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Regime-dependent causality between Chinese and U.S. equity markets: Evidence from Markov switching models☆

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ABSTRACT

This study analyses the dynamic interdependence between Chinese and U.S. equity markets using Markov regime-switching vector autoregressive (MS-VAR) models. We cover monthly data from May 2007 to August 2024 within a single-currency framework on the New York Stock Exchange. Two broad-based Exchange-Traded Funds (ETFs)—SPY for the U.S. and GXC for China—serve as proxies for equity returns. The study identifies two regimes: Regime 1, characterised by periods of crisis, and Regime 2, representing stable market conditions. Causality tests based on the MS-VAR model reveal bidirectional causality between the markets in Regime 2, a relationship not detected by conventional Granger tests. In Regime 1, causality is unidirectional from the U.S. to China, indicating that Chinese investors are more exposed to U.S.-driven shocks during periods of market turbulence. The findings suggest the need for collaborative strategies to reduce market risks, address vulnerabilities, and manage spillovers arising from geopolitical tensions.

1. Introduction

The interconnectedness of global financial markets has become increasingly important in recent years for investors, policymakers, and research scholars. The dynamic interplay between the Chinese and U.S. equity markets, in particular, has drawn significant attention due to the economic prominence of both nations. As the two largest economies, they account for a substantial portion of global GDP and international trade, making their interactions essential for understanding international financial dynamics. As discussed in the next section, fluctuations in these markets can have far-reaching effects, influencing global investment flows, economic policies, and financial stability. Understanding these interactions is crucial for assessing systemic risk and managing portfolio risk proxied by the extent of asset covariations.

By examining the dynamic impulse responses between Chinese and U.S. equity returns, this study offers a comparative framework for assessing the timing and propagation of shocks across varying market conditions. Understanding how shocks in one market transmit to the other can enhance investors' risk management strategies and support more precise portfolio adjustments to mitigate systemic risk. Therefore, this study investigates how each market reacts to hypothetical shocks (i.e., innovations) from the other country, with a focus on the duration and magnitude of return responses over the next 24 months. For meaningful and consistent comparisons, we focus on a sample period with the longest available monthly return data (May 2007-August 2024) for two broad-

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based ETFs. Both GXC and SPY are denominated in U.S. dollars to ensure comparability and to eliminate the confounding influence of exchange rate fluctuations. Using ETFs in the same currency allows for a clearer attribution of return dynamics to equity market movements rather than currency effects. The fluctuations of GXC might also have more to do with investors' preference for holding U.S.-dollar-denominated assets rather than solely reflecting the risk profile of the Chinese stock market.

These ETFs represent the substantial portion of each country: the Chinese market is represented by GXC, covering 1169 stocks, while the U.S. market is proxied by SPY, which tracks the S&P 500. This methodology ensures the robustness and cross-market comparability of the analysis within a consistent sample period and the same trading venue—the New York Stock Exchange—while preserving uniformity through denomination in U.S. dollars. Against this background, the main objectives of this study are to address the following questions:

1. Is there any unidirectional or bidirectional causality between Chinese and U.S. equity returns?
2. How do the dynamic impulse responses of Chinese (U.S.) equity returns to U.S. (Chinese) equity returns evolve over the next 24 months following a shock in each market?
3. What do the variance decompositions of shocks tell us about the source and persistence of shocks in the other market? To what extent can shocks in each market tend to influence the other market?

Individual stocks or sectors are subject to unique and often unpredictable shifts driven by factors such as earnings report shortfalls, regulatory adjustments, seasonal patterns, and the outcomes of mergers and acquisitions. These idiosyncratic fluctuations can profoundly influence the performance of individual stocks or sectors, independent of broader market movements. However, employing broad-based ETFs within a single currency over a common sample period can mitigate these challenges. Such ETFs offer diversified exposure that reduces the impact of idiosyncratic sector (stock) risks, while also circumventing the complexities introduced by foreign exchange and equity risks, arising from trading in multiple currencies. In addition, this study allows the estimated parameters to switch (shift) at any point during the sample period.

While the Markov switching framework is an established methodology, the contribution of this study lies in its empirical design, scope, and implementation. In this study, both markets are represented by broad-based ETFs—SPY for the U.S. and GXC for China—each traded in U.S. dollars and listed on the same exchange, ensuring direct comparability. This framework eliminates the confounding effects of currency fluctuations and enables meaningful performance comparisons that accurately reflect the underlying trajectories, cyclical tendencies, and relative return dynamics of the two markets. By focusing on the longest available common sample period from May 2007 to August 2024, the analysis captures multiple critical phases, including the global financial crisis, U.S.–China trade tensions, and the COVID-19 pandemic, thereby providing an all-encompassing perspective on cross-market interactions across distinct regimes. The empirical results reveal robust evidence of regime-dependent causality and asymmetric shock transmission, with bidirectional causality prevailing during stable periods and unidirectional causality from the U.S. to China during crises. These findings deepen our understanding of the evolving structure of financial linkages between the world's two largest equity markets and demonstrate how systemic shocks propagate differently under calm and turbulent conditions.

2. Literature review

2.1. *Contagion mechanisms and crisis-driven transmission*

Financial contagion, defined as the spread of disruptions from one market to others, has become a central focus in the study of increasingly interconnected global markets. Forbes and Rigobon (2002) distinguished contagion from simple interdependence, highlighting that shocks can propagate more intensely during periods of market stress. Early empirical studies documented this phenomenon across multiple crises. King and Wadhwani (1990) observed heightened stock return co-movements during the 1987 market crash. Calvo and Reinhart (1996) documented correlation shifts during the Mexican Crisis, and Baig and Goldfajn (1999) identified contagion effects during the East Asian financial crisis. Hon et al. (2007) further demonstrated that the 2000 burst of the U.S. Nasdaq technology bubble increased covariation with international markets.

Subsequent global crises illustrate the magnitude of cross-market contagion. The 2007 U.S. subprime mortgage crisis rapidly propagated across equity, bond, and derivative markets worldwide (Acemoglu et al., 2015). The COVID-19 pandemic similarly underscored global financial interconnectedness, producing pronounced contagion effects across a wide spectrum of asset classes (Yarovaya et al., 2022). Rapid financial integration has intensified these channels, increasing both the frequency and magnitude of cross-market transmissions (Albagli et al., 2019; Devereux and Yu, 2020).

Cross-asset and cross-country linkages have also attracted attention. Finta and Aboura (2020) highlighted the potential for multi-asset contagion, particularly among stocks, bonds, and currencies. Bollerslev et al. (2018) demonstrated the pervasive nature of risk across asset classes, emphasizing the need to consider both domestic and international interconnectedness when assessing financial stability.

2.2. *Nonlinear and regime-switching models*

Traditional approaches to co-movement analysis often relied on static correlation measures, which cannot adequately capture nonlinear, state-dependent dynamics. To address these limitations, recent research has increasingly employed advanced econometric methodologies, including regime-switching models, dynamic copulas, dynamic conditional correlation techniques, and nonparametric frameworks (Oh and Kim, 2024; Chen and Sun, 2024).

He and Lin (2023) demonstrated that incorporating stochastic liquidity conditions and economic-cycle-driven volatility substantially improves the modeling of asset-price dynamics, allowing for flexible adaptation to regime shifts and structural market frictions. Trabelsi and Bahloul (2022) applied VAR models across twelve MENA countries, identifying calm and crisis regimes in equity and currency markets. Dua and Tuteja (2021) employed a Markov-switching VAR framework to examine Eurozone, India, Japan, and U.S. markets, identifying bull and bear states with regime-dependent correlations. Jayech, Mazigh, and Abdennadher (2022) used Archimedean copulas to detect contagion effects on the Chinese stock market during the 2007–2010 global crises, confirming cross-country transmission. Dong et al. (2022) investigated co-skewness effects in China and the U.S., finding higher return demands for negatively co-skewed stocks, particularly in China. Li and Zhang (2013) showed that U.S. price changes produce short-run spillovers in Chinese markets. These studies highlight the value of nonlinear and regime-sensitive models for capturing complex market dynamics. By accommodating state-dependent behavior, these approaches provide a more accurate understanding of how shocks propagate across markets.

2.3. U.S.–China financial linkages and spillovers

The U.S. and Chinese financial markets have emerged as critical nodes in global market interconnectedness. Chen and Sun (2024) employed nonlinear and quantile Granger causality networks to analyze stock, bond, and FX markets, revealing stronger interconnections in the extreme tails of return distributions—a phenomenon described as the "smiling curve" of causality. Oh and Kim (2024) applied high-frequency jump-diffusion models to measure volatility contagion between U.S. and Chinese stocks, identifying shifts from integrated volatility to negative jump variation during the U.S.–China trade war.

Empirical studies further highlight asymmetries in risk spillovers. Wang and Xiao (2023) found that both U.S. and Chinese markets transmit risk to East Asian markets, though U.S. spillovers dominate, particularly in high-volatility periods. Qian et al. (2024) demonstrated that while China's global influence has grown, U.S. economic dominance continues to shape global market movements. Li and Zhang (2013) highlighted the predictive power of U.S. stock returns for short-term Chinese market performance. He et al. (2025) emphasized that liquidity conditions and macroeconomic cycles further influence these bilateral linkages. These studies support the view that U.S. markets remain the central driver of global financial dynamics, with China playing an emerging but secondary role. Understanding these bilateral linkages is crucial for evaluating cross-market risk transmission and informing policy decisions.

2.4. Behavioral dynamics and sentiment-driven contagion

Behavioral factors, particularly herding behavior, play an important role in financial contagion. Herding occurs when investors follow the actions of others, disregarding their private information, often amplifying systemic risk (Fu and Wu, 2021). Xing et al. (2024) found no herding in the U.S. stock market during the Global Financial Crisis or COVID-19 crisis. In contrast, significant herding occurred in the Chinese mainland stock market during COVID-19, primarily driven by investor sentiment. As can be seen, behavioral mechanisms provide a complementary perspective on contagion, explaining market-specific variations in sensitivity to shocks. Integrating these insights with structural and econometric approaches enhances understanding of cross-market dynamics under stress.

Based on the above studies, one can argue that there is a growing body of literature exploring the dynamic linkages between the U.S. and Chinese equity markets through approaches such as copula models, non-linear causality tests, high-frequency return spillover frameworks, and time-varying parameter models. However, few studies have explicitly investigated the evolving responses of each market to decomposed shocks across different regimes within a Markov-switching VAR framework using country-specific ETFs. By incorporating regime-dependent dynamics, this paper provides a more refined empirical assessment of the bilateral transmission mechanisms under changing market conditions. Our results therefore complement rather than supplant existing findings and contribute to a better understanding of the temporal asymmetry and structural variation in market interdependence between these two major economies.

3. Empirical methodology

To model the relationships between Chinese and U.S. equity returns using a VAR Markov Regime-Switching model, we follow the general model outlined by Hamilton (1994), Krolzig (1997), and Frühwirth-Schnatter (2006), which involves regime-switching behavior in a VAR process. We allow both intercepts and lagged endogenous variables to switch between two latent regimes (regime 1 = crisis and regime 2 = normal), while modeling the dynamics of the system through a k-dimensional VAR process. Let the two variables be $r_{1\,t}$ (Chinese equity returns) and $r_{2\,t}$ (U.S. equity returns) at time t. We assume that the returns evolve over time according to a VAR process with k lags, where the parameters (coefficients) change depending on the latent regime s., with the following 2-dimensional VAR model:

$$\begin{pmatrix} r_{1t} \\ r_{2t} \end{pmatrix} = \begin{pmatrix} C_{1,s} \\ C_{2,s} \end{pmatrix} + \sum_{i=1}^{k} \begin{pmatrix} a_{11i,s} & a_{12i,s} \\ a_{21i,s} & a_{22i,s} \end{pmatrix} \begin{pmatrix} r_{1t-i} \\ r_{2t-i} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \tag{1}$$

In a compact form we can also rewrite Eq. (1) as follows:

$$\mathbf{r}_t = \mathbf{C}_s + \sum_{i=1}^{k} \mathbf{A}_{i,s}\mathbf{r}_{t-i} + \boldsymbol{\varepsilon}_t \tag{2}$$

Where:

$\mathbf{r}_t = \begin{pmatrix} r_{1t} \\ r_{2t} \end{pmatrix}$ is is the vector of monthly returns for the Chinese and U.S. equity markets at time t,

$\mathbf{C}_s$ is the intercept vector, which may vary across regimes s (either crisis or normal),

$\mathbf{A}_{i,s} = \begin{pmatrix} a_{11i,s} & a_{12i,s} \\ a_{21i,s} & a_{22i,s} \end{pmatrix}$ is the coefficient matrix for the i^{th} lag of the VAR model, which also changes with the regime s,

$\mathbf{r}_{t-i}$ is the vector of lagged endogenous variables at time $t - i$,

$\boldsymbol{\varepsilon}_t$ is the error term at time t, which is assumed to follow a multivariate normal distribution [$\boldsymbol{\varepsilon}_t \sim N(0, \sum_s)$].

In the Appendix, we briefly explain how regime-dependent coefficients and probabilities are estimated in our Markov regime-switching VAR model, and how transition probabilities determine expected regime durations. While we employ a conventional Markov regime-switching VAR framework, recent literature has introduced important methodological advancements. For example, Hwang (2025) proposes a frequency-dependent MS-VAR model that differentiates regimes based on their spectral (frequency) characteristics. This approach captures how shocks at different frequencies—such as short-term fluctuations versus persistent low-frequency movements—manifest distinctly across regimes. Incorporating frequency-based dynamics enriches the understanding of dynamic contagion and is particularly relevant for analyzing market responses under calm versus crisis conditions. Consideration of these frequency-specific extensions is planned for future research to further enhance the regime-specific analysis. Furthermore, another recent study by Mensi et al. (2025) employs a combination of time-varying parameter vector autoregression and Markov-switching-dynamic-regression models to analyze sovereign credit default swap interconnectedness during major volatility episodes such as the COVID-19 pandemic and the Russia-Ukraine conflict. This methodological framework effectively captures the evolution of volatility spillovers across regimes, revealing intensified risk transmission during high-volatility periods.

Finally, it is important to acknowledge that extending a Markov regime-switching VAR model to accommodate three or more regimes substantially increases the complexity of parameter estimation and may hinder model convergence. For instance, estimating a bivariate specification with three regimes using EViews version 14 (2024) required nearly an hour, and several parameters proved inestimable due to convergence issues. Although regime-switching VAR models offer a powerful framework for addressing endogeneity, expanding the number of regimes, endogenous variables, or lag structures significantly intensifies computational demands. These challenges become even more pronounced when higher-frequency data, such as daily observations, are employed in place of monthly data. Moreover, incorporating additional markets—such as Europe or Japan—or substituting alternative ETFs can further complicate estimation, potentially leading to convergence failure or necessitating the truncation of the sample period due to limited data availability. In light of these constraints, we believe our model strikes an appropriate balance between addressing endogeneity concerns and maintaining parsimony, thereby ensuring a feasible and robust empirical specification.

4. Data

Monthly price returns for the two ETFs—GXC and SPY—were extracted from *investing.com*. We have used monthly nominal price returns, calculated as the logarithmic difference in prices, i.e., $\log(p_t) - \log(p_{t-1})$. This approach is standard in financial econometrics and reflects actual investor returns without adjusting for inflation. While we acknowledge the differing inflation experiences between China and the U.S., our focus was on nominal return dynamics as observed in the market. That is: $r_{1\,t} = \Delta Log(GXC_t)$ and $r_{2\,t} = \Delta Log(SPY_t)$. Table 1 summarizes the key characteristics of these two ETFs, including the number of holdings, dividend yields, inception dates, and expense ratios. SPY, a broad-based U.S. ETF, holds 503 stocks, with the top ten being Apple (6.8 %), Microsoft (6.8 %), and NVIDIA (6.2 %). GXC, a Chinese ETF, includes 1069 stocks, with top holdings in Tencent (12.9 %), Alibaba (6.6 %), and PDD (3.0 %).

One should note that both SPY and GXC are broad-based ETFs designed to track large segments of the U.S. and Chinese equity markets, respectively. SPY, which tracks the S&P 500 Index, includes approximately 500 of the largest U.S. companies and covers all 11 GICS sectors, providing substantial representation across the U.S. economy. GXC, which tracks the S&P China BMI Index, comprises over 900 Chinese equities spanning a wide array of sectors, including financials, industrials, consumer discretionary, and information technology. Although GXC does not explicitly cover the Sci-Tech Innovation Board (STAR Market), it captures a broad cross-section of China's publicly traded companies, including many in the technology and innovation-related sectors.

We acknowledge the observation that SPY does not include mid- and small-cap stocks. However, when we compare SPY with the U.

Table 1
Key characteristics of the ETFs.

ETF Name	Ticker	Number of Holdings	Dividend yield (%)	Inception date	Expense ratio (%)	Stock market representation
SPDR	GXC	1169	3.45 %	March 19, 2007	0.59	China
State Street	SPY	503	1.26 %	22 Jan 1993	0.09	U.S.

Notes: This table presents key characteristics (i.e., the number of holdings, dividend yields, inception dates, and expense ratios) of the two ETFs utilised in the present study.
Source: ww.etf.com as of 6 Sep 2024.

S. total market ETF (VTI), which includes over 4000 stocks across all capitalizations, we observed that the two indices track each other so closely that they become nearly indistinguishable in both level and return series over time (the graph is available from the authors upon request). This high degree of correlation reflects the dominance of large-cap stocks in driving overall U.S. market movements, thereby justifying the use of SPY as a practical and effective proxy for the broader U.S. equity market. Importantly, both SPY and GXC have longer historical data availability than their broader or alternative counterparts (e.g., VTI or STAR Market–focused ETFs). Adopting other alternative ETFs would have significantly shortened the sample period and reduced the robustness of our time-series analysis. For these reasons, SPY and GXC provide a balanced trade-off between representativeness and sample length, making them suitable for the purposes of this study.

We did not use the oldest ETF (i.e. FXI), despite its inception date was prior to that of GXC, because FXI is not an all-encompassing ETF, as it only includes the largest 50 Chinese companies. In contrast, GXC tracks a comprehensive, market-cap-weighted index of 1169 investable Chinese shares, spanning all market-cap sizes and including major share classes like A, B, H, Red Chips, P Chips, and foreign listings. The index is float-adjusted, only including shares available to the public, with weights determined by float-adjusted market capitalization.

Based on the inception dates listed in Table 1, the common sample period with available monthly data for both ETFs spans from May 2007 to August 2024, encompassing 208 monthly observations. Although numerous other Chinese ETFs are available in the U.S., they were excluded from this study due to their recent inception dates or limited sector and market capitalization exposures. Including them would have considerably shortened the sample period or introduced bias against certain sectors. For example, CQQQ (tech only) was launched in December 2009, MCHI (broad-based) in March 2011, KWEB (internet stocks) in July 2013, ASHR in November 2013, and CXSE in September 2017.

5. Empirical results

Table 2 shows that the average monthly equity return in the U.S. (0.64 %) was notably higher than that of China (0.10 %) over the sample period from May 2007 to August 2024 ($n = 208$). The return per unit of standard deviation for SPY is nearly 14 times greater than that of GXC, highlighting SPY's superior risk-adjusted performance. Both return series exhibit negative skewness, along with kurtosis values significantly exceeding 3, suggesting a higher frequency of extreme returns and substantial deviations from normality, as confirmed by the Jarque-Bera test. All series are found to be stationary based on both the Augmented Dickey-Fuller (ADF) test and the innovation outlier test (Perron and Vogelsang, 1992), confirming the suitability of return series for further analysis. These results indicate that any shocks to return series are likely to be temporary, with price returns eventually reverting to their long-term means The break dates identified endogenously—October 2007 for the Chinese series and February 2009 for SPY returns—coincide with key phases of the global financial crisis. These results suggest that the crisis generated a structural break in the Chinese market earlier than in the U.S. market, possibly reflecting earlier transmission of global stress or heightened sensitivity to external shocks.

Fig. 1 illustrates the divergence in performance between the Chinese equity ETF (GXC) and the U.S. equity ETF (SPY) from May 2007 to August 2024. The data reveals a significant and widening gap between the two ETFs, highlighting a marked disparity in market performance over the observed period. The divergence is apparent from the beginning of the sample period and has progressively worsened over time. A cointegration test was carried out, but due to the divergence between the two ETF prices, no evidence of cointegration could be established. Therefore, the analysis proceeded using VAR without error correction terms focusing on short-term dynamics. The cointegration test results are available from the author upon request.

Table 2
Descriptive statistics.

Description	Monthly returns	
	SPY	GXC
Mean (%)	0.64	0.10
Standard deviation (SD, %)	4.62	7.66
Mean/SD (%)	0.14	0.01
Skewness	-0.74	-0.27
Kurtosis	4.21	4.16
Jarque-Bera	31.90***	14.20***
ADF test	-14.03***	-13.45***
Innovation outlier test	-15.43	-14.37***
Break date	Feb 2009	Oct 2007

Notes: This table shows that the average monthly equity return in the U.S. (0.64 %) was significantly higher than that of China (0.10 %) during the sample period (May 2007 –August 2024, $n = 208$). The mean return per unit of standard deviation for SPY is nearly 14 times greater than that of GXC. Both return series are negatively skewed with a kurtosis well above 3, indicating frequent extreme returns and significant deviations from normality, as confirmed by the Jarque-Bera test. All series are stationary based on the ADF and innovation outlier tests. The endogenously determined break dates—February 2009 for SPY returns and October 2007 for the Chinese series—correspond to the global financial crisis. *** indicates that the corresponding null hypothesis is rejected at the 1 % level.

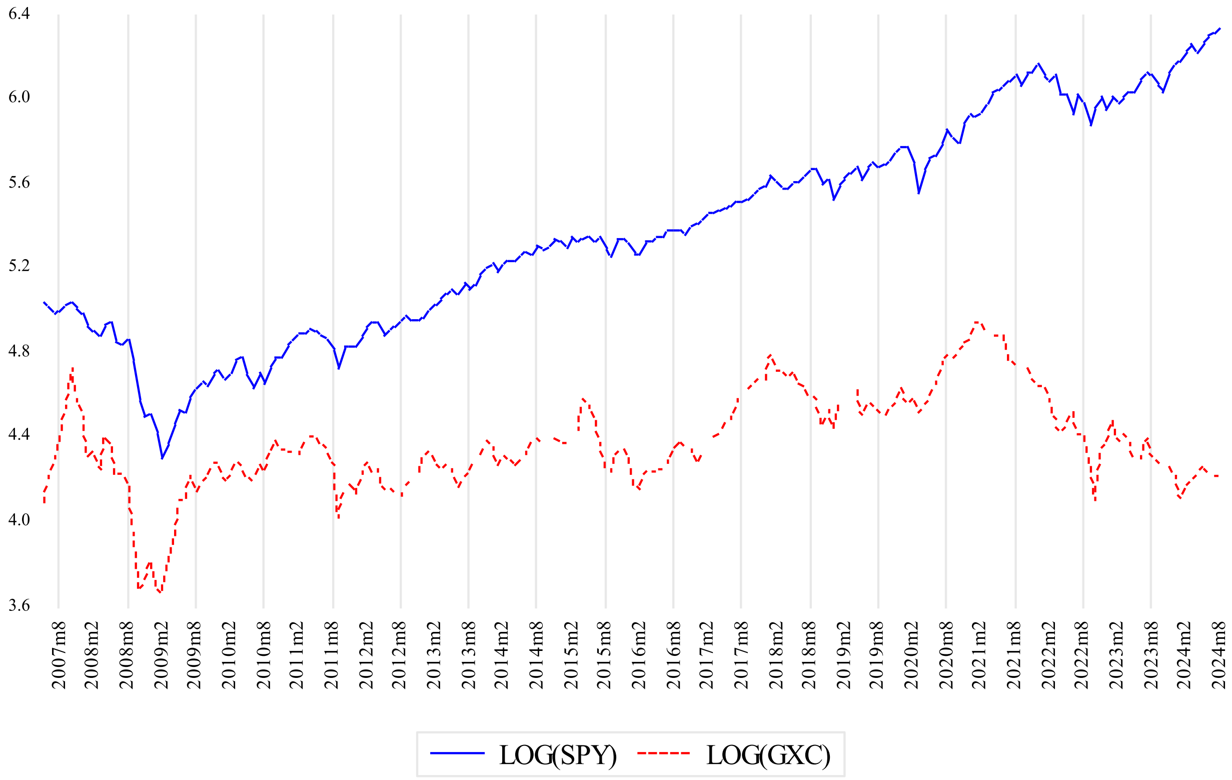

Fig. 1. Divergence between Chinese ETF (GXC) and U.S. ETF (SPY), *Notes:* This graph shows how the performance of the Chinese equity ETF (GXC) has diverged from the U.S. equity ETF (SPY) from May 2007 to August 2024. The increasing gap highlights that the U.S. market has consistently outperformed the Chinese market since the 2008 global financial crisis.

Before presenting the results of the RS-VAR models, it is important to first discuss the findings of the conventional Granger causality test, shown in Table 3, which assesses whether past returns in the Chinese market can predict future returns in the U.S. market, and vice versa. The optimal lag length in the VAR model is determined using the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) to balance model fit and complexity. Compared to the SIC, the AIC is generally more lenient and tends to suggest a greater number of lags. In this case, the optimal lag length is four (κ=4), indicating that the test considers returns from the past four months.

Table 3
Estimated non-switching VAR model.

Lagged dependent variables	Dependent variable			
	$r_{1\,t}$	z statistics	$r_{2\,t}$	z statistics
Intercept	0.000	0.01	0.006*	1.92
$r_{1t\text{-}1}$	0.044	0.50	0.056	1.09
$r_{1t\text{-}2}$	0.063	0.73	0.090*	1.77
$r_{1t\text{-}3}$	-0.060	-0.70	-0.064	-1.26
$r_{1t\text{-}4}$	0.033	0.38	0.066	1.30
$r_{2t\text{-}1}$	0.012	0.08	-0.022	-0.26
$r_{2t\text{-}2}$	-0.164	-1.15	-0.159*	-1.88
$r_{2t\text{-}3}$	0.057	0.40	0.166**	1.97
$r_{2t\text{-}4}$	-0.041	-0.28	0.036	0.42
AIC	-5.913			
SIC	-5.620			

Notes: This table presents the results of the conventional Granger (1969) causality test, using Eq. (A3) in Appendix, where the optimal lag length is (κ=4). Because none of the estimated coefficients d_{12}^{j} $(j = 1,2,3,4)$ are statisticaly significant at the 5 % level, one can conclude that the returns in the U.S. market do not Granger cause the returns in China. Except for (j = 2) which is only significant at the 10 % level, all the estimated coefficients d_{21}^{j} $(j = 1,3,4)$ are also statisticaly insignificant at 5 %. Therefore, one can conclude that at the 5 % level the returns in China also do not Granger cause the returns in the U.S. Also note that $r_{1\,t}=\Delta Log(GXC_t)$ and $r_{2\,t} = \Delta Log(SPY_t)$.

Because none of the estimated coefficients associated with lagged values of other series are statisticaly significant at the 5 % level, one can conclude that the returns in the U.S. market do not Granger cause the returns in China. Except for the second lag which is only significant at the 10 % level, all the estimated coefficients are statisticaly insignificant at 5 % level. The statistically insignificant z statistics for individual coefficients, indicating no-causality, were also corroborated by the F-statistics, which tested joint restrictions on these coefficients and produced consistent findings. These results are available from the authors upon request. Therefore, one can also conclude that at the 5 % level the returns in China also do not Granger cause the returns in the U.S. These findings indicate that the two markets operate independently in terms of return predictability. However, these inferences will change when we consider a regime-switching VAR model in Table 4.

Eq. (2) is estimated under the assumption of two regimes (M=2) and two monthly endogenous return series over the sample period spanning May 2007 to August 2024. The estimated Markov Switching VAR model is summarized in Table 4. To determine the optimal number of regimes, we relied on the SIC, which is known for its consistency in model selection and its ability to penalise over-parameterisation. The SIC value for the two-regime model was −5.7943, compared to −5.68691 for the three-regime model, supporting the selection of the more parsimonious two-regime specification. This approach reduces the risk of overfitting, which is particularly relevant in Markov regime-switching models. The optimal lag length was determined using the AIC, which indicated that two lags ($\kappa = 2$) were appropriate. These choices contribute to the robustness and reliability of the empirical results.

Table 5 presents the expected durations (Eq. A1 in appendix) and transition probabilities (Eq. A2) for both regimes. It appears that regime 2 (the regular or calm regime) is the dominant regime, with an average duration of approximately one year, whereas regime 1 (the occasional turbulent regime) is considerably shorter-lived. The transition probabilities in Table 5 suggest a 92 % likelihood of remaining in regime 2 once established, with only an 8 % probability of switching from regime 2 to regime 1. Conversely, when in the turbulent regime, there is a 41 % chance of remaining in regime 1, but a 59 % probability of returning to normalcy (regime 2).

The z statistics presented in Table 4 demonstrate that r_{2t-2} is statistically significant at the 5 % level in the equation for $r_{1\,t}$ in both regimes. This indicates that the U.S. market consistently exerts a strong Granger causal influence on the Chinese market in all circumstances. Moreover, Table 4 indicate that only in regime 2 r_{1t-1} and r_{1t-2} are statistically significant at the 1 % level in the equation for $r_{2\,t}$. The z- statistics for individual coefficients, which were significant and suggested causality, were supported by the F-statistics testing joint restrictions on these coefficients, yielding consistent results. This suggests that the Chinese market can Granger cause the U.S. market, but only during periods of normalcy (regime 2). Therefore, while the conventional VAR results in Table 3 may erroneously lead one to reject any evidence of causality between the Chinese and U.S. equity markets, the findings from the Markov Switching VAR model in Table 4 provide robust evidence of bidirectional causality during normal periods, and unidirectional causality from the U.S. to China during crisis times.

The findings suggest that U.S. market has a consistent and significant impact on the Chinese market, regardless of market conditions. For market participants, the bidirectional causality during normal periods implies that both U.S. and Chinese markets influence each other, highlighting the importance of understanding global market linkages. The unidirectional causality from the U.S. to China during crises highlights the Chinese market's vulnerability to shocks originating in the U.S. at all times, across both Regime 1 and Regime 2. These results also emphasize the importance of U.S.-China collaboration on socio-economic issues, as both countries—particularly China—stand to gain significantly from the prosperity and stability of both markets.

Fig. 2 presents the one-step-ahead predicted transition probabilities derived from the estimated switching VAR model, exhibiting significant spikes in regime 1 around 2008, 2011, and 2022, coinciding with the Global Financial Crisis and the COVID-19 pandemic. These spikes reflect heightened uncertainty and instability in the market during these critical periods. In contrast, the probabilities for regime 2 (normalcy) remain substantially higher than those for regime 1 (crises), indicating a strong tendency for the market to favor stable conditions (i.e. 87.5 % versus 12.5 % in Fig. 2). This preference for normalcy suggests that market participants generally expect and react more favorably to periods of relative stability, reinforcing the notion that proactive risk management strategies are essential during times of heightened volatility.

Table 4
Estimated regime-switching VAR model.

Lagged dependent variables	Regime 1				Regime 2			
	Dependent variable				Dependent variable			
	$r_{1\,t}$	z	$r_{2\,t}$	z	$r_{1\,t}$	z	$r_{2\,t}$	z
Intercept or μ(i)	0.114	0.61	0.041	0.43	-0.051	-0.56	-0.027	-0.59
r_{1t-1}	-0.087	-0.27	0.219	1.41	-0.091	-0.66	-0.204***	-2.93
r_{1t-2}	-0.745***	-2.51	-0.170	-1.09	-0.107	-0.77	-0.321***	-4.62
r_{2t-1}	0.068	0.30	-0.071	-0.67	-0.007	-0.08	0.097**	2.14
r_{2t-2}	-0.081***	-4.15	-0.075***	-5.66	0.012**	2.19	0.025***	8.03
AIC	-6.215							
SIC	-5.794							

Notes: This table shows that r_{2t-2} is statistically significant at the 5 % level in the equation for $r_{1\,t}$ in both regimes, indicating Granger causality running from the U.S. market to the Chinese market. Also r_{1t-1} and r_{1t-2} are significant at the 1 % level for the equation for $r_{2\,t}$ in regime 2, suggesting the Chinese market Granger causes the U.S. market only during normal periods. These results provide strong evidence of bidirectional causality in normal times and unidirectional causality from the U.S. to China during crises. Also *, ** and *** indicate that the corresponding null hypothesis is rejected at the 10 %, 5 % and 1 % levels, respectively

Table 5
Expected durations and transition probabilities *P(i, k)=P(s(t) = k | s(t-1) = i)*.

(row = *i* / column = *k*)	Regime 1	Regime 2
Regime 1	0.41	0.59
Regime 2	0.08	0.92
Expected durations (months)	1.70	12.26

Notes: This table presents the expected durations and transition probabilities for both regimes. Regime 2 (normalcy) is dominant, with an average duration of approximately 12.26 months, while regime 1 (the turbulent regime) lasts only about 1.7 months. The transition probabilities indicate a 92 % likelihood of remaining in regime 2 once established, with only an 8 % chance of switching to regime 1. In contrast, within regime 1, there is a 41 % probability of staying in that regime, but a 59 % chance of returning to regime 2.

Fig. 3 traces the dynamic responses of returns in each market to changes in the returns of the other market, utilizing generalized impulse responses. These responses generate an orthogonal set of innovations that are independent of VAR ordering (Pesaran and Shin, 1998). The analysis begins with a variable-specific Cholesky factor, positioning the j^{th} variable at the top of the Cholesky ordering, followed by the computation of impulse responses based on this modified arrangement. The responses are observed over a time horizon of up to 24 months, as indicated on the x-axis. Similar findings were observed when applying the Cholesky decomposition method.

The comparison of responses in regime 1 (shown in red) and regime 2 (shown in green) reveals that during normal periods, shocks to the U.S. or Chinese markets dissipate in less than five months (see the green lines). In contrast, the estimated impulse responses to generalized one standard deviation shocks in regime 2 can destabilize the other market for up to 20 months before converging to zero. This observation aligns with expectations, as shocks are typically short-lived in regime 1, while during crisis periods, they tend to persist.

Table 6 presents the regime-specific variance decomposition using Cholesky-adjusted factors, indicating that shocks originating from the Chinese market account for nearly 100 % of the forecast error variance of $r_{1\,t}$ over the next 24 months. This reveals the overwhelming influence of China on its own market. Regardless of the regime considered, the variance decomposition tells the same story: the Chinese market is capable of generating more shock waves than the U.S. market, further reinforcing the deep interdependence of global economies. The sinusoidal movements observed in the impulse response functions (depicted in Fig. 3) reflect cyclical adjustments driven by Chinese shocks, indicating periods of market realignment following the initial disturbances. Investors and policymakers must recognize the strong secondary influence of Chinese market dynamics particularly in regime 1 when making decisions, as these fluctuations have far-reaching and long-lasting consequences.

It is interesting to note that the observed unidirectional causality from the U.S. to China aligns broadly with findings in the existing literature on U.S.–China financial linkages and spillovers. Empirical studies indicate that U.S. markets continue to act as a dominant driver of global financial dynamics, while China, despite its growing influence, plays a more reactive role in international risk transmission. For instance, Li and Zhang (2013) showed that U.S. price changes produce short-term spillovers in Chinese markets, highlighting the predictive power of U.S. returns for China. Similarly, Wang and Xiao (2023) found that U.S. spillovers are stronger than China's in East Asian markets, particularly during high-volatility periods, whereas China's influence is comparatively limited. Qian et al. (2024) also suggest that while China's global financial footprint is expanding, U.S. economic dominance continues to shape international market movements.

Our empirical findings are largely consistent with these perspectives. Using a Markov Switching VAR framework, we find bidirectional causality during periods of normalcy (regime 2), indicating increasing market interdependence under stable conditions, whereas during turbulent periods (regime 1), causality is primarily unidirectional from the U.S. to China, reflecting the U.S. market's role as the main source of shocks during crises, with China's spillovers remaining muted. This pattern is also consistent with behavioral and sentiment-driven mechanisms: prior studies document stronger herding and sentiment effects in Chinese markets than in the U.S. (Xing et al., 2024; Fu and Wu, 2021), which may amplify the sensitivity of Chinese markets to external shocks without generating equivalent influence in the opposite direction.

6. Practical implications

The study's findings have important implications for investors. Prolonged instability in China's stock market could affect both the domestic economy and global financial stability. While China's policies aim for long-term growth, they may slow short-term recovery as the country deals with the real estate crisis, deflation, and geopolitical tensions. A cautious approach, favoring gradual reform over immediate stimulus, may delay the restoration of investor confidence, with consequences for global markets given China's central role in trade, investment, and growth. The link between Chinese and U.S. stock markets reflects broader economic and geopolitical trends. Cross-market spillovers are increasingly important, as Chinese market shocks can affect U.S. markets, especially during volatile periods. Cooperation between the U.S. and China is key to reducing systemic risk and supporting global market stability. The two economies are closely connected, relying on each other in trade, investment, and finance.

Investors risk missing opportunities if China fails to restore confidence, reconnect with the global economy, and limit the impact of falling property prices. China's economic health affects global stability, including that of the U.S., as a strong Chinese economy supports trade, investment, and growth worldwide. However, since COVID-19, China's stock market has underperformed due to

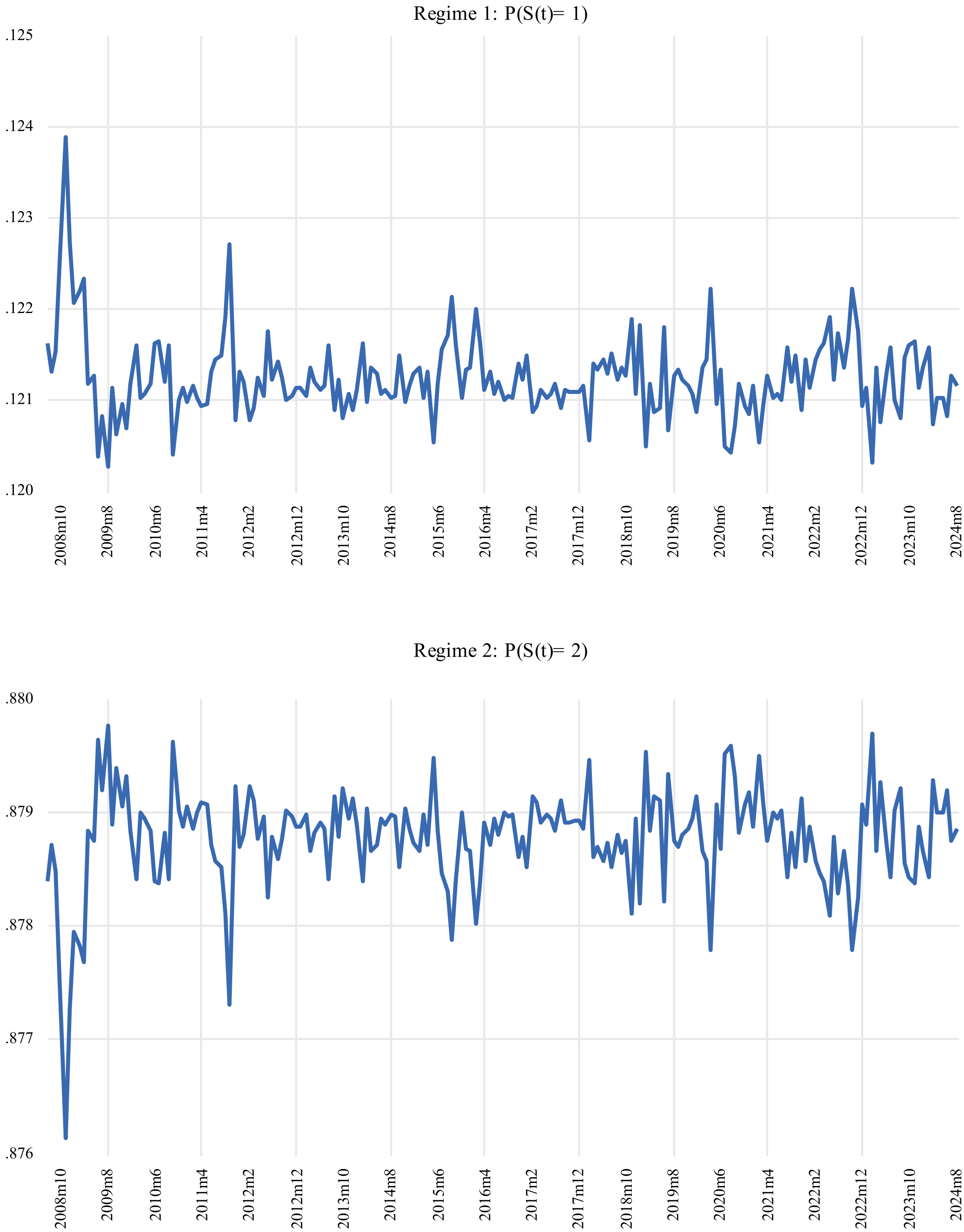

Fig. 2. Markov switching one-step ahead predicted regime probabilities. *Notes:* These graphs illustrate the one-step-ahead predicted transition probabilities, revealing notable spikes in regime 1 around 2008, 2011, and 2022, which correspond to the Global Financial Crisis and the COVID-19 pandemic. The probabilities for regime 2 (normalcy) are significantly higher than those for regime 1 (crises), indicating a clear preference for stable market conditions over turbulent periods (on average 87.9 % vs. 12.1 %).

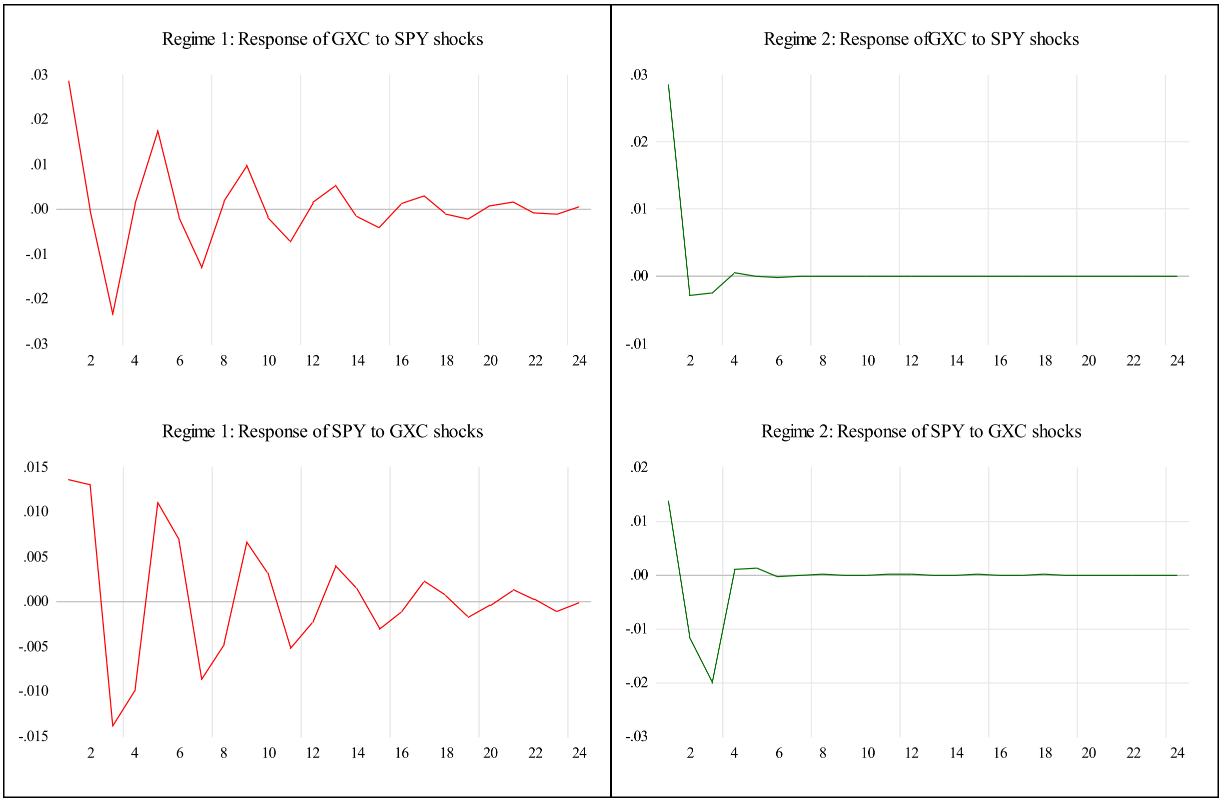

Fig. 3. Impulse responses to generalized one standard deviation innovations (shocks). *Notes:* The graphs show the dynamic responses of market returns to shocks in each other, highlighting key findings. During normal periods (regime 2), shocks to the U.S. or Chinese markets dissipate quickly, within five months. In contrast, during crisis periods (regime 1), the effects of one standard deviation shocks can destabilize the other market for up to 20 months before converging to zero. This suggests that while shocks are typically short-lived during periods of normalcy, they have prolonged impacts during turbulent times. Similar results were obtained when we used Cholesky decomposition method.

structural challenges, the real estate crisis, deflation, currency weakness, and declining foreign investment. Strict COVID-19 policies disrupted business, supply chains, and public confidence, slowing recovery. Current policies, focused on long-term growth through technology rather than traditional sectors, may not be enough to boost short-term activity or restore investor confidence. Rising tensions with the U.S. have added further challenges, particularly in trade and supply chains. Adaptive policies balancing short-term recovery with long-term reforms will be essential, as China's trajectory will have major effects on global investment and markets.

7. Conclusion

This study examines the dynamic interdependence between the Chinese and U.S. equity markets using a Markov regime-switching VAR framework applied to SPY and GXC over May 2007–August 2024. Two distinct regimes emerge: a crisis regime marked by heightened volatility and a calm regime representing normal market conditions. We found that causality is bidirectional during stable periods, whereas crises generate a one-way transmission from the U.S. to China. This pattern reflects the persistent vulnerability of the Chinese market, where investors remain exposed to U.S. shocks regardless of the prevailing regime, while U.S. markets remain largely insulated from Chinese fluctuations during periods of stress. The asymmetry becomes more pronounced during crises due to information frictions, differences in market efficiency, and the global flight-to-quality toward deeper and more liquid markets such as the U.S., suggesting the structural imbalance in cross-market influence.

The results point to several practical recommendations. Strengthening transparency, improving the reliability of market-relevant information, and reducing barriers to capital mobility would help moderate spillovers and increase China's resilience to external shocks. Measures that bolster investor confidence—such as clearer communication of macroeconomic strategies, targeted support for sectors facing balance-sheet stress, and reforms that enhance market depth—could reduce crisis-induced asymmetry. At the international level, maintaining cooperative economic channels between the U.S. and China would help limit systemic risk and support more balanced transmission mechanisms across markets.

For investors, these findings suggest that cross-market spillovers increasingly reflect broader economic and geopolitical conditions. Prolonged instability in China's equity market may suppress domestic recovery and influence global asset allocation, particularly if structural challenges—such as the property downturn, deflationary pressures, and reduced foreign participation—remain

Table 6
Regime-specific variance decomposition using Cholesky factors.

Period	Regime 1				Regime 2			
	Variance Decomposition of:				Variance Decomposition of:			
	China ($r_{1\,t}$):		*U.S.* ($r_{2\,t}$):		China ($r_{1\,t}$):		*U.S.* ($r_{2\,t}$):	
	$r_{1\,t}$	$r_{2\,t}$	$r_{1\,t}$	$r_{2\,t}$	$r_{1\,t}$	$r_{2\,t}$	$r_{1\,t}$	$r_{2\,t}$
1	100.00	0.00	19.57	80.43	100.00	0.00	19.57	80.43
2	99.92	0.08	31.77	68.23	100.00	0.00	29.60	70.40
3	99.84	0.16	41.65	58.35	100.00	0.00	48.65	51.35
4	99.83	0.17	45.49	54.51	100.00	0.00	48.68	51.32
5	99.80	0.20	49.81	50.19	100.00	0.00	48.74	51.26
6	99.79	0.21	51.26	48.74	100.00	0.00	48.74	51.26
7	99.78	0.22	53.43	46.57	100.00	0.00	48.74	51.26
8	99.78	0.22	54.04	45.96	100.00	0.00	48.74	51.26
9	99.77	0.23	55.22	44.78	100.00	0.00	48.74	51.26
10	99.77	0.23	55.49	44.51	100.00	0.00	48.74	51.26
11	99.77	0.23	56.15	43.85	100.00	0.00	48.74	51.26
12	99.77	0.23	56.27	43.73	100.00	0.00	48.74	51.26
13	99.76	0.24	56.65	43.35	100.00	0.00	48.74	51.26
14	99.76	0.24	56.71	43.29	100.00	0.00	48.74	51.26
15	99.76	0.24	56.93	43.07	100.00	0.00	48.74	51.26
16	99.76	0.24	56.95	43.05	100.00	0.00	48.74	51.26
17	99.76	0.24	57.08	42.92	100.00	0.00	48.74	51.26
18	99.76	0.24	57.09	42.91	100.00	0.00	48.74	51.26
19	99.76	0.24	57.16	42.84	100.00	0.00	48.74	51.26
20	99.76	0.24	57.17	42.83	100.00	0.00	48.74	51.26
21	99.76	0.24	57.21	42.79	100.00	0.00	48.74	51.26
22	99.76	0.24	57.21	42.79	100.00	0.00	48.74	51.26
23	99.76	0.24	57.24	42.76	100.00	0.00	48.74	51.26
24	99.76	0.24	57.24	42.76	100.00	0.00	48.74	51.26

Notes: This table presents the regime-specific variance decomposition using Cholesky (degree of freedom adjusted) factors. The results indicate that shocks to the Chinese market in both regimes can explain nearly 100 % of the forecast error variance of $r_{1\,t}$ over the next 24 months. In contrast, shocks to the U.S. market explain between 42 % and 80 % of the forecast error variance of $r_{2\,t}$, typically decreasing as the forecasting horizon expands. Regardless of the regime considered, the variance decomposition tells the same story: U.S. shocks have no significant short- or long-term effects on the Chinese market, whereas Chinese shocks have a notable impact on the U.S. market, starting at 20 % immediately (after one period) and rising to around 50 % within four to five periods.

unaddressed. A credible policy strategy that restores confidence and reconnects China with global markets will be crucial, as China's trajectory will shape future risk and return opportunities worldwide. Overall, the evidence highlights the importance of coordinated policy efforts, credible domestic reforms, and strengthened international engagement to mitigate asymmetry in U.S.–China equity market interactions and enhance stability during both calm and crisis periods.

Author statement

We declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere. We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed.

CRediT authorship contribution statement

Abbas Valadkhani: Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Hazem Marashdeh:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of Competing Interest

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. The authors are not aware of any conflict of interest that may affect the impartiality of his analysis.

Appendix

This appendix outlines the proposed Markov regime-switching VAR model, using the expectation-maximization algorithm to estimate regime-dependent coefficients and probabilities. It explains how transition probabilities determine expected regime durations, and how generalized impulse responses, variance decomposition, and regime-specific Granger causality tests assess shocks and directional market influences.

To estimate the parameters of the regime-switching VAR model, we use the Expectation-Maximization (EM) algorithm to jointly estimate the VAR coefficients and the probability of being in each regime at any given point in time. We estimate the transition probabilities, $P(s_{t-j} \mid s_{t-1}=i)$, for each possible regime transition. In the estimation process the coefficients $\mathbf{C_s}$ and $\mathbf{A}_{i,s}$ are estimated separately for each regime as the coefficients are regime-dependent. The expected duration $E(D_t)$ of staying in a particular regime can be derived from the transition probabilities. Using the Markov process assumptions, the expected duration in each regime is given by:

$$E(D_t|s_{t-1}=i)=\frac{1}{1-P(s_t=i|s_{t-1}=i)} \tag{A1}$$

Where $P(s_t=i|s_{t-1}=i)$is the transition probability of staying in the same regime at time t, given the regime at time t-1. The transition probabilities between regimes denoted by $P(s_t=j|s_{t-1}=i)$. According to Kim (1994), the conditional regime (state) probabilities are enhanced through a smoothing process that utilizes the entire sample information set in a single backward recursion through the data. The Markov property of transition probabilities involves a recursive estimation procedure. At each iteration, the process commences with filtered estimates of regime probabilities from the previous period. These filtered estimates are then utilized to generate one-step-ahead forecasts of regime probabilities, which in turn are used to construct the one-step-ahead joint densities of the regimes in period t. Subsequently, the likelihood contribution for period t is computed by aggregating the joint probabilities across unobserved regimes to derive the marginal distribution of the observed data. The one-step ahead predicted regime probabilities (i.e. the predicted probabilities of being in a given regime at time t (given information up to time $t-1$ are derived using the filtering technique based on the past data. That is:

$$\Pr(s_t=j|\mathbf{r}_{1:t-1})=\frac{\Pr(\mathbf{r}_t|s_t=j)P(s_t=j|s_{t-1})}{\sum_i\Pr(\mathbf{r}_t|s_t=i)P(s_t=i|s_{t-1})} \tag{A2}$$

Where $\Pr(\mathbf{r}_t|s_t=j)$is the likelihood of observing the data given regime j at time t.

To estimate the impulse response functions (IRF) in a regime-switching VAR framework, we consider the responses to a generalized one standard deviation shock. The IRF in a Markov regime switching VAR model captures the response of each variable to a shock (innovation) in another variable, taking into account the possible regime shifts. This is done separately for each regime, accounting for the nonlinearity arising from regime switching. For a generalized one-standard deviation innovation, the IRF in regime s at horizon h is estimated as follows:

$$IRF_{s,h}=\frac{\partial\mathbf{r}_t}{\partial\boldsymbol{\varepsilon}_{t-h}}=\mathbf{A}_s^h e_s \tag{A3}$$

Where$\mathbf{A}_s^h$ is the h-step ahead forecast matrix under regime s, and es is the vector of generalized shocks, typically one standard deviation shocks to each variable.

To analyze the dynamic responses of each market to shocks (innovations) in the other market, we employ generalized impulse response functions (Pesaran and Shin, 1998), which produce an orthogonal set of innovations (residuals) that are invariant to the ordering of the variables in the VAR model. Impulse response functions illustrate the dynamic effects of a shock to one variable on others within a VAR model over time. Variance decomposition, on the other hand, breaks down the variation in a series into parts caused by different shocks in the VAR. This helps us understand how important each shock is in influencing the variables in the model. The variance decomposition for each regime is computed by decomposing the variance-covariance matrix of the errors, Σ_s, for each regime. For each regime s, the Cholesky factorization of the covariance matrix is used to decompose the variance $\Sigma_s=LL^T$, where L is the lower triangular matrix obtained from the Cholesky decomposition. In regime switching VAR model, variance decomposition (VD) in regime s is computed using the Cholesky decomposition of the variance-covariance matrix Σs. For a forecast horizon h, the variance decomposition for variable i is given by:

$$VD_{i,s,h}=\frac{Var(\widehat{\mathbf{r}}_{i,t+h}|\mathbf{r}_t,\mathbf{e}_s)}{\sum_{j=1}^{k}Var(\widehat{\mathbf{r}}_{j,t+h}|\mathbf{r}_t,\boldsymbol{\varepsilon}_s)} \tag{A4}$$

Where $\widehat{\mathbf{r}}_{i,t+h}$is the forecast of the i^{th} variable at time $t+h$, and $\mathbf{e}_s$ denotes the shock vector corresponding to the s^{th} regime.

In addition to analysing the impulse response functions and variance decompositions, the present study will conduct both the conventional causality test (Granger, 1969) using a non- switching VAR model and an alternative causality test based on a regime-switching VAR model, as proposed by Psaradakis et al. (2005). In a standard VAR framework $r_{1\,t}$ is said not to Granger-cause $r_{2\,t}$ if the lagged coefficients of r_1 in the r_2 equation are all zero (Lütkepohl, 1993). To conduct the causality test in a Markov regime-switching VAR model, we need to extend the basic VAR causality model to account for the switching between two regimes. The causality between the two markets can be tested by analyzing how the returns in one market (e.g., the Chinese market) affect the returns in the other market (e.g., the U.S. market) within each regime. Let's assume there are two regimes, with s = 1 corresponding to a crisis period (Regime 1) and s = 2 corresponding to a normal time period (Regime 2). The VAR model in regime s for $k=2$

endogenous variables can be written as:

$$\begin{pmatrix} r_{1t} \\ r_{2t} \end{pmatrix} = \begin{pmatrix} C_{1,s} \\ C_{2,s} \end{pmatrix} + \sum_{l=1}^{k} \mathbf{A}_{1,s,l} \begin{pmatrix} r_{1t-l} \\ r_{2t-l} \end{pmatrix} + \sum_{l=1}^{k} \mathbf{A}_{2,s,l} \begin{pmatrix} r_{1t-l} \\ r_{2t-l} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \tag{A5}$$

Causality in a VAR context can be tested by checking if the lagged values of one variable influence the other, both within a regime and across regimes. Specifically, for testing causality from the U.S. market to the Chinese market (i.e., $r_{2\,t}$ causing $r_{1\,t}$). The null hypothesis for no causality from the U.S. market to the Chinese market is that all the coefficients of the lagged values of r2t in the Chinese market equation are zero:

$$H_0 : \mathbf{A}_{1,s,l} = 0, \ \textit{forall}\ l = 1, 2, \ldots, k \tag{A6}$$

The alternative hypothesis is that at least one coefficient in $\mathbf{A}_{1,s,l}$ is non-zero, indicating that past U.S. returns have a significant impact on Chinese returns in regime *s*. Similarly, for testing causality from the Chinese market to the U.S. market, the null hypothesis for no causality from the Chinese market to the U.S. market is that all the coefficients of the lagged values of $r_{1\,t}$ in the U.S. market equation are zero:

$$H_0 : \mathbf{A}_{2,s,l} = 0, \ \textit{forall}\ l = 1, 2, \ldots, k \tag{A7}$$

The alternative hypothesis is that at least one coefficient in $\mathbf{A}_{2,s,l}$ is non-zero, indicating that past Chinese returns have a significant impact on U.S. returns in regime *s*.

Data availability

Data will be made available on request.

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