Available online at www.HighTechJournal.org

HighTech and Innovation Journal

ISSN: 2723-9535

Vol. 6, No. 4, December, 2025

Financial Cycle Dependence of Monetary and Exchange Rate Policies in an Open Economy

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Received 25 August 2025; Revised 21 November 2025; Accepted 25 November 2025; Published 01 December 2025

Abstract

The deepening of globalization has posed challenges to open economies, such as fluctuations in international capital flows and intensified cross-border risk contagion. To explore the impact mechanism of FC on MP and ERP, this paper adopts TVP-VAR, MS-VAR, and MS-DSGE models, and introduces the SVR model as an auxiliary prediction tool to analyze policy dependency characteristics through standardization and periodic decomposition. The results showed that during the 2008 financial crisis, the growth rate of the broad money supply reached 17.0%-20.0%, the Shanghai Interbank Offered Rate rose to 3.6%-5.2%, and the asset price volatility exceeded 20%. During the COVID-19 pandemic in 2020, the volatility of real estate prices reached 7.2%-9.5%. In terms of policy transmission, the impact of asset price shocks on the consumer price index significantly increased after 3 months and reached its peak after 6 months. The regulatory coefficient of interest rate policy on the financial condition index under the high volatility regime was 1.1862, and the response coefficient of the growth rate of the broad money supply to the output gap under the low volatility regime was 0.2156. The SVR model had a prediction accuracy (R^2 of 0.85) for the impact of MP on ERVs, especially in capturing nonlinear relationships during financial expansion periods. This achievement demonstrates the significant effect of FC stages on the effectiveness of MP, providing an FC sensitive policy framework for open economies, helping to enhance macroeconomic resilience and maintain internal and external balance.

Keywords: Open Economy; Monetary Policy; Exchange Rate Policy; Financial Cycle; Policy Coordination.

1. Introduction

The deepening process of globalization has reshaped the world economic landscape. With the empowerment of computer technology, it has formed a complex open economic network in which the economies of various countries are linked in real-time through trade, investment, and capital flows. However, while this open pattern improves resource allocation efficiency and creates growth opportunities, it also poses unprecedented challenges to open economies, leading to intensified Financial Cycle (FC) fluctuations and profoundly affecting macroeconomic stability. For example, increased volatility in international capital flows, more diverse and rapid channels for cross-border risk contagion, and increasingly prominent impact of external shocks on domestic economic stability [1-3]. In the context of an open economy, Monetary Policy (MP) and Exchange Rate Policy (ERP), as core tools for regulating internal and external economic balance, are facing new challenges in terms of their implementation effectiveness, transmission path, and target balance mechanism. Under the conditions of an open economy, the cross-border flow of capital, the transmission of Exchange Rate Fluctuations (ERFs), and the linkage effect of the international market have led to a significant

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http://dx.doi.org/10.28991/HIJ-2025-06-04-08

dependence on the stage of the FC for the effectiveness of MP and ERP, the diffusion path of shocks, and even the trade-off between internal and external equilibrium goals by policy makers [4-5]. Therefore, exploring the impact of FC on policies in the context of an open economy requires the support of traditional macroeconomic theory, as well as the integration of computer technology and tools such as Support Vector Regression (SVR). This helps to deepen the understanding of the macro-financial dynamics of the open economy through algorithmic models, and also reveals how FC endogenously affects policy transmission and effectiveness through non-linear mechanisms. Thus, the open economy macro model, including financial frictions and technological variables, is enriched and developed [6, 7].

In terms of the Global Financial Cycle (GFC) and cross-border capital flows, Kaufmann [8] pointed out that the easing of U.S. MP will trigger global capital inflows through international investment fund channels and push up asset prices in various countries. Gupta & Dubey [9] further found that different forms of GFCs (such as stock and bond flows) have different impacts on MP independence, and Macroprudential Policies (MPPs) can play a certain buffering role. Secondly, at the level of financial frictions and MP transmission, Lakhchen [10] based on Morocco's DSGE model, verified that financial frictions will amplify the effect of capital quality shocks, emphasizing the necessity of considering financial frictions in policy formulation. In ERP and Dynamics, Kohler & Stockhammer [11] examined the traditional view that flexible exchange rates are necessarily “stabilizers” of external shocks. They pointed out that flexible exchange rates may be a driver of endogenous cycles in emerging markets. Rüth & Van der Veken [12] provided a new identification method for analyzing the relationship between MP and exchange rate anomalies through a structured vector autoregressive model.

For the micro-transmission mechanism, Kinnerud [13] found through the heterogeneous agency model that expansionary MP mainly drives aggregate demand through the mortgage refinancing behavior of a small number of households. This research revealed a previously ignored new channel of policy transmission based on the housing market. The research of Zhang et al. [14] revealed that China's MP tightening has significant negative spillover effects on global output, especially emerging economies, through trade channels. This research provided a new evidence for understanding the global impact of large emerging economies. In addition to the discussion of traditional transmission mechanisms, recent research has also begun to focus on the impact of FCs in broader dimensions. For example, P. Kuosmanen et al. [15] pointed out that during periods of unconventional MP (such as the zero lower bound), traditional financial predictors (such as term spreads) fail, and real stock returns become more robust predictors. Coban et al. [16] took Turkey as an example and revealed how the GFC affects a country's economic growth model, thereby profoundly shaping its domestic bureaucratic autonomy and institutional governance structure, linking financial fluctuations to political economy issues. In addition, DaSilva et al. [17] emphasized that the effectiveness of the MP transmission channel changes with the policy environment. They found that when the economy is at the zero-lower bound of interest rates, the role of the credit channel becomes extremely critical, and the traditional interest rate channel may fail.

In summary, although the above research has achieved fruitful results, there is still room for expansion. First, most studies focus on a single dimension or a single transmission mechanism of the FC and fail to fully integrate the typical fact that credit and asset prices fluctuate together in the FC. Therefore, it is difficult to fully capture its multi-dimensional characteristics and its time-varying and regional dependence on monetary and exchange rate policies. Second, in terms of methodology, existing models are often limited to a single mechanism and lack a combination of models that can simultaneously describe the time variability of parameters and mechanism switching, making it difficult to fully reveal the complex dynamic interaction between the FC and the macroeconomy. This study is dedicated to solving the coordination dilemma between MP and ERP at different stages of FC under the background of China's open economy. It aims to balance the conflicts between internal growth and price stability and external exchange rate and capital flow objectives. Compared with existing single-region or fixed-parameter models, the Time-Varying Parameter Vector Autoregression (TVP-VAR) model constructed in this paper can capture the continuous, smooth evolution of the economic structure. The Markov-Switching Vector Autoregression (MS-VAR) model is able to identify the mechanism jump characteristics of financial contraction and boom phases. This combined analysis framework goes beyond the limitations of previous studies that only focused on a single nonlinear mechanism. Furthermore, by constructing a Markov-Switching Dynamic Stochastic General Equilibrium (MS-DSGE) model that includes regional switching, this paper enables the key parameters of MP rules to be adjusted endogenously with financial conditions, thereby being closer to the discretionary decision-making characteristics shown in China's policy practice. In addition, the introduction of the SVR machine for policy effect prediction enhances the ability to capture complex non-linear relationships out of sample and provides an important forward-looking supplement to traditional econometric analysis.

The structure of this article is as follows: Section 1 is the introduction. Section 2 introduces the research methods and data, including the multi-dimensional construction of the FC, variable selection, and the setting of TVP-VAR, MS-VAR, MS-DSGE, and SVR models. Section 3 presents empirical results and analyzes the regional characteristics of the GFC and the dependence characteristics of policy coordination under different regional systems. Section 4 provides an in-depth discussion on the cyclical heterogeneity mechanism of policy transmission and its policy implications. Finally, Section 5 summarizes the full text and gives research conclusions.

2. Methods and materials

This study constructs an FC and macroeconomic variable indicator system that covers dimensions such as credit and asset prices. This system processes data through standardization, cycle decomposition, etc., analyzes the characteristics of GFC zoning, and presents the evolution of financial indicators and the rules of zoning conversion in different time periods. This study also explores the characteristics of policy coordination dependence under different regional systems, including the transmission of financial variables to real prices and the estimation results of related models. Finally, the SVR model is used to predict policy effects and explore its dependence on FC.

2.1. Multidimensional Construction of FCs and Macroeconomic Variables

In the context of an open economy, the fluctuations of FCs are reflected in the numerical changes of economic indicators, which are more deeply embedded in the texture of social and economic operations, and affect the interactive logic between micro subject behavior and macro policies. At the social level, the period of financial expansion often accompanies the rise of asset prices, and the household sector gains wealth effects through the appreciation of assets such as real estate and stocks, thereby increasing consumption willingness and credit demand. This behavior will amplify the stimulating effect of MP. During the period of financial contraction, asset price shrinkage leads to depreciation of household wealth, increased debt pressure, and an increase in social savings tendency. The contraction of consumption and investment demand will weaken the transmission efficiency of policy regulation. In terms of economic interaction, cross-border capital flows in an open economy have intensified the social impact of FCs. When the GFC is in a high phase, the influx of international capital drives domestic credit expansion, and the corporate sector tends to expand overseas financing and investment. This behavior enhances the sensitivity of ERP and makes the domestic financial system more susceptible to external risk shocks. During the global financial tightening period, capital outflow pressure has forced companies to reduce their overseas operations, banks to tighten credit standards, and social financing costs have increased, further strengthening the difficulty of policy regulation.

The FC is the core concept that characterizes the expansion and contraction of the financial system. Its fluctuations are reflected in the fluctuations of single indicators such as credit scale and asset prices, and further penetrate into macroeconomic levels such as Output Growth (OG), price stability, and fiscal sustainability through complex transmission mechanisms, forming dynamic interactions with the regulatory effects of MP and MPPs [18, 19]. The outbreak of the 2008 global financial crisis revealed a key fact: relying solely on a single financial indicator or being limited to a narrow macroeconomic scope makes it difficult to fully capture the linkage between FCs and the real economy [20, 21]. This study combines the synergistic characteristics of capital flows and GFCs in an open economy, and constructs an FC indicator system from the two core dimensions of credit and asset prices to capture the pro cyclical features of the financial system and its amplification effect on the real economy. The multidimensional construction of FCs and macroeconomic variables is shown in Figure 1.

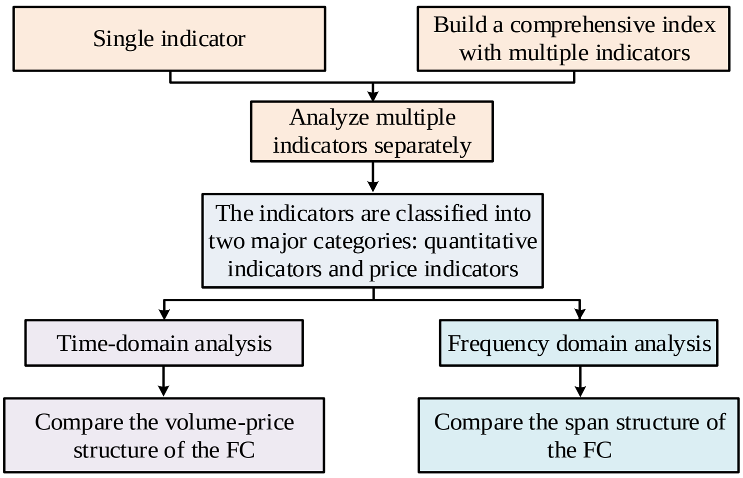


Figure 1. Depicts the financial cycle

In Figure 1, the expansion and contraction of the credit scale affect the real economy by influencing the social financing environment. The fluctuations in asset prices penetrate into the consumption and investment sectors through channels such as wealth effects and expectation transmission. Considering the time span limitation of social financing scale data, the Broad Measure of Money Supply (BMMS, M2) is adopted as the proxy variable M for credit quantity.

Its growth rate reflects the overall tightness of the credit environment [22]. To eliminate dimensional differences and facilitate cross-period comparisons, the original indicators are standardized as shown in Equation 1.

$$M_t^* = \frac{M_t - \min(M_t)}{\text{stdev}(M_t)} \tag{1}$$

In Equation 1, M_t^* is the normalized credit quantity cycle term, M_t is the original credit quantity, $min(M_t$ is the minimum value during the sample period, and $stdev(M_t$ is the standard deviation. The credit price dimension adopts the Shanghai Interbank Offered Rate (SHIBOR). This indicator directly reflects the cost of funds in the credit market, and its cyclical component S_t^* is separated through Hodrick-Prescott (HP) filtering, as shown in Equation 2 [23].

$$\begin{cases} \min\limits_{\{\tau_t\}} \left\{ \sum\limits_{t=1}^{T} (S_t - \tau_t)^2 + \lambda \sum\limits_{t=2}^{T} \left[(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1}) \right]^2 \right\} \\ S_t^* = S_t - \tau_t \end{cases} \tag{2}$$

In Equation 2, λ is the smoothing parameter that controls the decomposition strength of the trend and period. The HP filter decomposes the original sequence S_t into trend term τ_t by minimizing the loss function. Differences in financial market cycles can have an obvious impact on the volatility trajectory of the RMB Exchange Rate (RMB-ER) through various pathways such as cross-border capital flows and market expectations. The conduction path is shown in Figure 2.

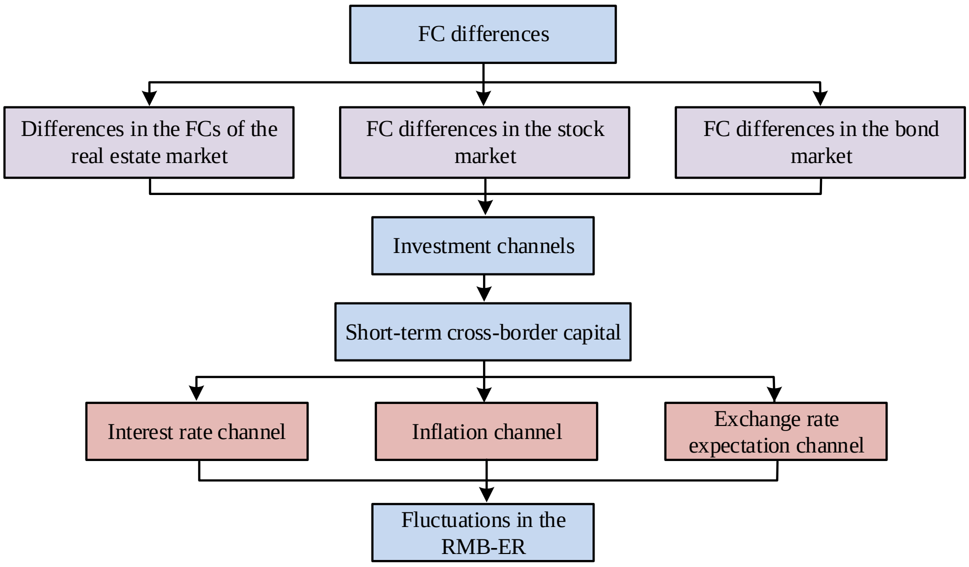


Figure 2. The fluctuation paths in the RMB-ER influenced by the differences in FCs

In Figure 2, the asset price dimension covers stocks, real estate, foreign exchange markets, and bonds. The sales unit price intuitively reflects price fluctuations, while the sales area of commercial housing directly reflects the activity level of market transactions. The combination of the two can comprehensively capture the supply and demand dynamics and valuation changes of the real estate market, and is a core indicator for measuring the real estate cycle. The stock market uses the trading volume and index position of the CSI Composite Index as proxies to capture the flow of funds and valuation changes in the capital market. The bond market uses the trading volume and turnover of treasury bond bonds of the Shanghai Stock Exchange (SSE) to measure the liquidity and yield changes of the fixed income market. The foreign exchange market characterizes cross-border capital flows and ERFs based on the proportion of foreign exchange reserves to Gross Domestic Product (GDP) and the real effective exchange rate of the renminbi. All asset price indicators are standardized to eliminate dimensional differences, as shown in Equation 3.

$$A_{i,t}^* = \frac{A_{i,t} - \min\left(A_{i,t}\right)}{\text{stdev}\left(A_{i,t}\right)} \tag{3}$$

In Equation 3, i represents different asset classes, and $A_{i,t}^*$ represents the standardized asset price cycle term. The selection of macroeconomic variables focuses on three dimensions: output, price level, and fiscal sustainability, to comprehensively reflect the impact of FCs on the real economy. This output uses the year-on-year growth rate of GDP as a proxy variable, and quarterly data are transformed into monthly data through local quadratic fitting to match high-frequency financial indicators. Price level differentiation of upstream and downstream transmission pathways downstream uses the Consumer Price Index (CPI) to reflect fluctuations in terminal consumer goods prices; Upstream, the Producer Price Index (PPI) is used to measure changes in the ex-factory prices of industrial products [16, 24]. The price gap between upstream and downstream is calculated by separating the trend term through HP filtering, as shown in Equation 4.

$$\mathrm{CPI}/\mathrm{GAP}_t = \mathrm{CPI}_t - \tau(\mathrm{CPI}_t)\mathrm{PPI}/\mathrm{GAP}_t = \mathrm{PPI}_t - \tau(\mathrm{PPI}_t) \tag{4}$$

The positive and negative values of the price gap represent inflation pressure and deflation risk, and their fluctuation amplitude reflects the effectiveness of the price transmission mechanism. The fiscal balance adopts the difference between the national public fiscal revenue and expenditure, and is adjusted for the Financial Neutral Output Gap (FNOG) to obtain the Structural Fiscal Balance (SFB). The FNOG is estimated through a state space model that includes financial variables, as shown in Equation 5.

$$\begin{cases} y_t = y_t^* + \gamma_1 x_1 + \gamma_2 x_2 + \varepsilon_{0,t} \\ B_t = F_t - \theta\left(y_t - y_t^*\right) \end{cases} \tag{5}$$

In Equation 5, y_t is the logarithm of actual output, and y_t^* is the logarithm of potential output. x_1 and x_2 are the logarithm of credit volume and real estate prices, while γ_1 and γ_2 are the coefficients of financial variables. $\varepsilon_{0,t}$ is a random perturbation term. B_t is the SFB, F_t is the original fiscal balance, and θ is the response coefficient of fiscal policy to the output gap. This model estimates potential output through Kalman filtering and calculates SFB.

The selection of policy variables covers three dimensions: MP, MPPs, and GFC synergy, to analyze the regulatory effects of policy tools at different stages of the FC. The quantity type in the MP tool is represented by the M -growth gap, reflecting the expansion or contraction of the money supply; The price type uses SHIBOR to characterize the price signal of the capital market. The MP position is standardized to form a comprehensive index MP_t, as shown in Equation 6.

$$\mathrm{MP}_t = \omega_1 \cdot M/\mathrm{GAP}_t + \omega_2 \cdot S_t^* \tag{6}$$

In Equation 6, ω_1 and ω_2 are weight coefficients determined through principal component analysis. The MPP tool selects liquidity ratio (reflecting a bank's short-term solvency), excess reserve requirement ratio (regulating bank liquidity), and core tier one capital adequacy ratio (measuring capital buffer level), representing three types of prudential tools: liquidity regulation, reserve management, and capital constraints. This study uses the CBOT Volatility Index (VIX) to characterize the degree of global market risk aversion, and divides it into high volatility regime ($s_t = 1$) and low volatility regime ($s_t = 2$) through MS-VAR. District 1 represents financial contraction, while District 2 represents financial boom, as shown in Equation 6.

$$\mathrm{VIX}_t = m(s_t) + \sigma(s_t) \cdot \varepsilon_t \tag{7}$$

In Equation 7, $m(s_t)$ is the conditional mean of regime dependence, $\sigma(s_t)$ is the standard deviation of regime dependence, and $\varepsilon_t \sim N(0,1)$. The regime transition probability is determined through maximum likelihood estimation and used to identify the impact of GFC on domestic policy transmission.

2.2. Model Settings

After clarifying the multidimensional construction logic of FCs and macroeconomic variables, to further quantify and analyze the regulatory effects and dynamic correlations of policy tools at different stages of FCs, specific model settings are needed to capture the complex interactive mechanisms between them. This study combines research objectives and data characteristics to construct TVP-VAR, MS-VAR, and MS-DSGE models, capturing the interaction mechanism between FCs and macroeconomics from different dimensions. The TVP-VAR, MS-VAR, MS-DSGE, and SVR models adopted in this study form a logically rigorous and functionally complementary progressive analysis framework, and their core logical flow is shown in Figure 3. Firstly, the TVP-VAR model serves as a preliminary detection tool to identify whether the dynamic correlations among MP, FCs, and macroeconomic variables evolve smoothly over time. Then, the MS-VAR model verifies whether there are more significant and discrete "regional transformation" features behind the dynamics indicated by TVP-VAR. Then, the MS-DSGE model is used to explain the intrinsic driving mechanism behind the differences confirmed by MS-VAR. Finally, the SVR model utilizes the key variables revealed by the aforementioned model to conduct out-of-sample predictions of policy effects at different stages of the FC.

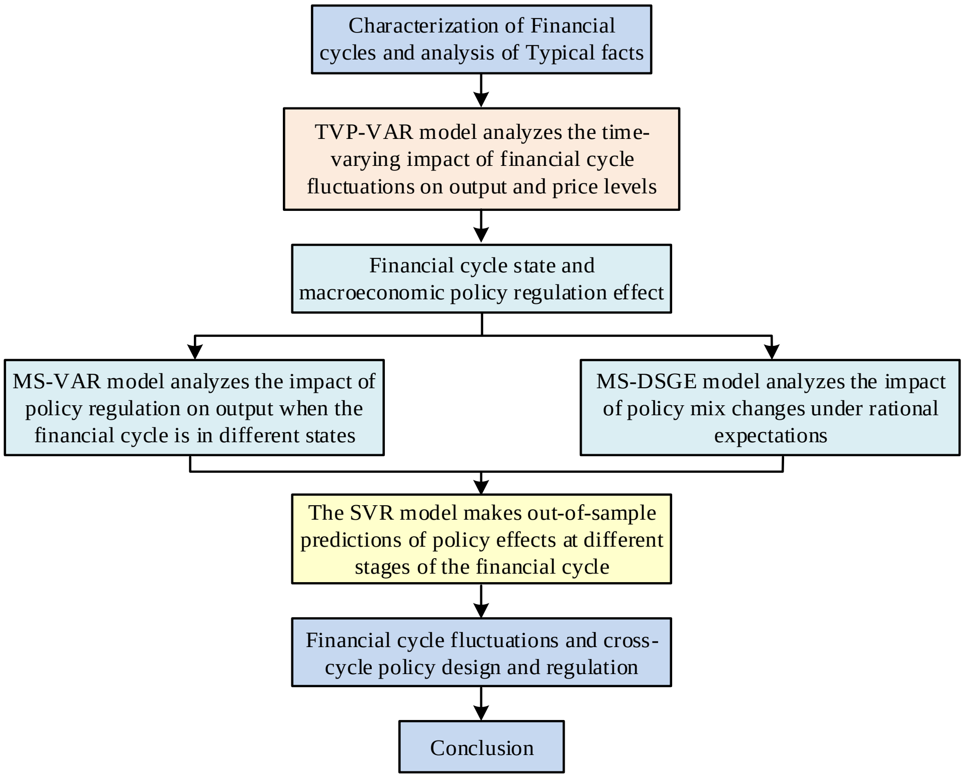


Figure 3. Schematic diagram of the model framework logic

In macroeconomic research, the impact of FCs on output and price levels is not static, but rather exhibits time-varying characteristics with factors such as economic structure and policy environment. The use of TVP-VAR can effectively capture this dynamic relationship. Its core advantage lies in allowing model parameters to change over time, thus being closer to the structural changes in the economic system in reality. The basic form of the model is set as shown in Equation 8.

$$y_t = x_t \beta_t + A_t^{-1} \sum_t \varepsilon_t \tag{8}$$

In Equation 8, $y_t = (H_t, Y_t, CPI_t, PPI_t)'$ is an endogenous variable vector that includes asset prices H_t, output Y_t, CPI CPI_t, and industrial PPI PPI_t. $x_t = I_k \otimes (y'_{t-1}, \ldots, y'_{t-s})$ is the lag term matrix, with a lag order of $s = 2$. β_t is the coefficient vector that varies over time. A_t is a lower triangular matrix that characterizes the current relationship between variables. $\varepsilon_t \sim N(0, I_k)$ is the perturbation term. The dynamic evolution of time-varying parameters follows a first-order random walk process, as shown in Equation 9.

$$\begin{cases} \beta_{t+1} = \beta_t + \mu_{\beta t} \\ a_{t+1} = a_t + \mu_{at} \\ h_{t+1} = h_t + \mu_{ht} \end{cases} \tag{9}$$

In Equation 9, a_t is the stacking vector of triangular elements under A_t. $h_t = (\log\sigma^2_{1t}, \ldots, \log\sigma^2_{kt})'$ is the logarithmic vector of volatility. $\mu_{\beta t} \sim N(0, \Sigma_\beta)$, $\mu_{at} \sim N(0, \Sigma_a)$, and $\mu_{ht} \sim N(0, \Sigma_h)$ are parameter perturbation terms that are independent of ε_t. To characterize the nonlinear regime characteristics of FCs (such as high and tight periods), the MS-VAR model was used to identify the state of FCs and analyze the output effects of MP and ERP under different regimes [25]. The model setting is shown in Equation 10.

$$Z_t = \alpha(s_t) + \sum_{j=1}^{p} \beta_j(s_t) Z_{t-j} + \xi_t \tag{10}$$

In Equation 10, $Z_t = (FCI_t, MP_t, MP_{r,t}, Y_t)'$ is a variable vector that includes the Financial Condition Index (FCI) FCI_t, quantitative MP MP_t, MPP_s $MP_{r,t}$, and output gap Y_t. $s_t \in \{1,2\}$ is an unobservable area variable. $\alpha(s_t)$ and $\beta_j(s_t)$ are intercept and coefficients dependent on the system. $\xi_t \sim N(0, \sum(s_t))$ is the covariance matrix of the disturbance term dependent on the regime. The probability of regime transition satisfies a first-order Markov process as shown in Equation 11.

$$P(s_t = j \mid s_{t-1} = i) = p_{ij}, \quad \sum_{j=1}^{2} p_{ij} = 1 \quad \forall i, j \tag{11}$$

In Equation 11, p_{ij} represents the probability of transitioning from regime i to regime j, and the transition matrix is $P = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix}$. To analyze the dynamic effects of the dual pillar policy combination under rational expectations, an MS-DSGE model containing three regime transitions is constructed [26]. The model includes four departments: family, entrepreneur, retailer, and government. The utility function U_t of the household sector depends on consumption, housing, and labor, as shown in Equation 12.

$$U_t = E_t \sum_{t=0}^{\infty} \beta^t \left[\log(C_t - hC_{t-1}) + j_t \log H_t^h - \frac{\chi}{1+\phi} L_t^{1+\phi} \right] \tag{12}$$

In Equation 12, β is the discount factor, h is the consumption habit parameter, and j_t is the housing preference shock. H_t^h is the housing ownership, χ is the labor preference parameter, and ϕ is the reciprocal of labor supply elasticity. L_t represents labor supply, and E_t is the mathematical expectation operator formed by the information set based on time t. The entrepreneurial sector produces intermediate goods through the Cobb-Douglas production function, and entrepreneurs face credit constraints, as shown in Equation 13.

$$\begin{cases} Y_{mt} = G_t L_t^{1-\mu-v} K_{t-1}^{\alpha} (H_t^e)^v \\ R_t B_t \leq m E_t (Q_{t+1} H_t^e \pi_{t+1}) \xi_t \end{cases} \tag{13}$$

In Equation 13, Y_{mt} is the intermediate goods output produced by the entrepreneurial sector, G_t represents the total factor productivity, and μ is the capital output elasticity. v is the elasticity of real estate output, K_{t-1} is the capital stock, and H_t^e is the production housing. B_t is the loan, m is the Loan-to-Value (LTV), Q_t is the housing price, ξ_t is the credit shock, and R_t is the loan interest rate. The MP rule adopts the Taylor rule, where interest rates respond to inflation, output gap, and credit gap, and the coefficients vary with the regime, as shown in Equation 14.

$$\frac{R_t}{R} = \left(\frac{\pi_t}{\pi}\right)^{\kappa_\pi(s_t)} \left(\frac{Y_t}{Y}\right)^{\kappa_y(s_t)} \left(\frac{B_t}{B}\right)^{\kappa_b(s_t)} \exp(\varepsilon_{R,t}) \tag{14}$$

In Equation 14, Y_t is the actual output at time t. Y is the output level at steady state. $s_t \in \{1,2,3\}$ is the three zone system of MP: moderately tight, steady, and moderately loose. κ_π, κ_y, and κ_b are the reaction coefficients of inflation, output, and credit. The probability of regional system transfer is calibrated with reference to China's macro policy practice. The MPPs rule adjusts credit by adjusting LTV countercyclically, as shown in Equation 15.

$$m_t = \bar{m} + \tau_b (B_t - \bar{B}) \tag{15}$$

In Equation 15, $\tau_b = 0.5$ is the macroprudential response coefficient and $\bar{B}$ is steady-state credit. The model parameters are determined through a combination of Bayesian estimation and calibration, with steady-state values referenced from macro data in China and policy rule coefficients calibrated based on historical impulse responses.

In an open economy, the effectiveness of MP and ERP is influenced by the stage of FC, exhibiting significant nonlinear characteristics. This study introduces SVR as an auxiliary forecasting tool for three main reasons. First, macroeconomic and financial data are mostly small and medium-sized samples. This study uses monthly data from 2006 to 2022, and the sample size is limited. SVR is based on the principle of structural risk minimization, and its generalization ability under limited samples is better than neural networks that rely on big data training. Second, SVR achieves a good balance between model complexity and interpretability. Its parameters have clear statistical meanings, and the model is highly transparent, making it easy to analyze economic mechanisms and avoid "black box" problems. Finally, this study focuses on robustly capturing the nonlinear relationships between variables rather than pursuing ultimate prediction accuracy. SVR has been proven to be an effective tool for dealing with such small and medium-sized samples and high-dimensional nonlinear problems. It can achieve research goals with a relatively simple structure and take into account efficiency and interpretability.

In the prediction of policy effects, the SVR sample x includes three types of variables: policy instrumental variables, FC indicators, and macroeconomic state variables. By training the model with historical data, the model can output the marginal effects of policy shocks at different FC stages, providing quantitative references for policy makers and improving the accuracy of policy coordination. The regression function can be expressed as Equation 16.

$$\begin{cases} f(x) = \sum_{i=1}^{m} \left(\hat{\alpha}_i - \alpha_i\right) \cdot K\left(x_i, x\right) + b \\ K(x_i, x) = \exp(-\beta \left\| x_i - x \right\|^2) \end{cases} \tag{16}$$

In Equation 16, $f(x)$ is the predicted value of policy effectiveness. m is the training sample size, which refers to the number of historical policy implementation cases. $\hat{\alpha}_i$ and α_i are Lagrange multipliers trained by the model to measure the impact of the i -th sample on the hyperplane. $K(x_i, x)$ is a Radial Basis Kernel Function (RBKF) used to map low dimensional features to high-dimensional space. β is the nuclear parameter. $\|x_i - x\|$ is the Euclidean distance between sample x_i and the sample x to be predicted. b is the bias term used to adjust the position of the hyperplane and ensure that the overall offset of the predicted value is reasonable.

This study implements SVR training and prediction using Python, with the core tool being the SVR module in the scikit-learn library. Firstly, input features such as benchmark interest rates, money supply growth rate, credit/GDP gap, Exchange Rate Volatility (ERV), etc., are standardized to eliminate dimensional differences. Then, Grid Search is used to optimize the core parameters. Among them, the search range of penalty coefficient C is [0.1, 1, 10, 100], and the search range of RBKF β is [0.01, 0.1, 1, 10], with the mean square error of 5-fold cross-validation as the optimization objective. Finally, the dataset is divided into a 7:3 ratio, with the training set used to fit the model and the testing set used to evaluate the prediction performance, and output the predicted values of the policy tool for the SERV at different FC stages.

3. Results

This study was based on high-frequency data from China from January 2006 to December 2022, analyzing the characteristics of GFC zoning and presenting the evolution of financial indicators and the transition patterns of VIX indicator zoning in different time periods. This study also explored the characteristics of policy coordination dependence under different regional systems, including the transmission of financial variables to real prices and the estimation results of related models.

3.1. Characteristics of GFC District System

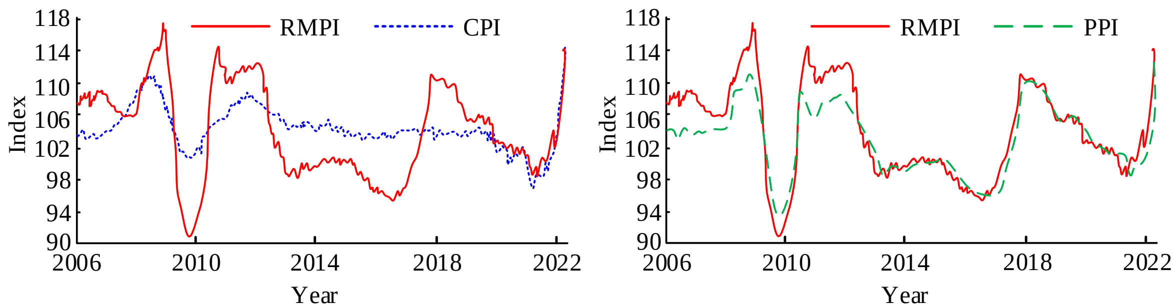
This study used high-frequency macroeconomic and financial data from China from January 2006 to December 2022. All original indicators were sourced from authoritative official institutions. In the FC indicators, the credit scale proxy variable BMMS M came from the monthly statistical data of the People's Bank of China; Credit prices were based on SHIBOR, with data sourced from the SHIBOR official website (www.shibor. org); The asset price dimension covers real estate, specifically including the sales area and unit price of commercial housing. The data came from the NBS and Wind databases of the National Bureau of Statistics (NBOS); The Shanghai Composite Index and trading volume were sourced from the SSE; Trading volume and turnover of treasury bond were from China Bond Information Network; The proportion of foreign exchange reserves to GDP and the real effective exchange rate came from the State Administration of Foreign Exchange and the Bank for International Settlements. Macroeconomic variables included GDP growth rate, which was sourced from quarterly data from the NBOS and converted to monthly frequency through local quadratic fitting; The CPI and PPI data were sourced from the monthly data of the NBOS; The financial balance data came from the monthly financial report of the Ministry of Finance. The policy variables involved MP tools, including M2 growth rate and 7-day interbank offered rate, and the data were from the People's Bank of China; Macro prudential indicators included liquidity ratio, excess reserve requirement ratio, and core tier one capital adequacy ratio, with data sourced from the China Banking and Insurance Regulatory Commission and the central bank's financial stability report; The GFC proxy variable VIX index data came from the Chicago Board Options Exchange.

Data processing followed standardization and cycle decomposition methods: the credit/asset price cycle term was extracted through HP filtering; The price gap was calculated separately based on CPI/PPI trends; The SFB was adjusted after estimating the potential output through the state space model (Kalman filter) containing financial variables. The details of parameter value settings are listed in Table 1. Among them, the smoothing parameter (λ =14400) was based on the setting logic of the eurozone FC by Brown & Hardy [27], and was used to precisely separate the trend terms and cycle terms of credit and asset prices, avoiding short-term noise interference. The transition probability was derived based on the MS-VAR parameter estimation method by Blampied & Mahadeo [28] through the maximum likelihood estimation of Chinese data from 2006 to 2022. The p_{11} was relatively high because high volatility is often triggered by external shocks such as crises and epidemics. After such shocks, the market was prone to maintain a short-term high volatility state. p_{12} was slightly lower, which is in line with the characteristic of being occasionally affected by policy adjustments and external disturbances during a period of low volatility.

Table 1. Parameter settings

Parameter category	Numerical value
HP filter smoothing parameter λ	14400
TVP-VAR lag order p	2
The probability of regional system transfer p_{11}	0.95
The probability of regional system transfer p_{12}	0.90
Discount factor β	0.995
The inflation response coefficient κ_π	Tightening period: 1.5, stable period: 1.2, loose period: 0.8
The reaction coefficient A of the output κ_y	Tightening period: 0.4, stable period: 0.3, loose period: 0.2
The response coefficient of credit κ_b	Tightening period: 0.3, stable period: 0.2, loose period: 0.1
The steady-state value of LTV θ	0.6

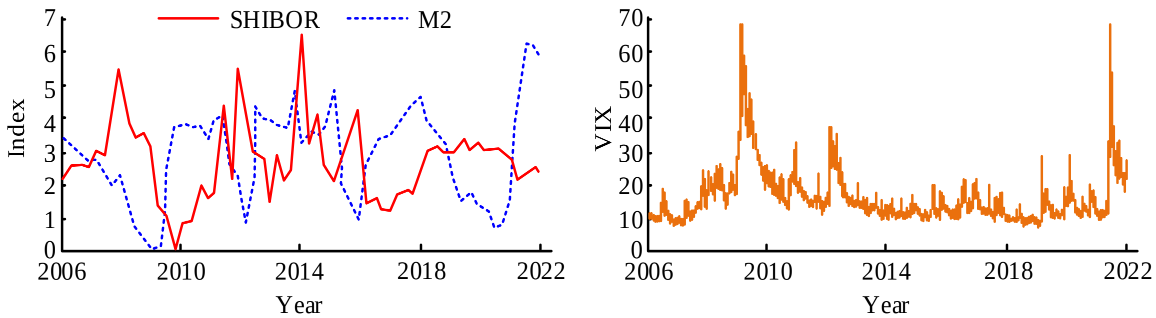
Figure 4 compares the trends of RMPI with CPI and PPI, visually presenting the dynamic correlation between the three from 2006 to 2022. In terms of the time dimension, from 2006 to 2007 (low volatility zone system), CPI, PPI, and RMPI all maintained a relatively stable synchronous trend, with slight fluctuations around the 100-106 range, reflecting the mild linkage between prices and related indices during the loose financial environment. From 2008 to 2012 (high volatility zone system, affected by the financial crisis), the volatility of the three factors significantly increased, and CPI and PPI were affected by shock transmission, resulting in an increase in deviation from the trend of RMPI. From 2013 to 2019 (returning to low volatility), the three factors once again stabilized. From 2020 to 2022 (due to high fluctuations caused by the epidemic), the trend has shown differentiation, reflecting the time-varying characteristics of RMPI and price index transmission under short-term risk events, confirming the phased impact of the FC on the transmission of real prices.



(a) Comparison of the trends of RMPI and CPI (b) Comparison of the trends of RMPI and PPI

Figure 4. Comparison chart of the trends of RMPI with CPI and PPI

Figure 5 shows the fluctuations of credit volume price indicators and VIX indicators. In Figure 5(a), between 2006 and 2022, SHIBOR and M2 exhibited different volatility characteristics. SHIBOR reached its peak around 2013, while M2 showed an overall upward trend, reflecting the dynamic changes in price and quantity indicators in the credit market. In Figure 5(b), the VIX index showed a significant peak in the financial crisis in 2008, the COVID-19 in 2020, and other periods, and remained relatively stable in the rest of the time, reflecting the cyclical characteristics of market volatility. These fluctuations corresponded to different stages of the FC, verifying the temporal and phased nature of FC fluctuations.



(a) Fluctuations in credit volume and price indicators (b) The fluctuations of the VIX indicator

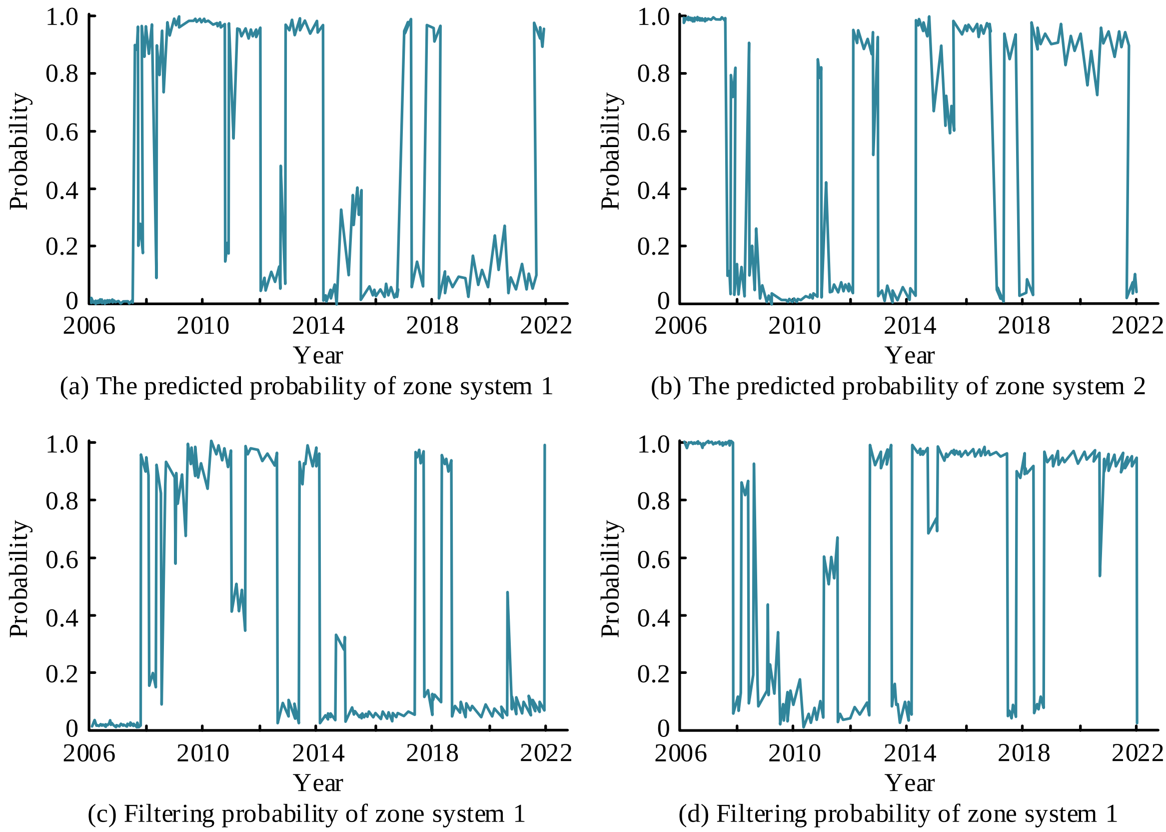
Figure 5. Fluctuations in the financial cycle

Table 2 shows the dynamic changes of major financial indicators from 2006Q1 to 2022Q4. From 2006Q1 to 2007Q4, it was in a low volatility zone, with M2 growth rate of 16.5-18.0 and SHIBOR of 2.8%-3.5%. The volatility of real estate and the Shanghai Composite Index was moderate, indicating a relaxed environment of credit expansion and a steady rise in asset prices. 2008Q1-2012Q4 entered a high volatility zone. Due to the impact of the crisis, the growth rate of M2 increased to 17.0-20.0, with SHIBOR ranging from 3.6% to 5.2%. The volatility of asset prices significantly expanded, reflecting severe fluctuations in the financial environment. 2013Q1-201914 was a return to low volatility, with indicators stabilizing and a mild FC. 2020Q1-202214 entered the high volatility zone again, and asset price fluctuations rebounded under the impact of the epidemic, reflecting the driving force of short-term risk events on the FC.

Table 2 Evolution characteristics of FC indicators in open economies (2006Q1-2022Q4)

Time period	Growth rate of M2	SHIBOR (%)	Real estate price volatility (%)	Volatility of the Shanghai Composite Index (%)	VIX index range system
2006Q1-2007Q4	16.5-18.0	2.8-3.5	5.2-7.8	12.3-15.6	District System 2
2008Q1-2012Q4	17.0-20.0	3.6-5.2	8.1-12.5	20.2-28.7	District System 1
2013Q1-2019Q4	10.0-13.5	2.3-3.2	4.5-6.8	10.5-14.2	District System 2
2020Q1-2022Q4	10.5-12.8	1.8-2.5	7.2-9.5	15.8-22.3	District System 1

Figure 6 shows the dynamic evolution characteristics of the filtering probability and prediction probability of the VIX index, depicting the regime transition law of market volatility. In Figs.6 (a) and (c), regime one represented a high volatility state, and its probability rapidly climbed to nearly 1 during the 2008 financial crisis. During the 2011 European debt crisis and the 2020 pandemic, there were also periodic peaks, reflecting the impact of risk events on market volatility. The probability remained low from 2012 to 2019, corresponding to a stable phase of low market volatility. In Figures 6 (b) and (d), System 2, as a low fluctuation state, maintained a probability of over 0.8 from 2004 to 2007, and continued to dominate after 2010, forming a clear complementarity with System 1. Comparing two probability sequences, the filtering probability had a more sensitive response to regime conversion, such as the steeper peak of the filtering probability during the 2008 crisis, while the predicted probability had a lag. This indicated that the market tended to maintain a low volatility state, while high volatility was often driven by short-term risk events [29]. This regional heterogeneity provided a key basis for understanding the time-varying characteristics of financial market volatility and also served as a reference for MP to respond to different volatility environments.



(a) The predicted probability of zone system 1

(b) The predicted probability of zone system 2

(c) Filtering probability of zone system 1

(d) Filtering probability of zone system 1

Figure 6. Filtering probability and prediction probability of the VIX indicator

3.2. The Dependence Characteristics of Policy Coordination Under Different Regional Systems

Figure 7 shows the dynamic transmission characteristics of financial variables on real prices, with periods 1, 3, and 6 corresponding to monthly, quarterly, and six-month periods. Figure 7(a) shows the impulse response of asset price shocks to CPI. The response of CPI to asset price shocks showed a trend change over time, with limited initial fluctuations in the first period, reflecting a lower immediate sensitivity of consumer prices to shocks. The significant increase in response amplitude in the third period indicated that the impact penetrated into consumer prices through channels such as income and expectations during the quarterly cycle. The peak response and persistence of Phase 6 have been further strengthened, verifying the time cumulative effect of asset price shocks on CPI. Figure 7(b) shows the impulse response of asset price shocks to PPI. The response curve of PPI was relatively flat, reflecting the differences in the transmission rhythm and sensitivity of the impact of production prices on asset prices compared to the consumption side.

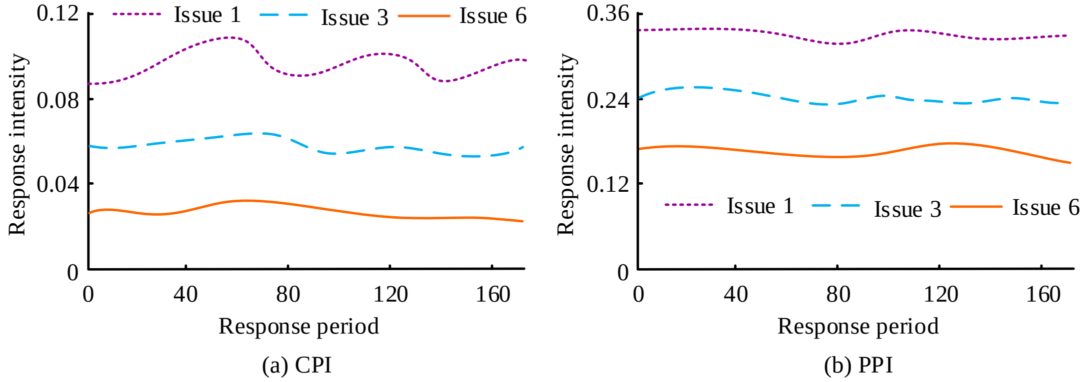


Figure 7. The equal-interval impulse responses of CPI and PPI under asset price shocks

Figure 8 reveals the heterogeneity of financial volatility transmission to real prices in different years through two curves from 2009 to 2016. In Figure 8(a), the response amplitude in 2009 was significantly higher than that in 2016, reflecting that asset price shocks have a stronger transmission efficiency to CPI through channels such as wealth effects and consumer expectations during the high FC. This required MP in an open economy to adapt to the FC stage, that is, during the expansion period of the cycle, it was necessary to strengthen the linkage monitoring between asset prices and consumer prices, and avoid excessive penetration of financial fluctuations into the consumer end. In Figure 8(b), the PPI's response to shocks increased faster in the early stages, indicating that the immediate transmission of asset fluctuations on the production side prices was more direct. In the context of an open economy, the effectiveness of ERP was more easily amplified by asset price fluctuations during the active period of the FC, which forced MP and ERP to adjust the focus weight of asset price channels according to the stage of the FC, thereby balancing internal and external price stability goals.

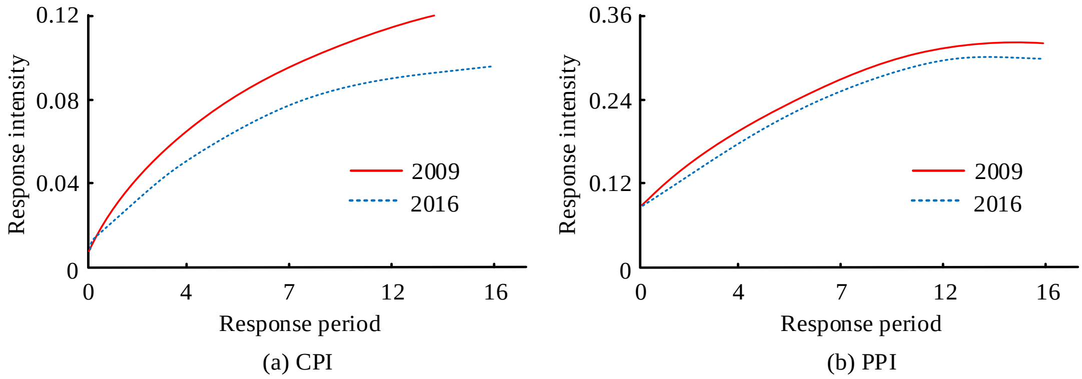


Figure 8. The point-in-time responses of CPI and PPI under asset price shocks

Table 3 shows the estimation data of the MS-VAR. There was significant heterogeneity in MP conduction. In Zone 1, the price-based MP lagged by a coefficient of 1.1862, highlighting the regulatory inertia of interest rate instruments on FCI and output Y_t. The M2 growth gap was only 0.0012 and not significant, reflecting the limited short-term effectiveness of quantitative policies. In Region 2, the lag coefficient of M2 was 0.0876, indicating a significant increase in the response coefficient of the output gap to policy shocks compared to Region 1, which confirmed the immediate expansion effect of quantitative tools in a relaxed environment. On the standard deviation of the disturbance term, the SE of each variable under regime 2 was lower than that under regime 1, indicating that the precision of policy regulation during the peak period has been enhanced.

Table 3. Estimation results of the MS-VAR model

Variable dimension	Project	FCI	Growth rate of M2	SHIBOR	Y_t
α	Zone system 1	-0.0321**	0.0012	-0.0405**	-0.0021
	Zone system 2	0.0513*	0.0008	0.0327	0.0035*
β_1	Zone system 1	0.1245	0.0217**	1.1862***	0.0423
	Zone system 2	0.3128**	0.0876***	0.9754**	0.2156***
β_2	Zone system 1	-0.0876	0.0103	-0.4987***	0.0152
	Zone system 2	-0.2765*	0.0432**	-0.3821**	0.1874**
Standard deviation of the disturbance term	Zone system 1	0.0385	0.0062	0.1873	0.0075
	Zone system 2	0.0972	0.0021	0.0534	0.0128
Model fitting index	Log-likelihood value (LL)	312.654			
	AIC Information Criterion	-18.235			
	SC Information Guidelines	-15.872			

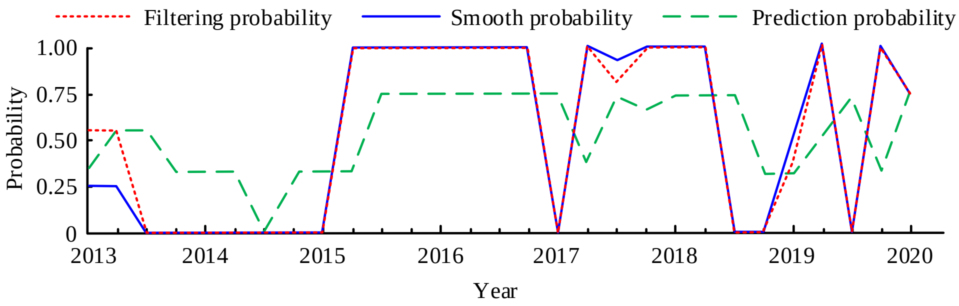
Note: ***, **, * indicate significance at the 1%, 5%, and 10% levels, and the coefficients are obtained through maximum likelihood estimation.

Table 4 presents the variable correlation coefficient matrix of the MS-VAR model under different regimes, revealing the impact of policy environment heterogeneity on variable linkage. In District One, there was a strong positive correlation between money supply and output gap of 0.6789, which was significant at the 1% level, confirming the outstanding direct regulatory effect of quantitative MP on output in this environment. The significant positive correlation between interest rates and output gap of 0.4456 reflected the linkage feature of output interest rates dominated by economic fundamentals. The significant negative correlation between FCI and interest rate, -0.4187, reflected the inverse adjustment relationship between stable financial markets and policy interest rates. In District 2, there was a significant positive correlation between FCI and interest rate conversion to 0.3462, indicating that the guiding effect of financial market fluctuations on policy interest rates was enhanced under the impact environment. The correlation coefficient between money supply and output gap has dropped to 0.5467 and the significance level has decreased, indicating a weakening of the marginal regulatory effect of quantity-based policies during the shock period. At the same time, the correlation between interest rates and output gap weakened to -0.0321 and was no longer significant, reflecting the limited direct impact of interest rate tools on output during the shock period.

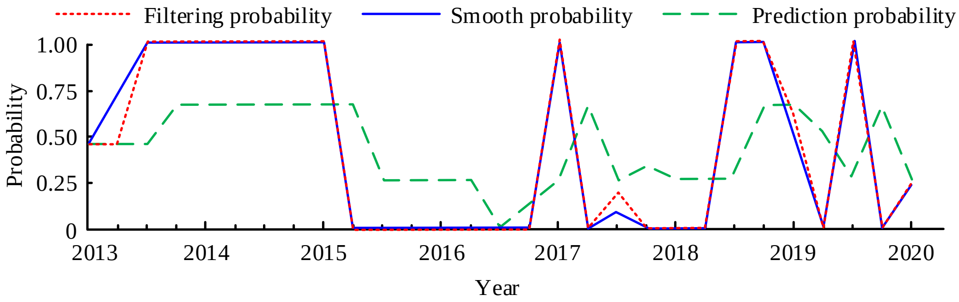
Table 4. Estimation results of the MP MS-VAR

	Variable dimension	FCI	M2	SHIBOR	Y_t
Zone system 1	FCI	1.0000	-0.1523	-0.4187**	-0.0965
	M2	-0.1523	1.0000	-0.2476	0.6789***
	SHIBOR	-0.4187**	-0.2476	1.0000	0.4456**
Zone system 2	Y_t	-0.0965	0.6789***	0.4456**	1.0000
	FCI	1.0000	-0.1178	0.3462*	0.2789
	M2	-0.1178	1.0000	-0.3789**	0.5467**
	SHIBOR	0.3462*	-0.3789**	1.0000	-0.0321
	Y_t	0.2789	0.5467**	-0.0321	1.0000

Figure 9 shows the partitioning characteristics of the MPMS-VAR model from 2013 to 2020, including the dynamic evolution of filtering probability, smoothing probability, and prediction probability for partitioning 1 and partitioning 2. In Zone 1, the filtering probability was sensitive to risk events and rapidly increased during the 2020 pandemic, with a peak close to 1.00, reflecting a high volatility state. The prediction probability lagged behind, indicating the market's inertial expectation of low volatility. As a low fluctuation state, the filtering probability and smoothing probability of Zone 2 mostly remained above 0.75 from 2013 to 2019, but significantly decreased in 2020 due to the epidemic. The frequent transition of the model regime, with an average maintenance of about 2 quarters, reflected the short-term volatility characteristics of the FC, providing a dynamic perspective for understanding the differences in MP transmission under different regimes.



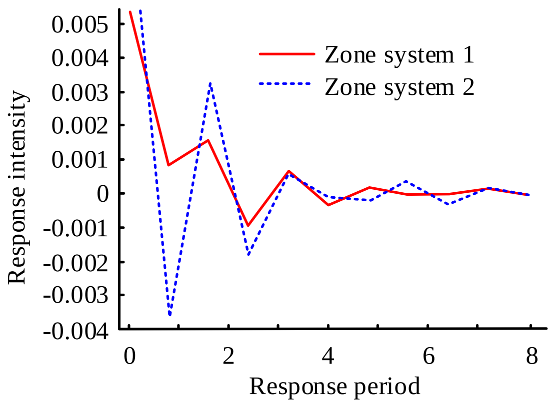
(a) Zone system 1



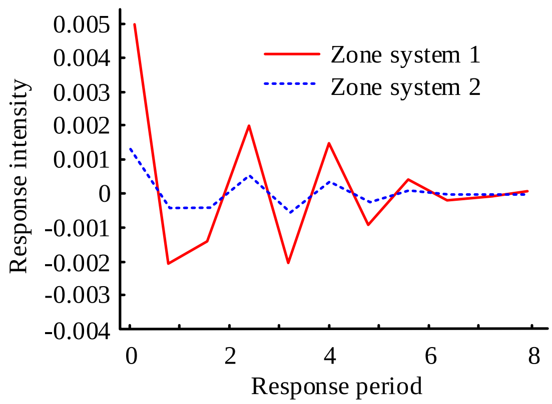
(b) Zone system 2

Figure 9. MP MS-VAR zone system characteristics

Figure 10 shows the Response Intensity (RI) of OG to BMMS and SHIBOR under different regional systems. In Zone 1, the RI of OG to BMMS shock reached about 0.005 at response period 0, then decreased to around 0 in response period 2, and then fluctuated and stabilized. The response strength to SHIBOR impact was about -0.004 at response period 0, rising to around 0 in response period 2, and then showing a fluctuating upward trend. In Region 2, the response strength of OG to BMMS shock was about -0.004 at response period 0, then risen to around 0 in response period 2, and slowly increased thereafter. The response strength to SHIBOR impact was about 0.002 at response period 0, and then fluctuated and decreased, tending to stabilize. Overall, there were differences in the response of OG to the impact of MP tools under different regional systems, which provided a visual basis for analyzing the effectiveness of MP in different economic states.



(a) The response of output growth to broad money supply



(b) Response of output growth to SHIBOR

Figure 10. Responses to OG under different regional systems

Figure 11 shows the response of different departments' credit to different exogenous shocks under the MS-DSGE model. In Figure 11(a), in the household sector, the credit RI showed different fluctuation trends with the response period under three policy environments: moderately tight, stable, and moderately loose. In Figure 11(b), the entrepreneurial sector showed an increase in RI under moderate tight shocks, a decrease followed by an increase under moderate loose shocks, and some fluctuations in a stable state. In Figures 11(c) and (d), the credit responses of the retail and government sectors also showed differences under different policy environments. These differences reflected that various departments had different patterns and degrees of credit response when facing external shocks due to their own economic characteristics and positions in the economic system.

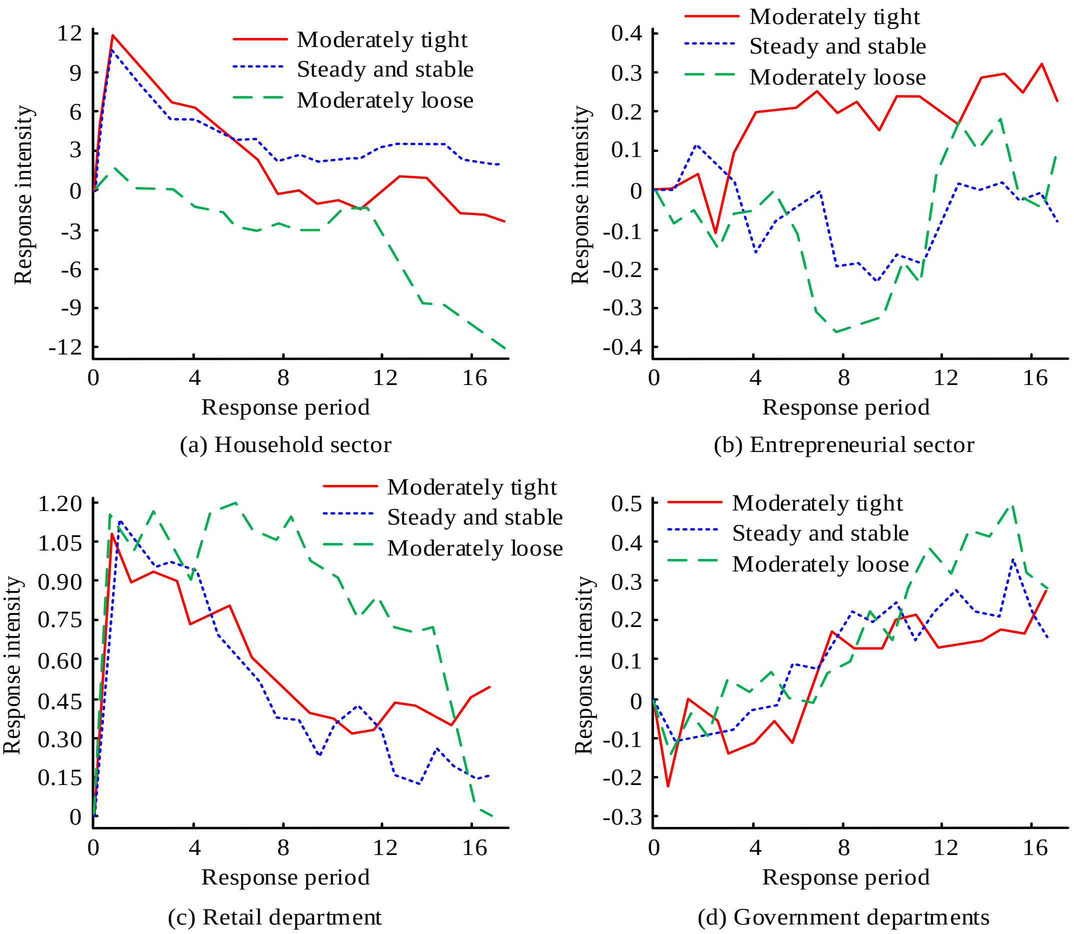


Figure 11. The response of credit to different exogenous shocks in the MS-DSGE model

This study aimed to predict the impact of the MP tool (interest rate adjustment) on RVs and compared the predictive performance of SVR with traditional Linear Regression (LR) and Random Forest (RF) models, as shown in Table 5. VR performed the best in both full and periodic samples, with Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) smaller than LR and RF, and R^2 closer to 1. This indicated that SVR could more accurately capture the nonlinear relationship between policy tools and ERF. During the financial contraction period, the prediction accuracy of all models was higher than during the expansion period, and SVR showed a 0.21 improvement in R^2 compared to LR during the expansion period, indicating that it is more adaptable to predicting policy effects with high volatility and strong nonlinearity. In summary, SVR effectively solved the complex dependence problem between policy effectiveness and FC in an open economy, quantifying the marginal effects of policies at different stages.

Table 5. Comparison of the prediction effects of three models on the impact of MP on ERF at various stages of the FC

Model	Evaluation index	Full sample prediction	The period of financial expansion	Financial contraction period
LR	RMSE	0.042	0.051	0.038
	MAE	0.031	0.039	0.027
	R^2	0.68	0.590	0.720
RF	RMSE	0.035	0.042	0.030
	MAE	0.025	0.031	0.021
	R^2	0.76	0.680	0.810
SVR	RMSE	0.028	0.032	0.023
	MAE	0.02	0.024	0.017
	R^2	0.85	0.800	0.890

4. Discussion

4.1. The Cyclical Heterogeneity Mechanism of Policy Transmission

The results of this study clearly reveal that the effects of MP and ERP are significantly dependent on the stage of the FC, and their core mechanisms are rooted in the state-dependent characteristics of financial intermediary behavior and market constraints. During the period of financial tightening and high volatility, the core contradiction of the economic system shifted from liquidity supply to liquidity demand and transmission channels. First, the credit supply capacity of financial intermediaries has shrunk. As stated by Ahmed et al. [29], traders and banks faced pressures from lower leverage, deteriorating asset quality, and sharp declines in risk appetite. Even if the central bank injects a large amount of liquidity into the banking system through easing operations (shown as high M2 growth), the damage to bank balance sheets and strict internal risk control will also cause banks to "be reluctant to lend". This will cause liquidity to stay in the inter-bank market, making it difficult to smoothly transmit it to the real economy. Secondly, the credit demand of micro entities has weakened. When businesses and households face extremely high uncertainty about the future, they will postpone investment and expenditure on durable consumer goods, and their financing needs will naturally decline. On the contrary, price-based tools (such as lowering SHIBOR) can more directly improve the cash flow of enterprises and residents by directly reducing the interest burden and marginal financing cost of existing debt. Thus, it can provide a relatively more effective transmission path in an environment where credit channels are blocked. This explains why in the same region, the adjustment coefficient of interest rate policy (1.1862) is significant and effective.

During the financial tightening period, the credit price indicator SHIBOR rose to 3.6%-5.2%, which was significantly higher than during the easing period, which directly led to the contraction of credit supply capacity and amplified fluctuations in the real economy. This process is similar to the mechanism by which debt constraints undermined the effectiveness of MP during the Eurozone crisis described by Herrala and Turk Ariss [30]. In other words, market discipline during the tightening period will endogenously form resistance to policy transmission, causing MPs of the same intensity to produce differentiated effects at different stages of the cycle.

In terms of asset price transmission, this study found that there is a significant linkage between the volume and price indicators of the real estate market and the foreign exchange market. Fluctuations in real estate indicators such as commercial housing sales area and unit price will affect the real effective exchange rate of the RMB through cross-border capital flow channels. This is essentially a reflection of the linkage between global risk preferences and domestic asset returns. During the financial boom, global capital inflows accelerated due to rising real estate income, putting up pressure on exchange rate appreciation. Capital outflows during the contraction period amplified exchange rate depreciation through risk contagion channels, forming a cycle-driven ERF cycle. Through the TVP-VAR model, this study further reveals that the linkage between China's FC and macroeconomics exhibits the characteristics of "moderate in the short-term and intensified in the medium-term." The impact of financial variables on the macroeconomy is limited in the month, significantly enhanced in the quarter, and further intensified in the half-year. This characterization of the dynamic path more fully captures nonlinear dynamics through a multi-model combination compared to Franta's [31] quantile regression analysis of the US FC.

In addition, the MS-VAR results of this study show that in Region 1 (financial tightening period), the short-term effect of quantitative MP (M2 growth gap) is limited (the coefficient is only 0.0012 and not significant), while in Region 2 (financial easing period), the response coefficient of the output gap to policy shocks increases significantly. This regional dependence contrasts with Mansour-Ibrahim's [32] findings on the convergence of financial and business cycles in the Eurozone, highlighting the characteristics of China's FC being more affected by domestic policies and more volatile.

4.2. The Deep Logic of Policy Implications

The results of this study provide forward-looking and practical implications for policy coordination in an open economy. To more clearly display the logical chain from empirical findings to policy practice, Table 6 systematically sorts out the core conclusions, derived policy implications, and expected macro-stabilizing effects. For example, the M2 growth gap coefficient based on MS-VAR Region 1 is not significant (0.0012). Policies need to prioritize the use of price-based tools during the period of financial tightening and embed leverage-sensitive regulatory factors to ease the contraction of the credit market. TVP-VAR shows that asset price shocks peak in response to CPI and PPI within 6 months. It is recommended to establish a linkage mechanism between real estate fluctuations and cross-border financing. When house price fluctuations exceed 12.5%, the macro-prudential coefficient will be automatically increased. The SVR model predicts that the full-sample R^2 of MP on ERFs reaches 0.85, indicating that machine learning tools can improve the foresight of policy coordination. To block the negative feedback loop between asset prices and cross-border capital, it is advocated to establish a macro-prudential spatial and cyclical dual-dimensional framework.

Table 6. Correlation table of empirical findings, policy implications and expected macro effects

Empirical findings	Policy implications	Expected macro effects
In Region 1, the adjustment coefficient of interest rate policy on FCI is 1.1862 (1% significant), and the M2 growth gap coefficient is 0.0012 (not significant); in Region 2, the response coefficient of M2 to the output gap is 0.2156 (1% significant).	High-volatility zones prioritize using interest rates (price-based) to regulate financial conditions, while low-volatility zones prioritize using M2 (quantity-based) to stimulate output.	Avoid the "liquidity trap" caused by quantity-based policies in high-volatility areas and the "cost impact" caused by price-based policies in low-volatility areas, and reduce the cost of policy trial and error.
There is a time lag in the transmission of asset price shocks to CPI: significant in 3 months, peaking in 6 months, and PPI response is gentle	Strengthen price-end transmission monitoring, focus on the 3-6 month transmission window, and take into account the differences between the consumption side and the production side.	Predict the transmission peak of asset prices to CPI in advance, and promptly introduce hedging policies (such as raising interest rates to curb demand) to avoid the spread of inflation.
The R^2 predicted by SVR for MP-ERV during the financial expansion period is 0.21 higher than that of LR, and the nonlinear characteristics are significant.	During the financial expansion period, SVR is used to optimize MP's prediction of ERV. During the contraction period, a linear model can be combined to balance accuracy and cost.	Accurately predict the impact of MP on ERV through SVR, adjust capital flows in advance and reduce exchange rate overshooting
MS-DSGE shows significant heterogeneity in the credit response of households/enterprises/government sectors to policy shocks	Formulate segmented policies for households, businesses, and governments, and embed leverage-sensitive supervision	While maintaining exchange rate flexibility, we should stabilize domestic price expectations, reduce the interference of external fluctuations on internal equilibrium, and enhance macroeconomic resilience.

4.3. Implications for China’s Policy Coordination and International Applicability

The conclusions of this study have clear guiding significance for the coordination between the People's Bank of China and the State Administration of Foreign Exchange in the future FC. During the period of financial tightening, the People's Bank of China should focus on maintaining credit market stability through price-based and structural instruments. The State Administration of Foreign Exchange needs to strengthen macro-prudential management of cross-border capital flows and closely monitor and manage the risk of exchange rate depreciation caused by capital outflows. During the financial boom, the two departments should establish a joint monitoring and response mechanism to dynamically adjust macro-prudential parameters based on the fluctuation threshold of core asset prices, such as real estate, and jointly prevent asset bubbles and exchange rate overshooting caused by hot money inflows.

In addition, the analytical framework and conclusions of this study also have reference value for other open economies. Small open economies such as South Korea and Singapore are also deeply involved in the global financial crisis, and their exchange rate regimes and monetary policies face similar challenges. They can draw on the multi-dimensional indicator system of FCs constructed in this study to more accurately identify the financial stage in which their country is located. At the same time, the SVR prediction model verified in this study can be used as an effective auxiliary tool for central banks and financial regulatory agencies to optimize the coordination of MP and ERP. In particular, Singapore is highly dependent on the real estate and financial markets. It can learn from the "real estate fluctuations - cross-border financing" linkage mechanism proposed in this study and implement more spatially differentiated macro-prudential supervision to enhance the resilience of its policy framework in response to GFC shocks.

5. Conclusion

This study constructed an FC and macroeconomic variable indicator system covering dimensions such as credit and asset prices, and combined high-frequency data from China from January 2008 to December 2023. Using TVP-VAR, MS-VAR, and MS-DSGE, the study analyzed the FC dependence characteristics of MP and ERP in the context of an open economy. The results indicated that the FC had a significant impact on policy effectiveness. During the financial tightening period, the transmission efficiency of MP was systematically weakened. According to the MS-DSGE, the inflation response coefficient at this time was 1.5. In the estimation results of the MS-VAR, the short-term effectiveness of quantitative policies was limited, and the M2 growth gap coefficient in Zone 1 was only 0.0012 and not significant. There were differences in the effectiveness of output regulation during periods of loose regulation, and the response coefficient of the output gap to policy shocks in Region 2 has significantly increased. At the same time, ERP was driven by cross-border capital flows, and there was a significant linkage between the sales area and unit price of commercial housing in the real estate market and the actual effective exchange rate of RMB in the foreign exchange market. Asset price fluctuations affected exchange rates through cross-border capital flows, forming a cycle-driven ERF loop. The prediction results of SVR showed that its full sample R^2 on the impact of MP on ERV was 0.85, verifying its ability to capture the nonlinear relationship between FC and policy effects. The research results have deepened the understanding of the macro financial dynamics of an open economy and provided key decision-making references for policy makers. This study contributes to enhancing the foresight, effectiveness, and coordination of policies, strengthening the resilience of macroeconomic and financial systems, and has important practical significance for maintaining the internal and external balance and long-term stability of open economies.

6. Declarations

6.1. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.2. Funding

The research is supported by 2020 Jiangsu Provincial University Philosophy and Social Science Fund Project: Research on the Influence of Jiangsu's 13 Municipal Advanced Manufacturing Industry Clusters on Regional Economic Development (Project number: 2020SJA0666).

6.3. Institutional Review Board Statement

Not applicable.

6.4. Informed Consent Statement

Not applicable.

6.5. Declaration of Competing Interest

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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