tiwari et al., 2022; X. Q. Wang et al., 2025b). For example, the initially positive impact from CPU to GS implies that the prosperity of GS may attract more funds from the GB market, which results in the decline of GB price. Second, China's early GB market is relatively small and subject to various risks, such as regulation risk (Su et al., 2024a). Thus, the increasing uncertainty risk of climate policy may crack the market's confidence in the GB market. Nevertheless, the GB's hedging ability begins to strengthen in recent years. Specifically, the negative impact at 3- and 6-periods ahead begins to decrease since 2017. Furthermore, the medium and short-term impact from CPU to GB turn positive in 2019 and 2020, respectively. This may be explained by the standardisation work on the issuance of GB. Specifically, China's government has vigorously promoted the standardization of GB issuance in recent years. For example, in June 2022, China issued the Guidelines for Green Finance in the Banking and Insurance Industries, which clearly defines the development of GB (K.-H. Wang et al., 2025a), which enhances investor's confidence in the GB market. Thus, the vulnerability of GB in the face of CPU has decreased with the improvement of GB market system.

Besides, the impact from CPU to the GS and GB at 12-periods are both positive, which implies that the green assets are effective to hedge CPU risks in the long-term. One of reasons is that China's green economy has made tremendous progress due to the climate policy support in the long run. Meanwhile, with the popularity of green investment concepts, more investors and institutions start to hold GS and GB as an opportunity to demonstrate good social image. Thus, the GS and GB may be the trustworthy assets to hedge CPU risks in the long-term.



Note: Since the TVP-SV-VAR model constructed in this paper involves four variables, there should be 16 impulse responses plots. We select six impulse response plots that are closely related to our analysis.

Figure 3. Impulse response results for different ahead periods

Then, this paper explores the impulse responses among CPU, GS, and GB under different event contexts, and the results are displayed in Figure 4. The reason for choosing the three time-points is that some important events occur during the periods, leading to significant variable fluctuations, which may provide valuable implications for understanding the interrelationships among the variables.

The first event point (May 2018) delegates the period when China strengthens the disclosure of green finance information (Razzaq et al., 2023). During the period between 2018: M1-2018: M5, the government proposes various measures to standardise the green finance industry, including information disclosure and the supervision of the green fund (Tang et al., 2023). The measures increase the market's concern as the strict scrutiny may influence the normal progress of green projects, and CPU rose to 274.567 in September 2018. However, GS and GB react differently to CPU changes. Specifically, CPU influences GS positively during the first six time periods, and the impact turns negative at the seventh time periods. Meanwhile, the reaction of GB is entirely opposite to that of GS, which may be explained by the substitution effect (Tiwari et al., 2022). Since GS receives more attention than GB in China, investors may prefer to invest in GS. Therefore, the GS displays a better hedging ability for the CPU risks in May 2018.

The second event point (February 2020) implies the COVID-19. Affected by the epidemic, the production order has been disrupted, and the CPU oscillates around 100. The results demonstrate that CPU positively impacts GS in the first six time periods except for the fourth period. Meanwhile, the reaction of GB is different. The rising CPU influences GB negatively at the first two periods, while the impact turns into positive in the following seven periods. This suggests that compared to the GB, the GS may hedge the CPU risks effectively at the beginning of the COVID-19 period. Although the outbreak of the epidemic has caused social panic greatly, it has also further increased investors' attention to the green investment (Feng et al., 2023; Wen et al., 2025). Since the GS receives more attention than the GB, the increasing attention not only pushes the GS price, but also attracts funds from the GB market, which influences the GB price negatively. However, the positive impact from CPU to the GB after the third period implies that the correlation between the variables is time-varying. One explanation is the synchronicity effect (Pham, 2021). Specifically, the boom in the GS market increases market's confidence in the GB, which strengthens the hedging ability of the GB.

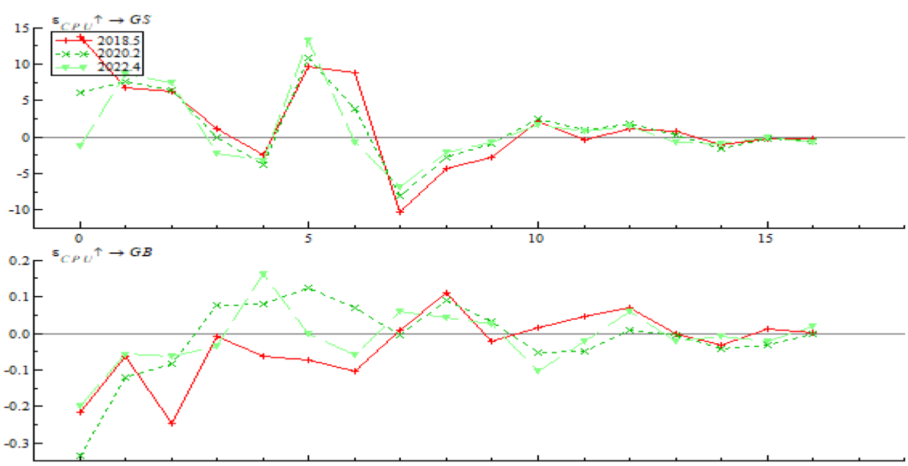


Figure 4. Impulse response results at different time points

The third time point (April 2022) represents the Russia-Ukraine conflict. In February 2022, the intensification of the conflict between Russia and Ukraine struck both the traditional energy and renewable energy markets (Su et al., 2025), which increases CPU from 167.238 to 437.506. Furthermore, the impulse responses suggest that the reactions of GS and GB are different. Specifically, we can find positive impact and negative impact from CPU to the GS and GB, respectively. This suggests that when facing the rising CPU during the Russia-Ukraine conflict period, the GS displays a better hedging uncertainty risks ability than the GB. This finding is consistent with the results in the first and second time points. Therefore, it is concluded that when unexpected shocks happen, holding GS rather than the GB may be a better choice to hedge the CPU risks at the beginning.

5. Conclusions and policy implications

This investigation tries to explore whether GS and GB can resist the rising CPU risks by estimating the correlations among the variables in China. In summary, the coefficient estimation and MCMC validity tests demonstrate that the regression estimates are accurate. Thus, we may effectively explore the inter-relationship among the variables. Based on the TVP-SV-VAR model, the results suggest that there are time-dependent impacts from CPU to the green assets. This implies that the hedging ability of GS and GB varies over time. Specifically, according to the results of 3-period and 6-period ahead, the rising CPU exerts positive and negative impact on the GS and GB, respectively, which implies that the GS may display better hedging CPU risks in the short and medium term. In addition, the different reactions of the GS and GB to the rising CPU evidence the substitution effect between green assets. Meanwhile, we also find positive impact from CPU to the GS and GB at the 12-period ahead, which suggests that the green assets may hedge the CPU risks effectively in the long term. One explanation is that although China's CPU has risen significantly, the green economy has also achieved long-term development due to the climate policies support, which strengthens the hedging uncertainty abilities of the green assets. Furthermore, the impulse responses at various time points indicate that compared to the GB, GS can better resist the CPU risks when unexpected shocks happen.

Based on the above analyses, this paper offers practical suggestions for both the investors and the government. First, it is necessary to conduct various asset al.ocation strategies for different investors. Specifically, considering the positive impact from CPU to GS in the 3- and 6-period ahead, for the investors who prefer the short and medium-term trading, holding GS rather than the GB may offer the maximum hedging benefits. Besides, the positive impact suggests that holding the green assets in the long term is a wise choice. Second, it is critical to implement various measures to reduce the uncertainty of climate policy. We find although the rising CPU may drive up the GS price by attracting market attention at the beginning of the sample period, the impact turns into negative in recent years. One of explanations is that the complex economic environment and high CPU level have stroke investors' confidence in green assets. Thus, to promote the GS market, it is necessary for the government to reduce information asymmetry. For example, when the CPU reaches a high level, the government should organize the climate policy publicity timely to explain the important issues that the market concerns. Third, the government needs to promote the standardisation of GB further. Specifically, we find the vulnerability of GB is reduced in recent years, which may be explained by the market standardization. Thus, further improving the regulatory system and reduce the green project risks is important. The government should formulate specific climate policy to encourage the green technology innovation, which reduces the green project risks. Besides, the government should strengthen the supervision of GB, including the raising and use of the GB funds.

Finally, due to the limitation of the article length, this paper only focuses on the relationship among CPU, GB and GS. However, there are also many kinds of other green assets, including green credit and carbon trading prices. Thus, future research may extend the investigation to the relationship between CPU and other green assets.

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Disclosure statement

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.

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APPENDIX

To ensure the accuracy of the results, we adjust the frequency of simulations from 10000 to 20000. The results are exhibited in Figures A1–A2, respectively, which indicates that there are no obvious changes between the robustness tests results and the experimental results. This implies that the results and the conclusions are reliable.

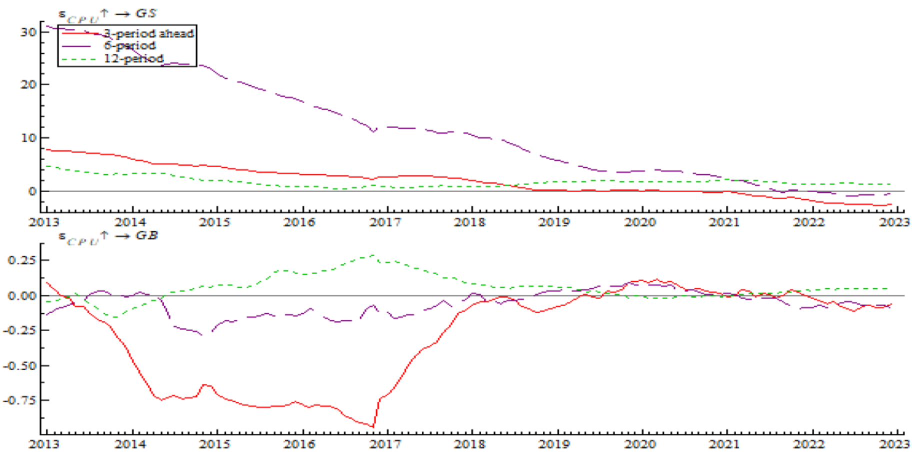

Figure A1. Impulse response robustness results for different ahead periods

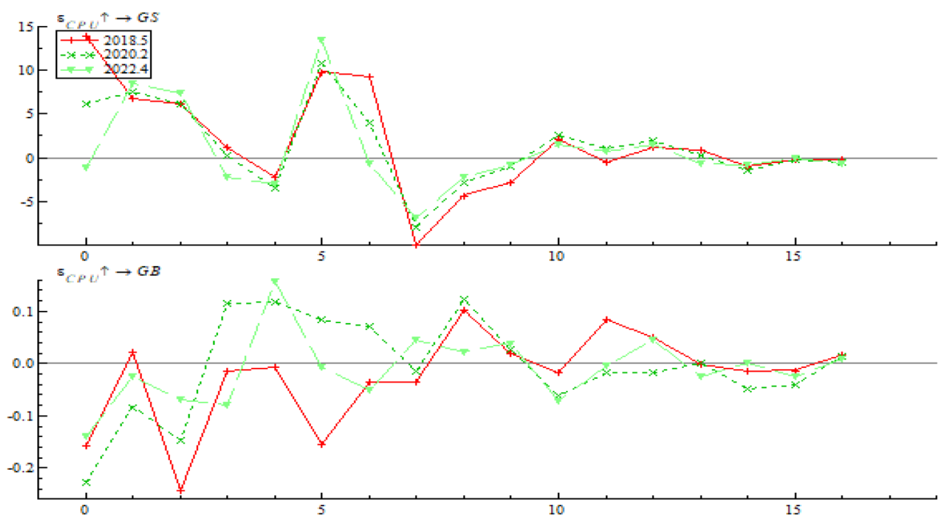

Figure A2. Impulse response robustness results at different time points

We further investigate the correlations among CPU, green assets' volatility and green assets' liquidity risk. According to Bali et al. (2014) measurement of asset liquidity risk, we use daily asset returns and trading volume to calculate monthly green asset liquidity risk, including green stock liquidity risk (GSL) and green bond liquidity risk (GBL). The rising liquidity risk implies that the asset liquidity is decreasing. Besides, we choose the volatility of the past 12 months to represent the volatility of the green assets, including Green Stock Volatility (GSV) and Green Bond Volatility (GBV). All the data is derived from the Wind database. To avoid the article being too verbose, we just present the correlations among the variables, which is exhibited in the Figure A3.

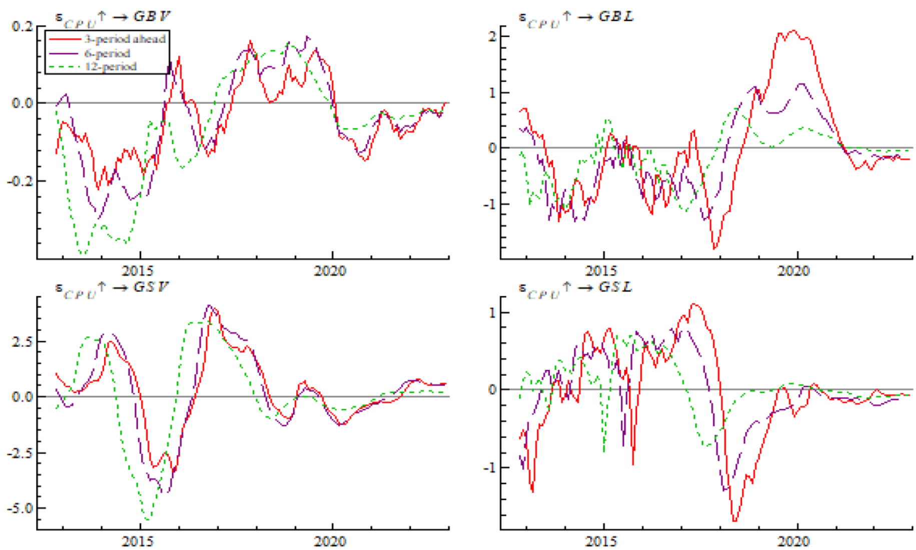

Figure A3. Dynamic correlations among CPU, GBV, GBL, GSV, and GSL

Based on the empirical results in the Figure A3, we can find three interesting features. First, although there is no significant difference between short and long-term impacts, the impact from CPU to green assets' volatility and liquidity risk is dynamic. This implies just holding GS or GB cannot effectively help the investors to hedge the volatility or liquidity risk. Second, in the term of volatility and liquidity risk, we find that the reactions of GS and GB are different. This suggest that there are substitution effects between GS and GB. Thus, holding GS and GB together may maximize the diversification benefit to hedge the liquidity risk and volatility risk. Finally, we find that the impact from CPU to GSL turns negative in the recent years, while the reaction of GBL is opposite. This implies that investors prefer to trade GS rather than GB when CPU rises, which mitigates the liquidity risk of GS. Meanwhile, considering that the impact from CPU to GSV is positive in most periods, it is concluded that the volatility of GS is more sensitive when facing the rising CPU.