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## International spillovers of U.S. monetary uncertainty and equity market volatility to China's stock markets

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## ABSTRACT

Due to the global economy that is currently being increasingly integrated and liberalized, the cross-country transmission of U.S. monetary policy surprises has become a critical issue attracting scholarly attention. This research thus extends the existing literature by assessing the causal linkages among U.S. monetary policy uncertainty (USMPU), equity market volatility, and China's stock price index over the period from January 1994 to August 2021. We apply Granger causality in quantile analysis to explore the relationships in each quantile of the distribution in a comprehensible manner. The results indicate that equity market volatility and China's stock price dynamics play little role in affecting USMPU. We also find that only greater changes in both positive monetary policy uncertainty and stock prices lead to changes in equity market volatility. Furthermore, fluctuations in monetary policy uncertainty and equity market volatility in the United States Granger-cause China's stock prices. Knowing such causality results could prevent market participants from adopting a one-size-fits-all strategy.

## 1. Introduction

The global financial integration and the crucial driving role of U.S. monetary policy are of great interest to many researchers and can provide insight into transmission channels through which monetary policy changes affect international financial markets (Bekaert et al., 2013; Juhro et al., 2021; Miranda-Agrippino & Rey, 2020; Hussain & Lee, 2022). However, the causality association between U.S. monetary policy and international stock market dynamics is still not completely understood, and the existing evidence remains elusive. From a global perspective, detecting the direction of causality among these variables has great value; it can offer insights into portfolio diversification and demonstrate how fluctuations in U.S. monetary policy impact China's stock prices.

When exploring how monetary policy causes stock price fluctuations, the financial theory postulates that asset prices reflect expectations regarding the discounted values of firms' future cash flows, which are frequently affected by macroeconomic fluctuations (Lee et al., 2019; Lee et al., 2022; Narayan, 2019; Narayan et al., 2022). Any monetary shock affects investors' expectations, which cause fluctuations in stock prices (Adediran & Akpa, 2022; Fama & Schwert, 1977; Gangopadhyay, 2008). Specifically, contractionary (expansionary) monetary policy shocks raise (reduce) discount rates and reduce (increase) future operating activity and associated cash flows, thereby causing a decline (rise) in stock prices (Cepni & Gupta, 2021; Wang et al., 2022a). These mechanisms have received much attention and even become a central issue in contemporary research (Handayani & Kacaribu, 2021; Prabheesh, Juhro, & Harun, 2021; Tiwari, Abakah, Adewuvi, & Lee, 2022).

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The rational expectation viewpoint conversely posits that only unanticipated policy changes impact the stock market because the expected effects of policy actions are reflected in stock prices (Mishkin, 2001; Ye et al., 2022). Pearce and Rokey (1983) indicated that stock prices decrease with increased unforeseen monetary uncertainties. Bomfim (2003) also found that unanticipated innovations in monetary action by the U.S. Federal Reserve exert a positive influence on stock market volatility. Bloom (2014) stressed that stock market volatility caused by monetary surprises exacerbates investors' anxiety and postpones their investment, resulting in decreased stock prices.

Although the abovementioned works provide valuable remarks on the relation between monetary shocks and stock price dynamics, only few studies that provide quantitative analysis on international spillover effects of changes in U.S. monetary policy uncertainty (USMPU), with some exceptions. Given the trend of global economic integration and the dominant role of the U.S. financial market (Lee et al., 2020; Wang et al., 2022b; Wen et al., 2023), any monetary fluctuation in the United States is expected to spread to the rest of the world and thus influence equity market performance (Chadwick, 2019; Georgiadis, 2016; Zou et al., 2022). For example, after the global financial crisis in 2008, aggressive quantitative easing (QE) policies by the U.S. Federal Reserve created a massive quantity of capital flows that spread across the globe and therefore affected global financial markets (Bhattarai et al., 2021; Hussain et al., 2022; Lakdawala, 2021; Xu & La, 2017). Therefore, learning more about the international spillover effects of USMPU is essential and can help managers and policymakers formulate more efficient strategies for stabilizing financial markets.

The present research examines the international spillover effects among USMPU, equity market volatility (EMV), and China's stock price index (CNSI) over the period from January 1994 to August 2021. The intuition behind such a consideration can be summarized as follows. From an uncertainty premium perspective, two channels explain the transmission mechanism of USMPU to China's stock market (Albagli et al., 2019; Chiang, 2021; Zhang et al., 2022). The uncertainty contagion effect indicates that fluctuations in U.S. monetary policy cause changes in China's monetary policy and thus affect their stock market. The market co-movement effect suggests that U.S. monetary shocks affect its domestic stock markets and then follow co-movement in the international market. From an alternative capital flow aspect, a flight to safety channel posits that USMPU encourages investors to remove their money from countries that are perceived to be riskier than the United States (Lakdawala et al., 2021; Li et al., 2021). Following this vein, we utilize the recently published MPU index of Baker et al. (2019) and a novel method of Granger-causality in quantiles (GCQ) test introduced by Troster (2018) to detect the causal linkages among series across all quantiles of the distribution.

The contributions of our study are fourfold. First, we build upon current research on the rapidly increasing diffusion of global macroeconomic shocks. Given the increasing importance of the U.S. economy on the global economy, our findings on the international spillover effect thus provide implications for managing risks and making investment decisions. Second, earlier studies measuring monetary uncertainty mostly rely on a model-based approach, which not only suffers from misspecification of the forecasting model but also ignores the information context of news (Lakdawala et al., 2021; Lakdawala, 2021). Differently, taking the advantage of news-based policy uncertainty (Lee & Wang, 2022; Lee et al., 2021; Nong, 2021) and using the MPU index, which reflects the uncertainty of public perception caused by the Federal Reserve's actions, our work aims to provide more robust estimates. Third, unlike most previous studies, we focus on uncovering the causal links among variables of interest. These efforts allow us to enrich the related research on the lead-lag nexus by showing how rapidly one market impacts another. Finally, many financial variables are believed to have nonlinear dynamics (Abakah et al., 2022; Bal & Mohanty, 2021; Lee et al., 2022c; Liu et al., 2023; Wei et al., 2022; Zhao et al., 2022; Zhu & Lee, 2022). To gain more insight into this nature, we employ quantile-based methods. As a result, we can assess the asymmetric causality relationships among USMPU, EMV, and CNSI under various market states.

The remainder of the work is organized into six sections: Section 2 presents the empirical frameworks, Section 3 outlines the data, Section 4 discusses the empirical results, and Section 5 rounds off with conclusions and implications.

## 2. Methodology

Causality in the framework of Granger (1969) is indicated when past  $X_t$  has explanatory power in regression  $Y_t$  on past  $X_t$  and  $Y_t$ . On the contrary, if past  $X_t$  does not contribute to predicting other series in such a regression system, then  $Y_t$  is considered to be weakly exogenous in the regression model. To further account for Granger-causality in the entire quantiles, the GCQ test of Troster (2018) is applied here.

Suppose that we have an explanatory vector  $I_t \equiv (I_t^Y, I_t^X)' \in \mathbb{R}^d$  that is made up of the past information set of  $T \subset [0, 1]$  and  $I_t^X$ , where  $d = s + q$  and  $I_t^Y := (X_{t-1}, \dots, X_{t-s})' \in \mathbb{R}^s$  and  $I_t^X := (X_{t-1}, \dots, X_{t-q})' \in \mathbb{R}^q$  represent the past information set of  $Y_t$  and  $X_t$ , respectively. The mathematical model for the null hypothesis of Granger non-causality from  $X_t$  to  $Y_t$  is thus indicated as

$$H_0^{X \rightarrow Y} = F_Y(y|I_t^Y, I_t^X) = F_Y(y|I_t^Y), \text{ for all } y \in \mathbb{R}, \tag{1}$$

where  $F_Y(y|I_t^Y, I_t^X)$  denotes the conditional quantile function of  $Y_t$  given  $(I_t^Y, I_t^X)$ .

Owing to the estimation of conditional distributions being practically complicated, one simple and preferred way in previous research is to detect Granger non-causality in the mean equations. As such,  $X_t \not\Rightarrow Y_t$  at the mean levels can be specified as follows:

$$E(Y_t|I_t^Y, I_t^X) = E(Y_t|I_t^Y), \tag{2}$$

where  $E(Y_t|I_t^Y, I_t^X)$  and  $E(Y_t|I_t^Y)$  are the means of  $F_Y(y|I_t^Y, I_t^X)$  and  $F_Y(y|I_t^Y)$ , respectively. However, Granger non-causality in the mean perhaps obtains misleading inferences if there is possible dependence existing in different quantiles.

To detect non-causality across various quantiles, we assume that  $Q_\tau^{Y,X}(\cdot|I_t^Y, I_t^X)$  is the  $\tau$ -quantile of  $F_Y(\cdot|I_t^Y, I_t^X)$  and rewrite the null

hypothesis in Eq. (1) as

$$H_0^{Q^{X \leftrightarrow Y}} = Q_\tau^{Y,X}(Y_t | I_t^Y, I_t^X) = Q_\tau^Y(Y_t | I_t^Y), \text{ for all } \tau \in T, \tag{3}$$

where T refers to a closed subset specifying that  $T \subset [0, 1]$ . The  $\tau$  – quantile of  $Y_t$  therefore fulfills the restrictions listed as follows:

$$\begin{aligned} Pr\{Y_t \leq Q_\tau^Y(Y_t | I_t^Y) | I_t^Y\} &:= \tau, \text{ for all } \tau \in T \\ Pr\{Y_t \leq Q_\tau^{Y,X}(Y_t | I_t^Y, I_t^X) | I_t^Y, I_t^X\} &:= \tau, \text{ for all } \tau \in T \end{aligned} \tag{4}$$

For a given independent variable  $I_t$ ,  $Pr\{Y_t \leq Q_\tau(Y_t | I_t) | I_t\} = E\{1[Y_t \leq Q_\tau(Y_t | I_t)] | I_t\}$ ,  $1[Y_t \leq y]$  denotes an indicator function fulfilling  $Y_t \leq y$ . Hence, the null hypothesis in Eq. (3) is equivalent to

$$E\{1[Y_t \leq Q_\tau^{Y,X}(Y_t | I_t^Y, I_t^X)] | I_t^Y, I_t^X\} = E\{1[Y_t \leq Q_\tau^Y(Y_t | I_t^Y)] | I_t^Y\}, \text{ for all } \tau \in T. \tag{5}$$

Here,  $E\{1[Y_t \leq Q_\tau^{Y,X}(Y_t | I_t^Y, I_t^X)] | I_t^Y, I_t^X\}$  is equal to the  $\tau$ -quantile of  $F_{Y_t}(\cdot | I_t^Y, I_t^X)$ . As Troster (2018) suggests, a parametric model can be applied to estimate the  $\tau$ -quantile of  $F_{Y_t}(\cdot | I_t)$ . Let  $Q_\tau^Y(\cdot | I_t^Y)$  be set by  $m(\cdot, \theta(\tau))$ , which belongs as:

$$M = \{m(\cdot, \theta(\tau)) | \theta(\cdot) : \tau \mapsto \theta(\tau) \in \Theta \subset \mathfrak{R}^p, \text{ for } \tau \in T \subset [0, 1]\} \tag{6}$$

On the basis of Eq. (5), the true conditional quantile of  $Q_\tau^Y(\cdot | I_t^Y)$  is precisely explained by the above framework  $m(I_t^Y, \theta_0(\tau))$  given  $I_t^Y$ . We then express the testing hypotheses based on Eq. (5) by

$$H_0^{X \leftrightarrow Y} : E\{1[Y_t \leq m(I_t^Y, \theta_0(\tau))] | I_t^Y, I_t^X\} = \tau, \text{ for all } \tau \in T \tag{7}$$

$$H_1^{X \leftrightarrow Y} : E\{1[Y_t \leq m(I_t^Y, \theta_0(\tau))] | I_t^Y, I_t^X\} \neq \tau, \text{ for all } \tau \in T \tag{8}$$

where  $m(I_t^Y, \theta_0(\tau))$  clarifies the true conditional quantile  $Q_\tau^Y(\cdot | I_t^Y)$ , for all  $\tau \in T$ . Accordingly, Eq. (7) is equivalent to Eq. (9) and can be characterized by Eq. (10) as:

$$H_0^{X \leftrightarrow Y} : E\{1[Y_t \leq m(I_t^Y, \theta_0(\tau))] | I_t^Y, I_t^X\} = \tau, \text{ for all } \tau \in T. \tag{9}$$

$$E\{[1(Y_t - m(I_t^Y, \theta_0(\tau)) \leq 0) - \tau] \exp(i\omega' I_t)\} = 0, \text{ for all } \tau \in T, \tag{10}$$

where  $\exp(i\omega' I_t) := \exp[i(\omega_1(Y_{t-1}, X_{t-1})' + \dots + \omega_r(Y_{t-r}, X_{t-r})')]$  refers to a weighted function for entire  $\omega \in \mathfrak{R}^r$  with  $r \leq d$ , and  $i = \sqrt{-1}$  represents a fictional root. Thus, the test statistic can be obtained by  $E\{[1(Y_t - m(I_t^Y, \theta_0(\tau)) \leq 0) - \tau] \exp(i\omega' I_t)\}$ :

$$v_T(\omega, \tau) := \frac{1}{\sqrt{T}} \sum_{t=1}^T [1(Y_t - m(I_t^Y, \theta_T(\tau)) \leq 0) - \tau] \exp(i\omega' I_t), \tag{11}$$

where  $\theta_T(\tau)$  is a  $\sqrt{T}$  – consistent estimator of  $\theta_0(\tau)$ , for all  $\tau \in T$ .

For each  $\tau$ , the corresponding statistic is presented by

$$S_T := \int_T \int_w |v_T(\omega, \tau)|^2 dF_\omega(\omega) dF_\tau(\tau), \tag{12}$$

where  $F_\omega(\cdot)$  is the conditional scattering function of a standard normal vector  $\omega \in \mathfrak{R}^d$ , and  $F_\tau(\cdot)$  follows an equal discrete grid distribution over  $T_n = \{T_j\}_{j=1}^n$ . Let  $\psi_{i,j} = \Psi_{\tau_j}(Y_i - m(I_i^Y, \theta_T(\tau_j)))$ .

We present the test statistic in Eq. (12) below:

$$S_T = \frac{1}{T_n} \sum_{j=1}^n |\psi_j' W \psi_j|, \tag{13}$$

where  $w_{t,s} = \exp[-0.5(I_t - I_s)^2]$ , and  $\psi_j'$  denotes the  $j^{th}$  column of  $\Psi$ . Hence, the null hypothesis of Granger non-causality is tested by comparing  $S_T$  with their critical values computed using the subsampling technique. We choose a subsample set under the criterion of  $b = \lfloor kT^{2/5} \rfloor$ , where  $k$  is a constant parameter.

### 3. Data description

This research explored the causal dynamics among USMPU, EMV, and CNSI. We collected monthly data for these variables over the period from January 1994 to August 2021. We selected these variables on the basis of the literature, subject to data availability. Both MPU and EMV were sourced from the newspaper-based index of Baker et al. (2016); Baker et al. (2019).<sup>1</sup> The former index captures

<sup>1</sup> Available at <https://www.policyuncertainty.com/>.

**Table 1**  
Summary statistics.

Statistics	MPU	EMV	CNSI
Mean	85.366	21.157	2180.298
Std. Dev.	55.535	8.226	1013.323
Minimum	16.575	9.570	333.920
Maximum	407.941	69.835	5954.770
Skewness	1.942	2.311	0.509
Kurtosis	8.643	10.918	3.177
Jarque–Bera	649.060 ***	1162.861 ***	14.782 ***
Observations	332	332	332

Note: The variables include USMPU, EMV, and CNSI over the period from January 1994 to August 2021.

public perception about monetary uncertainty based on search results relating to the uncertainty of the U.S. Federal Reserve's policy actions in newspapers, while the latter reflects public sentiment about stock market uncertainty and moves with the VIX and realized volatility of the S&P 500 index. The stock price indices taken for this study are the Shanghai Stock Exchange Component Index, which can be downloaded from the website of the Shanghai Stock Exchange. All variables were processed in logarithmic form to the interference of extreme values on the regression model (Lee et al., 2023; Peng et al., 2022).

Table 1 exhibits the relevant descriptive statistics and the statistics of Jarque and Bera's (1980) normality test. These tests strongly reject the null hypothesis of normality for all series, which implies a possible bias from using linear frameworks and validates the application of the quantile approach. Fig. 1 portrays the time series and box plots that illustrate the tentative findings throughout the sampling era. Compared with EMV and CNSI, MPU appears to be highly volatile during the sample period.

## 4. Empirical results

### 4.1. Preliminary investigations

Prior to conducting a further investigation, the stationarity properties of the data series must be assessed. To this end, we employed the quantile autoregressive (QAR) unit root tests introduced by Koenker and Xiao (2004) and Galvao (2009) to test whether the variable is characterized as a unit-root process over the quantiles of the distribution. Table 2 reports the estimating results of the persistence parameters for the associated t-statistics for an equally spaced grid of quantiles with a 0.05 step length for  $\tau \in [0.05, 0.95]$ . The statistical results consistently reveal that the CNSI series cannot reject the null hypothesis of unit root for each quantile. However, the unit root properties of the entire distribution of MPU and EMV are not constant. Evidence reveals that MPU contains a unit root at extreme low quantiles, while such property also holds in EMV at extreme high quantiles. These results allow us to conclude that the conditional distribution of the variables presents at least weak nonstationarity and suggests that one-size-fits-all linear analyses are inappropriate for modeling dynamic causality, which therefore justifies the application of the GCQ approach.

To further detect the possible presence of cointegration among the variables, we next utilized the quantile cointegration technique of Xiao (2009) to examine the long-run relationship on each pairwise combination under different quantiles. Table 3 presents corresponding results for the stability tests of the coefficients of the linear term  $\beta$  and the quadratic term  $\gamma$ , as well as the associated critical values generated by Monte Carlo of 1000 replications. Evidence only reveals a statistically significant existence of a nonlinear cointegration relationship between MPU and EMV, suggesting that they are co-movement with each other. Although the above analysis allows us to understand how each pairwise combination achieves its long-run equilibrium, knowledge is still limited on how past values of one variable predict another. In this regard, a further examination of causal linkages is needed in analyzing the correlations.

### 4.2. GCQ analysis

In this section, we employ the GCQ approach to explore the possible correlation among the variables in the system. To this end, we conduct the  $S_T$  statistical test in Eq. (13) with three different specifications of QAR models for each dependent variable with lags ranging from 1 to 3 periods. Panels A–C of Table 4 report the  $p$ -values of the testing statistics for the MPU, EMV, and CNSI series. We first evaluate Granger-causality at all quantiles and then look at the regression in each conditional quantile. As expected, the results reveal different patterns in testing significance, depending upon which quantiles of the distribution are considered.

As shown in Panel A of Table 4, the testing statistics reveal little evidence of Granger-causality from EMV or CNSI to MPU. When all quantiles of the distribution are solely considered, evidence suggests that changes in EMV or CNSI only cause shifts in USMPU on a long-term basis. When further examining causal relationships at different quantiles, we find that causality among the variables varies with the conditional distribution, indicating the validity of GCQ analysis. Granger-causality only exists at intermediate quantiles of the conditional distributions, suggesting that only a few moderate market phases' EMV or CNSI Granger-causes fluctuations in USMPU, and the causality is relatively weak. Overall, these results not only illustrate that EMV exerts a small role in altering monetary policy uncertainty but also document that CNSI provides less power to affect monetary policy uncertainty.

The results reported in Panel B of Table 4 show strong causality from MPU or CNSI to EMV at a significance level of 5% when considering all quantiles of the distribution. The results are robust to divergent QAR specifications. However, the effect of USMPU changes or CNSI changes is heterogeneous under divergent market conditions, indicating that these shocks do not have a simple and

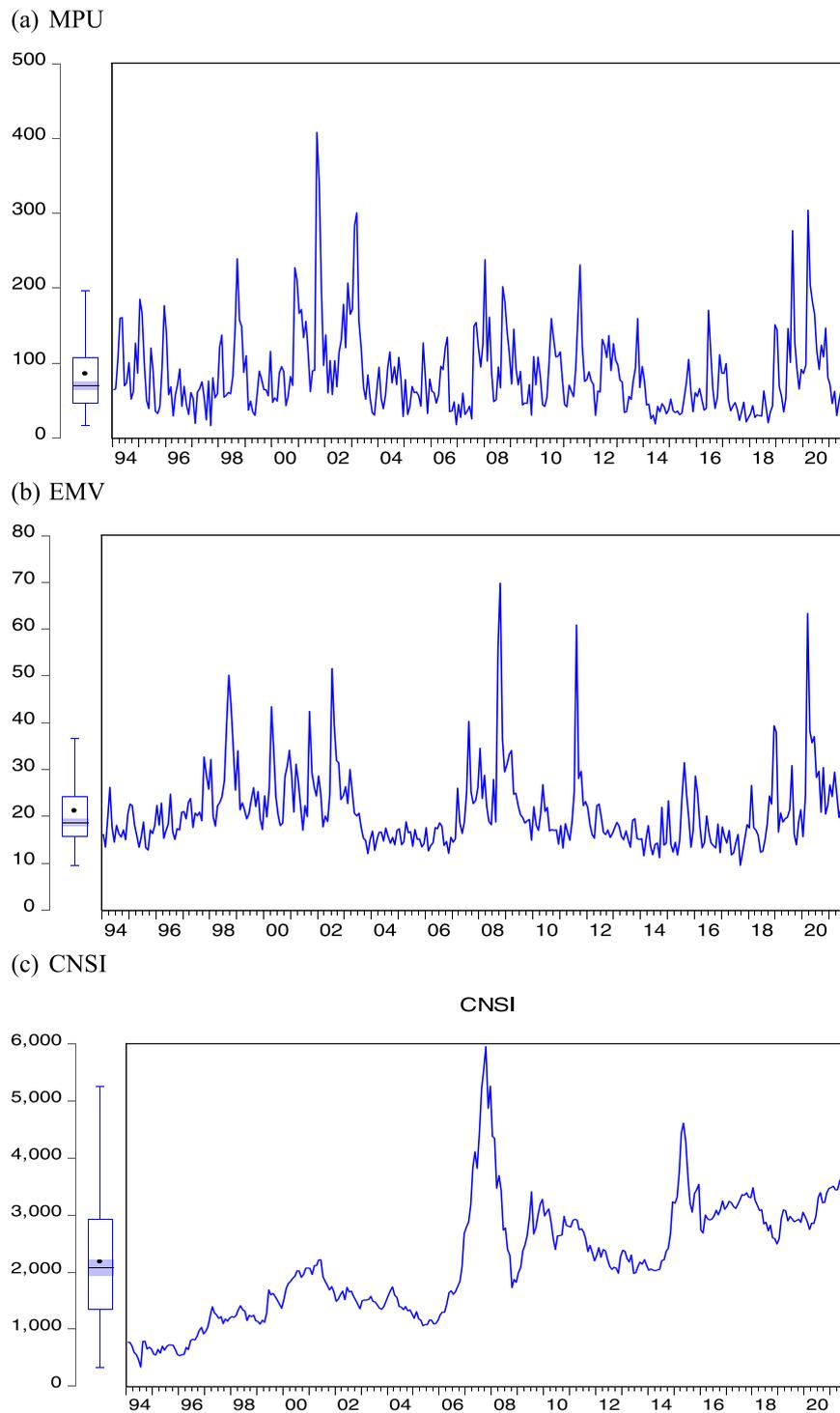


Fig. 1. The underlying series for 1994–2021.

consistent impact on EMV. Changes in USMPU Granger-cause market volatility in all distributions except at the extreme lower quantiles of the distribution, i.e.,  $\tau = \{0.20, 0.30\}$ . This result confirms the findings of previous studies that unanticipated monetary shocks trigger changes in stock market volatility (Bloom, 2014; Bomfim, 2003). Our results further indicate that such interaction varies with different quantiles. In a bearish market, any policy aimed at stabilizing the monetary market would not impact stock market volatility. We also find that fluctuations in CNSI Granger-cause market volatility at upper-tail quantiles, i.e.,  $\tau \in [0.55, 0.90]$ . These outcomes suggest that the explanatory power of USMPU or stock market fluctuations in China is divergent across different market

**Table 2**  
Quantile unit-root test.

$\tau$	MPU			EMV			CNSI		
	$\hat{\alpha}$	t-stats	CV	$\hat{\alpha}$	t-stats	CV	$\hat{\alpha}$	t-stats	CV
0.05	0.790	-1.623	-2.698	0.528	-8.814 <sup>b</sup>	-2.737	0.914	-1.014	-2.808
0.10	0.790	-1.623	-2.698	0.572	-6.755 <sup>b</sup>	-2.826	0.931	-2.193	-2.884
0.15	0.597	-5.278 <sup>b</sup>	-2.972	0.618	-6.480 <sup>b</sup>	-2.687	0.941	-2.141	-2.903
0.20	0.632	-5.200 <sup>b</sup>	-3.029	0.590	-8.000 <sup>b</sup>	-2.852	0.961	-1.867	-3.107
0.25	0.655	-5.566 <sup>b</sup>	-3.044	0.611	-8.749 <sup>b</sup>	-2.901	0.957	-2.233	-3.167
0.30	0.625	-6.352 <sup>b</sup>	-3.095	0.607	-8.852 <sup>b</sup>	-2.913	0.958	-2.249	-3.193
0.35	0.623	-6.814 <sup>b</sup>	-3.177	0.601	-8.937 <sup>b</sup>	-2.885	0.959	-2.364	-3.180
0.40	0.629	-6.864 <sup>b</sup>	-3.128	0.629	-8.955 <sup>b</sup>	-2.929	0.977	-1.398	-3.206
0.45	0.667	-5.820 <sup>b</sup>	-3.046	0.641	-8.044 <sup>b</sup>	-2.934	0.995	-0.333	-3.187
0.50	0.643	-6.628 <sup>b</sup>	-3.040	0.627	-7.983 <sup>b</sup>	-3.045	0.995	-0.289	-3.249
0.55	0.622	-6.807 <sup>b</sup>	-3.147	0.652	-7.152 <sup>b</sup>	-3.055	1.007	0.431	-3.346
0.60	0.588	-7.672 <sup>b</sup>	-3.170	0.649	-7.261 <sup>b</sup>	-3.175	1.003	0.159	-3.382
0.65	0.562	-7.707 <sup>b</sup>	-3.093	0.632	-6.984 <sup>b</sup>	-3.271	1.000	-0.024	-3.328
0.70	0.572	-7.584 <sup>b</sup>	-3.046	0.680	-5.640 <sup>b</sup>	-3.208	1.003	0.184	-3.268
0.75	0.597	-7.320 <sup>b</sup>	-2.972	0.729	-3.960 <sup>b</sup>	-3.159	0.987	-0.695	-3.226
0.80	0.572	-7.019 <sup>b</sup>	-3.037	0.735	-3.543 <sup>b</sup>	-3.109	1.000	-0.008	-3.036
0.85	0.565	-5.076 <sup>b</sup>	-2.905	0.743	-3.152 <sup>b</sup>	-2.924	0.991	-0.304	-3.220
0.90	0.550	-4.376 <sup>b</sup>	-2.819	0.905	-0.925	-2.740	0.979	-0.547	-3.201
0.95	0.460	-3.448 <sup>b</sup>	-2.811	0.948	-0.253	-2.659	0.971	-0.265	-3.016

Notes: The variables include USMPU, EMV, and CNSI. “b” indicates a significance level of 5%.

**Table 3**  
Quantile cointegration test.

Model	Coeff.	Statistic	CV1	CV5	CV10
EMU vs. EMV	$\beta$	2118.43 <sup>a</sup>	288.67	193.59	161.69
	$\gamma$	338.16 <sup>a</sup>	37.93	23.97	17.71
EMU vs. CNSI	$\beta$	865.79	5720.69	3945.35	3149.49
	$\gamma$	58.10	378.98	188.45	138.29
EMV vs. CNSI	$\beta$	677.63	3920.31	2183.22	1689.21
	$\gamma$	44.21	101.30	68.61	48.07

Notes: Critical values came from 1000 Monte Carlo simulations. The superscript “a” represents a significance level of 1%.

conditions. Only greater changes in both positive monetary policy uncertainty and the stock market lead to changes in EMV.

The findings in Panel C of [Table 4](#) also indicate that changes in USMPU or fluctuations in EMV Granger-cause CNSI at a significance level of 1% when focusing on all quantiles of the distribution. Such a result not only indicates that USMPU has a strong ability to predict the dynamics of stock prices in China but also suggests that EMV has explanatory power for said stock prices. However, the effects of monetary policy uncertainty or EMV on China’s stock price dynamics exhibit differences at various quantiles. There is strong evidence of Granger-causality in the extreme quantiles of the distribution, i.e.,  $\tau \in [0.10, 0.40]$  or  $\tau \in [0.60, 0.90]$ . Therefore, greater positive or negative fluctuations in USMPU or EMV cause changes in China’s stock prices. This result is consistent with [Chadwick \(2019\)](#), who found that emerging countries are greatly affected by USMPU.

To guarantee the credibility and dependability of our empirical results, we further conduct two alternative tests by replacing either the measures of the performance of China’s stock markets or the proxy of U.S. monetary uncertainty. The Shenzhen Stock Exchange Component Index (CNSZI) and Husted et al.’s (2020) MPU index (HMPU) for GCQ analyses. Panel A (B) of [Table 5](#) reports the Granger-causality from and to CNSZI (HMPU), which still supports our prior findings illustrated in [Table 4](#). Monetary policy uncertainty or EMV exerts a quantile-varying effect on China’s stock price dynamics. Therefore, we are confident that the results are robust.

To obtain additional insights into the magnitude of the impact among the variables, [Table 6](#) presents the estimated coefficients of the quantile regression model for all conditional quantiles. For the Granger-causality from MPU to EMV, the coefficients have a positive sign at upper-tail quantiles, suggesting that large shocks in USMPU positively affect EMV. This result is consistent with the findings of [Chiang \(2020\)](#), [Lakdawala \(2021\)](#), and [Shaikh \(2020\)](#) in that market volatility increases with the degree of policy uncertainty. Put differently, the estimated coefficients have a negative sign for the analysis from CNSI to EMV at upper-tail quantiles, suggesting that large shocks in CNSI negatively affect EMV. In addition, regarding the Granger-causality analysis from MPU to CNSI, we find that large negative variations in USMPU have a positive impact on China’s stock prices, whereas large positive fluctuations have a negative influence. These results are in line with the international uncertainty premium hypothesis, which postulates that monetary policy uncertainty negatively affects the international stock market through contagion spillover and market co-movement effects ([Chiang, 2020, 2021](#); [Lee et al., 2023b](#); [Yahya and Lee, 2023](#)). As for the analysis from EMV to CNSI, the estimated coefficients have a negative sign for almost all conditional quantiles, indicating that fluctuations in EMV cause adverse impacts on China’s stock prices. These results confirm the findings of [Chiang \(2021\)](#) on the global stock market.

**Table 4**  
Granger-causality in quantiles.

Panel A	EMV to MPU			CNSI to MPU		
	Lags= 1	Lags= 2	Lags= 3	Lags= 1	Lags= 2	Lags= 3
ALL	0.154	0.154	<b>0.003<sup>a</sup></b>	0.408	0.458	<b>0.010<sup>b</sup></b>
0.10	0.197	0.415	0.177	0.197	0.498	0.194
0.20	0.385	0.221	0.358	0.378	0.231	0.441
0.30	0.428	0.331	0.264	0.525	0.465	0.211
0.40	0.324	0.271	0.495	0.478	0.391	0.816
0.45	0.274	0.291	0.622	0.562	0.525	0.836
0.50	<b>0.023<sup>b</sup></b>	0.204	<b>0.003<sup>a</sup></b>	<b>0.047<sup>b</sup></b>	0.385	<b>0.003<sup>a</sup></b>
0.55	<b>0.020<sup>b</sup></b>	<b>0.070<sup>c</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.033<sup>b</sup></b>	0.117	<b>0.020<sup>b</sup></b>
0.60	0.254	0.177	<b>0.020<sup>b</sup></b>	0.522	0.421	<b>0.033<sup>b</sup></b>
0.70	0.381	0.271	0.241	0.572	0.351	0.344
0.80	0.468	0.365	<b>0.033<sup>b</sup></b>	0.525	0.522	<b>0.097<sup>c</sup></b>
0.90	0.709	0.361	0.375	0.890	0.766	0.866
Panel B	MPU to EMV			CNSI to EMV		
	Lags= 1	Lags= 2	Lags= 3	Lags= 1	Lags= 2	Lags= 3
ALL	<b>0.047<sup>b</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.047<sup>b</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.007<sup>a</sup></b>
0.10	<b>0.003<sup>a</sup></b>	0.184	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	0.184	<b>0.003<sup>a</sup></b>
0.20	0.736	0.187	0.268	0.478	<b>0.097<sup>c</sup></b>	0.161
0.30	0.763	0.555	0.569	0.589	0.328	0.458
0.40	0.120	0.144	<b>0.013<sup>b</sup></b>	0.147	0.278	<b>0.067<sup>c</sup></b>
0.45	0.167	<b>0.077<sup>c</sup></b>	<b>0.043<sup>b</sup></b>	0.361	0.194	0.120
0.50	0.204	<b>0.054<sup>c</sup></b>	<b>0.050<sup>c</sup></b>	0.241	0.201	0.151
0.55	<b>0.043<sup>b</sup></b>	<b>0.050<sup>c</sup></b>	0.147	<b>0.074<sup>c</sup></b>	<b>0.084<sup>c</sup></b>	0.224
0.60	0.100	<b>0.027<sup>b</sup></b>	<b>0.033<sup>b</sup></b>	<b>0.090<sup>c</sup></b>	<b>0.037<sup>b</sup></b>	<b>0.060<sup>c</sup></b>
0.70	0.157	<b>0.010<sup>b</sup></b>	<b>0.017<sup>b</sup></b>	0.124	<b>0.003<sup>a</sup></b>	<b>0.010<sup>b</sup></b>
0.80	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.007<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.010<sup>b</sup></b>
0.90	0.107	0.217	0.110	<b>0.023<sup>b</sup></b>	<b>0.037<sup>b</sup></b>	<b>0.054<sup>c</sup></b>
Panel C	MPU to CNSI			EMV to CNSI		
	Lags= 1	Lags= 2	Lags= 3	Lags= 1	Lags= 2	Lags= 3
ALL	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>
0.10	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>
0.20	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>
0.30	<b>0.037<sup>b</sup></b>	<b>0.013<sup>b</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.037<sup>b</sup></b>	<b>0.013<sup>b</sup></b>	<b>0.003<sup>a</sup></b>
0.40	<b>0.094<sup>c</sup></b>	<b>0.050<sup>c</sup></b>	<b>0.033<sup>b</sup></b>	<b>0.057<sup>c</sup></b>	<b>0.037<sup>b</sup></b>	<b>0.013<sup>b</sup></b>
0.45	0.171	0.181	0.120	0.144	0.104	<b>0.067<sup>c</sup></b>
0.50	0.458	0.652	0.515	0.528	0.625	0.569
0.55	0.224	0.224	<b>0.084<sup>c</sup></b>	0.221	0.231	0.154
0.60	<b>0.013<sup>b</sup></b>	<b>0.007<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.033<sup>b</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>
0.70	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>
0.80	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>
0.90	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>

Notes: The variables include USMPU, EMV, and CNSI. The figures indicate the subsampling  $p$ -values. "a," "b," and "c" signify significance levels of 1%, 5%, and 10%, respectively.

## 5. Concluding remarks

The actions of U.S. monetary policy have been broadly explored in the past due to their economic and financial importance and relevance. While the related literature is critical for increasing our understanding of the spillover effect of monetary policy shocks and financial activities, whether and how U.S. monetary policy uncertainty might be transmitted to the global stock markets still awaits a more in-depth exploration. Using the recently published MPU index of Baker et al. (2019) and a novel approach of GCQ analysis introduced by Troster (2018), this research assesses the causal nexus among USMPU, EMV, and CNSI over the period from January 1994 to August 2021 in each quantile of the distribution.

Unlike linear-based causality tests that are ineffective at detecting potential nonlinearity in the dynamic dependence structure, GCQ analysis enables us to investigate various types of conditional heterogeneity and provides more detailed information about any causal relationship that exists over the entire distribution. Our research demonstrates that the causal correlations among USMPU, EMV, and CNSI vary across divergent market conditions, confirming the suitability of the GCQ approach for modeling these critical variables. Understanding these divergent relationships can help market participants adjust their decisions under various market conditions. Thus, our findings have significant practical consequences for investors, market participants, and policymakers.

Our empirical results first indicate that equity market volatility and China's stock price dynamics play a small role in affecting U.S. monetary policy uncertainty. In this regard, monetary authorities should pay more attention to economic fundamentals rather than stock market variations. Second, we find that only greater changes in positive monetary policy uncertainty and stock prices lead to

Table 5

Robust checks: alternative proxies.

Panel A	CNSZI to MPU			CNSZI to EMV			MPU to CNSZI			EMV to CNSZI		
	Lags= 1	Lags= 2	Lags= 3	Lags= 1	Lags= 2	Lags= 3	Lags= 1	Lags= 2	Lags= 3	Lags= 1	Lags= 2	Lags= 3
τ												
ALL	0.395	0.425	<b>0.003<sup>a</sup></b>	<b>0.043<sup>b</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.007<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>
0.10	0.197	0.502	0.181	<b>0.003<sup>a</sup></b>	0.184	<b>0.003<sup>a</sup></b>	<b>0.054<sup>c</sup></b>	<b>0.013<sup>b</sup></b>	<b>0.013<sup>b</sup></b>	<b>0.030<sup>b</sup></b>	<b>0.013<sup>b</sup></b>	<b>0.013<sup>b</sup></b>
0.20	0.355	0.221	0.452	0.468	<b>0.090<sup>c</sup></b>	0.151	<b>0.077<sup>c</sup></b>	<b>0.023<sup>b</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.060<sup>c</sup></b>	<b>0.020<sup>b</sup></b>	<b>0.003<sup>a</sup></b>
0.30	0.525	0.455	0.214	0.589	0.318	0.452	0.130	<b>0.043<sup>b</sup></b>	0.167	<b>0.064<sup>c</sup></b>	<b>0.027<sup>b</sup></b>	0.100
0.40	0.452	0.378	0.826	0.137	0.278	<b>0.067<sup>c</sup></b>	<b>0.084<sup>c</sup></b>	<b>0.043<sup>b</sup></b>	<b>0.030<sup>b</sup></b>	<b>0.040<sup>b</sup></b>	<b>0.030<sup>b</sup></b>	<b>0.020<sup>b</sup></b>
0.45	0.552	0.518	0.843	0.361	0.194	<b>0.097<sup>c</sup></b>	0.294	0.324	0.585	0.251	0.161	0.388
0.50	<b>0.040<sup>b</sup></b>	0.378	<b>0.003<sup>a</sup></b>	0.231	0.181	0.151	0.819	0.642	0.886	1.000	0.642	0.823
0.55	<b>0.033<sup>b</sup></b>	0.107	<b>0.020<sup>b</sup></b>	<b>0.067<sup>c</sup></b>	<b>0.084<sup>c</sup></b>	0.224	0.247	0.288	0.140	0.247	0.278	0.144
0.60	0.508	0.415	<b>0.033<sup>b</sup></b>	<b>0.090<sup>c</sup></b>	<b>0.037<sup>b</sup></b>	<b>0.060<sup>c</sup></b>	<b>0.033<sup>b</sup></b>	0.104	<b>0.054<sup>c</sup></b>	<b>0.030<sup>b</sup></b>	0.104	<b>0.030<sup>b</sup></b>
0.70	0.569	0.341	0.338	0.124	<b>0.003<sup>a</sup></b>	<b>0.010<sup>b</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>
0.80	0.518	0.518	<b>0.087<sup>c</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.010<sup>b</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>
0.90	0.863	0.749	0.856	<b>0.023<sup>b</sup></b>	<b>0.037<sup>b</sup></b>	0.054	0.117	0.174	0.181	0.264	0.314	0.361
Panel B	HMPU to EMV			HMPU to CNSI			EMV to HMPU			CNSI to HMPU		
τ	Lags= 1	Lags= 2	Lags= 3	Lags= 1	Lags= 2	Lags= 3	Lags= 1	Lags= 2	Lags= 3	Lags= 1	Lags= 2	Lags= 3
ALL	0.134	<b>0.003<sup>a</sup></b>	<b>0.020<sup>b</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.010<sup>b</sup></b>	<b>0.057</b>	<b>0.023<sup>b</sup></b>	<b>0.033<sup>b</sup></b>	0.137	0.157
0.10	<b>0.003<sup>a</sup></b>	0.181	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	0.783	0.870	0.890	0.789	0.870	0.893
0.20	0.839	0.151	0.207	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	0.946	0.294	<b>0.013<sup>b</sup></b>	0.970	0.298	<b>0.013<sup>b</sup></b>
0.30	0.766	0.532	0.592	<b>0.074<sup>c</sup></b>	<b>0.047<sup>b</sup></b>	<b>0.003<sup>a</sup></b>	0.261	0.732	0.328	0.278	0.759	0.365
0.40	0.258	0.261	<b>0.077<sup>c</sup></b>	<b>0.077<sup>c</sup></b>	<b>0.037<sup>b</sup></b>	<b>0.043<sup>b</sup></b>	0.344	0.211	0.174	0.455	0.244	0.214
0.45	0.452	0.201	0.181	0.171	0.147	<b>0.084</b>	0.274	0.465	0.431	0.495	0.522	0.452
0.50	0.365	0.247	0.181	0.341	0.475	0.408	0.328	0.261	0.154	0.555	0.525	0.344
0.55	<b>0.067<sup>c</sup></b>	0.144	0.334	0.197	0.334	0.100	0.338	0.274	0.344	0.756	0.462	0.669
0.60	0.187	<b>0.067<sup>c</sup></b>	0.104	<b>0.027<sup>b</sup></b>	<b>0.007<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.077<sup>c</sup></b>	0.140	0.120	0.107	0.274	0.191
0.70	0.197	<b>0.010<sup>b</sup></b>	<b>0.010<sup>b</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.074<sup>c</sup></b>	0.134	0.181	0.110	0.201	0.254
0.80	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.020<sup>b</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.033<sup>b</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.007<sup>a</sup></b>	<b>0.074<sup>c</sup></b>
0.90	<b>0.097<sup>c</sup></b>	0.140	0.107	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.003<sup>a</sup></b>	<b>0.064<sup>c</sup></b>	0.187	<b>0.003<sup>a</sup></b>	0.120	0.241

Notes: CNSZI denotes the Shenzhen Stock Exchange Component Index, while HMPU stands for the Husted et al.'s (2020) MPU index. The figures indicate the subsampling *p*-values. "a," "b," and "c" signify significance levels of 1%, 5%, and 10%, respectively.

**Table 6**  
Quantile regression estimated coefficients.

$\tau$	EMV toMPU	CNSI toMPU	MPU toEMV	CNSI toEMV	MPU toCNSI	EMV toCNSI
0.10	0.231	-0.400	0.059	-0.145	0.021	-0.070
0.20	0.190	-0.368	0.049	-0.158	0.006	-0.014
0.30	0.259	-0.581	0.042	0.035	0.002	-0.017
0.40	0.209	-0.324	0.033	0.049	-0.003	-0.022
0.45	0.254	-0.201	0.048	0.169	-0.003	-0.017
0.50	0.264	-0.334	0.045	0.009	-0.006	-0.017
0.55	0.332	-0.392	0.033	-0.033	-0.010	-0.024
0.60	0.399	-0.366	0.040	-0.085	-0.014	-0.025
0.70	0.385	-0.066	0.031	-0.138	-0.013	-0.013
0.80	0.624	-0.232	0.033	-0.266	-0.001	-0.008
0.90	0.604	-0.265	0.065	-0.207	0.006	0.000

Note: The variables include USMPU, EMV, and CNSI.

changes in equity market volatility. Under this situation, investors in the United States should keep a close eye on Federal Reserve actions and the price movement in China's stock markets to better understand future stock market volatilities. Finally, large changes (either positive or negative) in USMPU and equity market volatility Granger-cause China's stock prices. As a result, when making portfolio and hedging decisions, investors and fund managers can consider this asymmetric causality and nonlinear transmission mechanism. Investors in China should be aware of fluctuations in monetary policy and stock market volatilities in the United States, particularly during extreme market conditions.

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## Conflict of interest

The authors declare that they have no conflict of interest. This research does not contain any experiments with human participants or animals performed by any of the authors.

## Data availability statement

Data are available from the authors upon request.

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