*Journal of Infrastructure, Policy and Development* 2024, 8(16), 9227.
https://doi.org/10.24294/jipd9227

Article

# Does China's stock market volatility affect agricultural loan market volatility?

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**CITATION**

Yan K, Yu H. (2024). Does China's stock market volatility affect agricultural loan market volatility?. Journal of Infrastructure, Policy and Development. 8(16): 9227. https://doi.org/10.24294/jipd9227

**ARTICLE INFO**

Received: 20 September 2024
Accepted: 21 October 2024
Available online: 31 December 2024



**Abstract:** This study uses a Time-Varying Parameter Stochastic Volatility Vector Autoregression (TVP-SV-VAR) model to conduct an empirical analysis of the dynamic effects of China's stock market volatility on the agricultural loan market and its channels. The results show that the relationship between stock market and agricultural loan market volatility is time varying and is always positive. The investor sentiment is a major conduit through which the effect takes place. This time-varying effect and transmission mechanism are most apparent between 2011 and 2017 and have since waned and stabilized. These have significant implications for the stable and orderly development of the agricultural loan market, highlighting the importance of the sound financial market system and timely policy, better market monitoring and early warning system and the formation of a mature and sound agricultural credit mechanism.

**Keywords:** stock market volatility; investor sentiment; agricultural loan market volatility; TVP-SV-VAR model

**JEL Codes:** G12 (asset pricing; trading volume; bond interest rates); Q14 (agricultural finance); C32 (time-series models; dynamic quantile regressions)

## 1. Introduction

Financial market risk affects agricultural credit through changes in the supply and price of credit, as well as changes in interest risk and fund availability (Barry et al., 1981; Hughes, 1981). During the 1970s and 1980s, very high interest rates and high risk in the US financial market affected large scale farm owners and lenders especially those with high debt and high leverage (Barry and Lee, 1983). Likewise, financial insecurity in Europe impacted the agriculture through enhancing the variation in agricultural credit rates among the EU member countries (Pietola et al., 2011). In the West African countries, it has also been established that financial market risks influence the supply and availability of agricultural credit (Kassouri and Kacou, 2022). The stock market as one of the sub-markets in the capital market tends to illustrate the overall risk level of the financial system in the economy (Shan and Wang, 2024) and any changes in the stock market are likely to have direct effects on the agricultural loan market via changes in the financial environment.

Investigations on the effects of stock market volatility on investments indicate that stock prices continue to play a role in determining the results of investments despite other factors (Fischer and Merton, 1984). Nevertheless, although prior research has analyzed the overall connection between financial market fluctuations and agriculture credit, the impact of the stock market has been relatively understudied. Many previous works addressing this subject have used methods such as VAR or

SVAR, which impose fixed coefficients and disturbance variances and therefore are not suitable for capturing time-varying impacts (Zhang et al., 2022). On the other hand, Time-Varying Parameter Stochastic Volatility Vector Autoregression (TVP-SV-VAR) model proposed by Primiceri (2005) is less rigid since it allows time variation in both coefficients and the variance-covariance matrices. This model is able to introduce time-dependency and volatility clustering in the covariance matrix of multivariate financial returns to yield a comprehensive depiction of the dynamic evolution of cross-section dependence of financial markets particularly stock markets. But the TVP-SV-VAR model has not been employed to evaluate the impact of stock market volatility on the agricultural loan market which is still a relatively unexplored field of study.

The nature of the Chinese stock market is that there are a large number of individual speculators, so there is a large fluctuation in stock prices (He et al., 2024). Additionally, the financial services system in rural China is still in its early stages of development (Zhang and Yu, 2023). Compared to developed countries, China, as an emerging country in transition, has a less mature financial market (Lü et al., 2023), with both the stock market and agricultural loan market exhibiting high volatility and sensitivity to external influences. As a crucial component of the financial market, stock market volatility inevitably impacts the agricultural loan market. Modern behavioral finance theory has significantly relaxed the stringent assumptions of the traditional efficient market hypothesis by incorporating psychological and behavioral factors of investors into the existing financial analysis framework, leading to a more realistic understanding and interpretation of financial market dynamics. Research by Xu and Zheng (2023) found that the impact of the COVID-19 pandemic led to investor pessimism, which indirectly worsened corporate financing constraints. Therefore, stock market volatility might also affect investor confidence, indirectly influencing the agricultural loan market. How does stock market volatility impact the agricultural loan market? Does stock market volatility affect the agricultural loan market through investor sentiment? What is the efficiency of this transmission? These questions have significant theoretical value and policy implications, yet few scholars have provided substantial responses. This study, using China as a case example and employing impulse response analysis with the TVP-SV-VAR model, offers a new explanation of the impact of stock market volatility on agricultural loan market volatility and provides empirical evidence to address these questions more comprehensively. Based on this, the study has two hypotheses: first, that the impact of stock market volatility on agricultural loan market volatility exhibits time-varying characteristics and is primarily positive, given the complex interrelations under different development stages and external influences; second, that investor sentiment is a significant channel for the effect transmission, due to the agricultural loan market's sensitivity to changes in investor sentiment.

This study incorporates stock market volatility, investor sentiment, and agricultural loan market volatility into a single TVP-SV-VAR model to investigate whether an increase in stock market volatility leads to a rise in agricultural loan market volatility, and to examine the existence and specific mechanisms of this positive relationship in detail. As stock market volatility increases, retail investors tend to exhibit stronger speculative impulses and behavioral tendencies, aiming for higher short-term investment returns through active participation in financial market activities (Xing and Guan, 2020). Stock prices may increase because of sentiment of investors, this leads to increased investment (Morck et al., 2000). These fluctuations impact the psychology of the investors and subsequently their decision making and behavior in the market. This emotional transmission may extend to other financial markets including the agricultural loan market (Akay and Hirshleifer, 2021). Investor sentiment is considered a significant channel for effect transmission because emotional fluctuations can cause dramatic market swings in the short term, impacting investor decisions and market participants' behavior (You et al., 2024; Xing and Wang, 2022; Gao and Liang, 2023).

The contributions of this study are mainly reflected in two aspects. Theoretically, it focuses on the impact of the stock market on the agricultural loan market and its transmission mechanisms, specifically examining an important secondary sub-market within the financial sector. Methodologically, the study innovatively applies the TVP-SV-VAR model to analyze the issue from a time-varying perspective. The significance of this research is twofold. Firstly, from a theoretical standpoint, gaining a deeper understanding of the potential influence between these two markets can provide a more comprehensive insight into the stability of financial markets. Exploring how stock market volatility transmits to the agricultural loan market helps in better understanding the specific impact mechanisms involved. Secondly, as the agricultural loan market is a critical financing channel for supporting agricultural production and rural development, its stability and healthy development are crucial for the rural revitalization in China. The Central Document No. 1 of 2023 emphasized the need for financial institutions to provide strong financial support for rural revitalization areas and to increase loan support. The Central Document No. 1 of 2024 called for enhanced coordination between fiscal and financial policies and the implementation of pilot programs for loan interest subsidies in agricultural sectors such as high-standard farmland and facility agriculture. This research can provide valuable references for policymakers and regulatory agencies to formulate scientific and effective policy measures, thereby promoting the healthy development of the agricultural loan market.

This article is structured as follows: Sections 2 and 3 disclosed the synopsis of studies and methods. Section 4 summarizes main findings. Section 4 presents empirical results and provides further discussions. Section 5 concludes.

## 2. Literature review and theoretical framework

### 2.1. Literature review

The stock market is a crucial component of the financial market, while the agricultural loan market is an important sector within it. The time-varying characteristics of the impact of stock market volatility on agricultural loan market volatility are influenced by various factors such as capital flows, price elasticity of demand, and macroeconomic conditions. Albulescu (2021) found that health crises exacerbated the realized volatility of the S&P 500 index in the United States. Corbet et al. (2021) showed that the COVID-19 pandemic had an exceptionally significant and persistent impact on the Chinese financial market. In terms of the connection between macroeconomic policies and financial market volatility, Li and Zheng (2022) discovered that fiscal policy significantly affects the stock market at the micro level, while trade policy has a notable impact on both the stock and bond markets. Liu and Shen (2022) indicated that central bank communication has a stabilizing effect on the financial market, mitigating market volatility. Thiem (2020) found that, compared to the U.S., the Japanese stock market, particularly the exchange rate volatility index, is more affected by economic policy uncertainty (EPU) spillovers. Regarding the transmission of financial market volatility, Huang et al. (2021) discovered significant group relationships in the financial market, including stocks, commodity futures, and currency markets, as well as bonds and foreign exchange markets. Different types of "black swan" events have shown significant differences in their impact on the convergence level of the Chinese financial market. Fang and Su (2021) found that uncertainty is a key channel for the transmission of financial market volatility in the U.S., with financial uncertainty being the most central node in the financial market network.

Managing and predicting financial market volatility is crucial for understanding and forecasting volatility. In the field of stock market volatility research, scholars from various countries have studied factors influencing volatility, market characteristics, and volatility in emerging markets. Emerging stock markets are characterized by significant volatility, and time series econometric models can be used to quantify financial volatility (Schwert, 1990). Xu (2018) found that stock index futures speculators generally did not have a significant impact on stock market volatility. Yu (2013) discovered that from 2003 to 2011, the volatility directions of the Chinese government bond market and the stock market were significantly opposite.

In the study of agricultural loan market volatility, only a few scholars have explored the volatility of the agricultural loan market and its influencing factors. LaDue and Leatham (1984) analyzed the impact of changes in the financial market environment on agricultural lenders and borrowers from a historical perspective, focusing particularly on the challenges posed by interest rate fluctuations. Hubbs and Kuethe (2017) used a structural imbalance model to highlight supply and demand volatility in private markets for non-real estate agricultural loans. Kuethe and Hubbs (2021) investigated the relationship between economic fluctuations in the agricultural sector and financial distress, and developed an effective warning model.

In the relationship between financial markets and the agricultural loan market, existing research indicates that factors such as the high variability of market interest rates, changes in monetary policy, and trends in financialization have intensified the relationship between agriculture and finance, presenting unprecedented challenges for both agricultural lenders and borrowers. The financial liberalization, shift in the mode of monetary policy and rapid changes in inflation have greatly affected the financial market place for agricultural lending and borrowing. Interest rates in the market have greatly shifted, and rural lending institutions cannot afford to be isolated from these market forces (LaDue and Leatham, 1984). The political decision to target monetary aggregates since 1979 has made interest rates more volatile and the high capital intensity and increased use of debt financing in the last decade has made the capital formation and financial performance of the agriculture sector more sensitive to interest rates change (Drabenstott and Heffernan, 1984). Since 2006, due to financialization, the fluctuation in price of food and agricultural products has increased the role of agriculture and finance (Clapp et al., 2017). Regmi and Featherstone (2022) revealed that the level and proportion of agricultural loans in the United States are U-shaped in the context of bank competition. About 40 percent of the US farm debt is with agricultural banks and a decline in the number of agricultural banks or reduced competition amongst agricultural banks can harm relationship lending.

In terms of the impact of financial market volatility on agricultural loan market volatility, scholars from various countries have examined this issue from perspectives such as agricultural loan interest rates, volatility transmission under macroeconomic conditions, and the effects of government policy interventions. Regarding agricultural loan interest rates, Pietola et al. (2011) found that financial instability in Europe has permeated the agricultural sector, leading to increasing disparities in agricultural credit rates among countries. Barry and Lee (1983) noted that unprecedentedly high interest rates and volatility in the financial markets have diminished the hedging capability of agricultural credit in the U.S. domestic and international markets, with the most severe effects on relatively fewer but highly leveraged and debt-laden large farm owners and lenders. In the context of volatility transmission under macroeconomic conditions, Shane and Liefert (2000) found that macroeconomic factors play a crucial role in transmitting financial market volatility to the agricultural loan market. International financial crises and their effects on key macroeconomic variables have had significant impacts on agricultural trade and income, including exchange rates, consumer income, and interest rates. McKibbin et al. (2001) explored the impact of the Asian financial crisis on global economic adjustments and its implications for U.S. agriculture, revealing that it not only reduced U.S. exports but also led to lower interest rates and reduced costs for production inputs. Regarding the effects of government policy interventions, Ghosh (2020) documented that, even in a context of tightening monetary policy, there has been an expansion of agricultural loan volumes and a reduction in interest costs due to political intervention, highlighting the importance of government involvement in the functioning of credit markets.

The polarization of investor sentiment can lead to systemic risks in the market, especially during sudden financial events (Yu et al., 2022). In the research on the transmission effects of investor sentiment, scholars have primarily focused on its impact on the stock market. Bourveau and Schoenfeld (2017) found that high levels of ESG (Environmental, Social, and Governance) information disclosure are generally perceived as positive signals among investor groups. Ordinary investors exhibit higher stability in their emotions when faced with such favorable information, which leads to more rational decision-making. Wang and Liu (2024) discovered that increased goodwill from mergers and acquisitions heightens investors' pessimistic tendencies. When the market encounters adverse news, this sentiment can trigger a herd effect, resulting in large-scale stock sell-offs and significantly increasing the risk of market crashes. Zhao et al. (2024) showed that uncertainty in monetary and foreign exchange policies has a significant negative impact on the underpricing of IPOs on the Sci-Tech Innovation Board, with investor sentiment playing an intermediary role. Wen (2017) found that changes in monetary policy can significantly alter investor sentiment and have a substantial impact on stock prices. Li et al. (2023) explored the indirect time-varying impact mechanisms of interest rates on stock prices under different economic cycles, using investor sentiment as an intermediary variable. Fewer scholars have studied the impact of investor sentiment as a transmission effect on other economic variables. Xu and Zheng (2023) found that the pandemic-induced prolonged low state of investor sentiment led to worsening corporate financing conditions when investor sentiment was included as an intermediary variable in their analytical framework.

In the application of the TVP-SV-VAR model, scholars from various countries have extensively used this model to study the relationships between different economic variables. Reif (2022) examined the time-varying dynamics of the German economic cycle over the past fifty years, revealing significant changes in long-term growth rates and shock volatility over time. Aastveit et al. (2023) investigated whether the Federal Reserve systematically responds to house prices and stock prices, and whether this response changes over time. Rodriguez et al. (2023) analyzed the impact of external shocks on output growth and inflation in Peru. Lü et al. (2023) studied the efficiency of monetary policy rate transmission to bond and credit markets. Zhou et al. (2023) explored the relationships between climate policy uncertainty, oil prices, and renewable energy consumption. Cui and Zhao (2023) conducted a dynamic analysis of the relationships and transmission mechanisms between economic policy uncertainty, entrepreneurial confidence, and export trade in China. Wang et al. (2023) investigated the dynamic spillover effects of U.S. fiscal policy, monetary policy, and their interactions on the Chinese economy, providing a detailed analysis of three transmission channels: interest rates, exchange rates, and asset prices. Song and Zhang (2023) systematically analyzed the time-varying dynamic relationships among economic policy uncertainty, financial stability, and economic volatility in China.

In summary, although financial market volatility, stock market volatility, and investor sentiment have become popular research topics, there are still limitations in the existing literature. First, scholars have primarily focused on the interactions between macroeconomic variables, while research on agricultural loan market volatility at the micro level is relatively scarce, and studies on the impact of stock market volatility on agricultural loan market volatility are even fewer. Second, while the effect of investor sentiment on the stock market is a popular research area, studies on its role as an intermediary transmission mechanism are limited. Existing research mainly concentrates on the direct impact of investor sentiment on the stock market, with insufficient empirical analysis on how stock market volatility affects investor sentiment and subsequently transmits to the agricultural loan market. Third, although the TVP-SV-VAR model is widely used in macroeconomic variable research, its application in micro markets, particularly in the study of agricultural loan market volatility, remains relatively rare. While some studies have explored the transmission mechanisms of investor sentiment (e.g., You et al., 2024; Li et al., 2023), systematic investigations into the effect transmission mechanisms of investor sentiment on specific markets, such as the agricultural loan market, are still lacking.

## 2.2. Theoretical framework

Being one of the subsectors of the financial sector, the stock market is affected by numerous factors such as economic factors, political factors, national policies, and investor sentiments (Luo, 2020). However, the agricultural loan market is largely influenced by national and local government policies and regulation, apart from the financial institutions and the producers of agricultural products. Since all the markets are interrelated, changes in the stock market may indirectly affect the agricultural loan market in terms of liquidity, investor confidence, and changes in the general economic policies. The way these dynamics work is important for evaluating the stability of agricultural credit, especially in highly volatile markets.

The Chinese capital market is highly dominated by individuals investing in the market and hence distinguishes it from the institutional markets as are seen in the U.S or Europe. Data show that of the 160 million investors in China's stock A-share market, more than 90% are retail investors (Yi, 2020). This dominance of retail participants has fundamental implications on the behaviour of the markets since retail investors are known to have higher risk-taking propensity and short term orientation compared to institutional investors (He et al., 2024).

The high proportion of retail investors also leads to increased fluctuations in the market, since their actions are based on emotions, information from the media and rumors received on the stock exchange. This makes the Chinese market highly sensitive to market sentiments, and this is because, during periods of volatility, the retail investors will either ‘buy high and sell low’ or they will be herding during periods of market turmoil (Wang and Wang, 2014). It is important to grasp this relationship in order to assess how fluctuations in stock market can impact other markets, for instance the market for agricultural loans, via factors like investors’ sentiment.

The stock market serves as a barometer of the macroeconomy, reflecting the state of economic operations, with stock market return volatility providing a direct measure of market risk (Zhu et al., 2019). As a crucial component of the capital market, the stock market is also a major source of risk spillovers (Shan and Wang, 2024). Its fluctuations not only reflect changes in the macroeconomic environment but also directly impact investor confidence, the operation of commercial banks, and the formulation of national macroeconomic policies. These factors, in turn, can directly or indirectly affect the agricultural loan market.

Firstly, in China’s capital market, retail investors make up a significant portion and often lack specialized investment knowledge and effective information, their psychology may be influenced by short-term preferences and biased opinions, leading to noise trading (Wang and Wang, 2014). As an emerging market characterized by short-term trading and a “buy high, sell low” strategy, and with incomplete regulation, the Chinese stock market experiences substantial market frictions, bubbles, and noise behaviors due to investor reaction biases (Wang et al., 2009). Investor sentiment is typically seen as irrational investment behavior driven by psychological factors, leading to systematic biases in future predictions (Yang et al., 2021). Giglio et al. (2020) found through a survey of retail investors that during the peak of the pandemic, following the crash of U.S. stocks, ordinary investors had a more pessimistic outlook on short-term economic conditions and the stock market. Gao and Liang (2023) found that as stock market returns rise, investor sentiment remains high, and investors hold an optimistic view of future stock market trends; conversely, when returns decline, investor sentiment also falls, and investment enthusiasm wanes. Ritter, in the market mood hypothesis, points out that when stocks generally rise and the market mood is exuberant, investors face higher risks. At this time, the herd mentality of investors can lead to a “herding effect” (Xing and Wang, 2022). When there are severe fluctuations or crashes in the stock market, it can trigger panic emotions, which may spread to other asset classes, leading to price declines or increased volatility (Shan and Wang, 2024). Stock market volatility significantly impacts investor sentiment, which in turn affects their psychological expectations and risk preferences. The transmission mechanism of investor sentiment is shown in **Figure 1**, an increase in stock market volatility indicates substantial market price swings, reflecting either market highs or lows, which increases market uncertainty and risk, thereby undermining investor confidence, reducing sentiment, leading to decreased agricultural loans, and increasing agricultural loan market volatility.

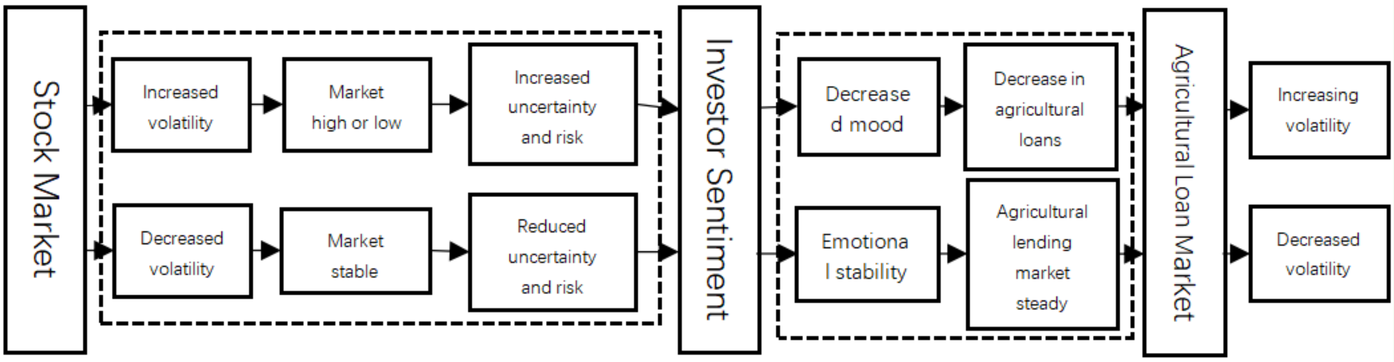


**Figure 1.** Investor sentiment transmission mechanism.

Second, with the increasing interconnectedness and business cooperation between different sectors of China's financial system, the correlation between financial markets has been continuously strengthening. This means that financial institutions not only face risks in their own operations but are also impacted by the spillover effects of stock market risks on commercial banks (Sun and Zhu, 2022). Stock market risks may trigger liquidity crises in commercial banks. When the stock market is performing well, it may lead to a liquidity shortage crisis, while poor market performance may result in excess liquidity. Stock market volatility affects the sustainable and stable operations of commercial banks, forcing them to maintain high liquidity levels, which in turn impacts the quality of bank loans by reducing effective credit demand and high-quality clients (Lu, 2008). As commercial banks are key participants in the agricultural loan market, their performance inevitably affects the volatility of the agricultural loan market as well.

Third, a stock market crash or sharp decline may trigger investor panic, leading to instability across the entire financial system, and stock market risk events could also result in large-scale capital outflows (Shan and Wang, 2024). When stock market volatility threatens macroeconomic stability, central banks typically employ various conventional and unconventional monetary policy tools, as well as central bank communication, to stabilize the market. In their paper "Credit, Money, and Aggregate Demand", Bernanke and Blinder (1988) proposed the monetary policy credit transmission framework, emphasizing the crucial role of bank credit in achieving monetary policy goals. Central banks aim to fine-tune credit market interest rates and liquidity conditions through the formulation and implementation of monetary policy tools. There is a confirmation of the effectiveness of traditional money supply instruments in capital markets (Fang et al., 2011; Fernández-Amador et al., 2013;

Zheng et al., 2010), and the effect of non-traditional monetary instruments on stock market volatility has also been studied by scholars (Haitsma et al., 2016; Hung and Ma, 2017; Moessner, 2014). It has been established that information from central banks has a great impact on stock returns (Zou et al., 2020) and that it helps to minimize stock market fluctuations and thus keep asset prices stable (Hayo and Neuenkirch, 2015). In some large-scale non-expected shocks, the communication of the central bank can effectively reduce the volatility of the stock market in the short term (Wang and Liu, 2022). In addition to impacting the return volatility of the stock market, it also passes through its effectiveness to other markets (Zhu et al., 2019), while among others, the credit channel is effective for the People's Bank of China's monetary policy on the loan market (Breitenlechner and Nuutilainen, 2023). It is important for agricultural lending that the central bank written communications can guide the markets and stabilize the financial environment by using reports on financial stability (Du et al., 2023). It is found that central bank communication can change the market expectation, shift the stock prices and in an indirect manner influence the lending behavior. Research shows that positive communications from the central bank have a positive effect on stock prices and that these can spur lending activity.

Affected by the fluctuation of the stock market, the three major players have different concerns and objectives, and therefore implement contrasting operational responses. This, in turn, leads to variations in the agricultural loan market as depicted in the **Figure 2** below.

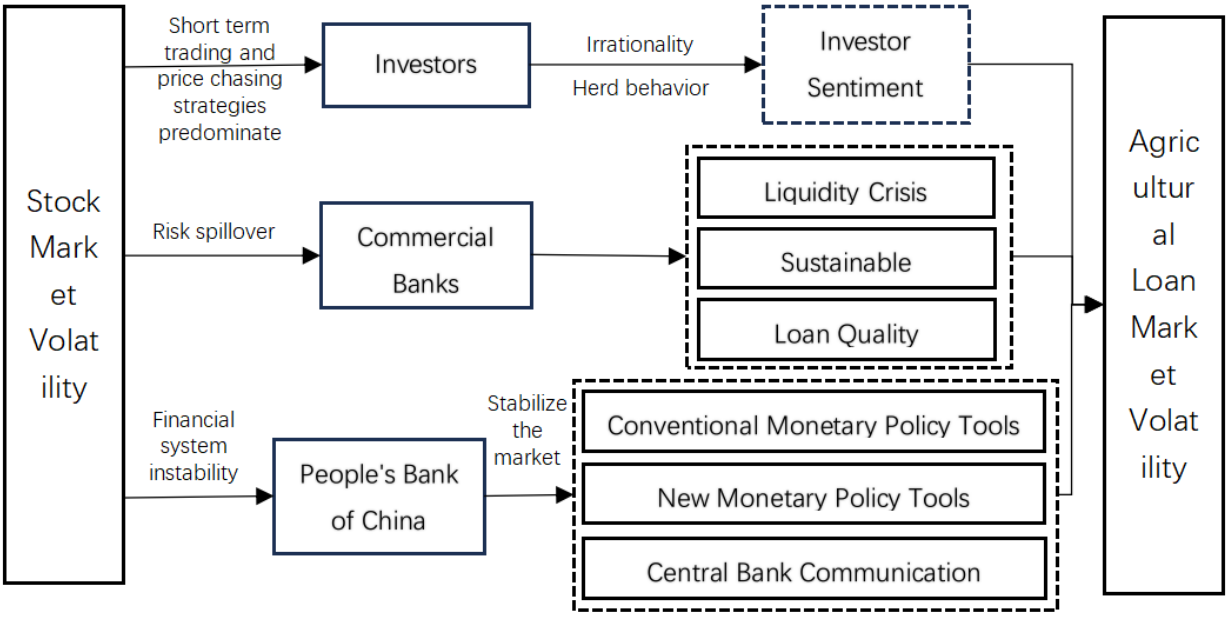


**Figure 2.** Theoretical mechanism of stock market volatility in china impacting the agricultural loan market based on stakeholder behavior.

**Causal relationships between stock market volatility and investor sentiment**

The relationship between the stock market and investor sentiment is bidirectional, with each influencing the other. While stock market volatility can affect investor sentiment by increasing uncertainty and affecting investor psychology, numerous studies have shown that investor sentiment itself can drive stock market fluctuations.

For instance, when the investors are optimistic, then they take on more risk and push up the price of stocks, while when the investors are bearish, they sell assets and thus pull down the prices of stocks (Ren et al., 2024).

In this study, the focus is on how stock market volatility influences investor sentiment, which in turn affects the agricultural loan market. However, it is also recognized that investor sentiment can act as a feedback loop, further amplifying stock market volatility. As investor confidence wanes in response to market downturns, this can lead to further price declines, creating a self-reinforcing cycle of volatility. Thus, the causal relationship between stock market fluctuations and investor sentiment is dynamic and operates in both directions, with sentiment both influencing and being influenced by market conditions.

## 3. Data and methods

### 3.1. Data and stationarity tests

Before going any further in the estimation process using the TVP-SV-VAR model, it is crucial to check for the integration of all the variables since the model does not allow for unit root. To test for stationarity, the Augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) test were applied to all variables: stock market fluctuation, investors' attitude, and fluctuation in agricultural loan market.

The results of the two tests shown in **Table 1** show that all the variables are stationary at their levels, thus rejecting the null hypothesis of unit root at 1% level of significance. These results provide evidence that the data do not have a unit root, which makes the TVP-SV-VAR model appropriate.

**Table 1.** Stationarity test results (ADF and PP tests).

| Variable | ADF Test Statistic | PP Test Statistic | *Critical* Value (1%) | Conclusion |
|---|---|---|---|---|
| Stock Market Volatility | −3.89 | −4.12 | −3.50 | Stationary |
| Investor Sentiment | −4.03 | −4.15 | −3.50 | Stationary |
| Agricultural Loan Volatility | −3.92 | −4.08 | −3.50 | Stationary |

### 3.2. Data

This study incorporates stock market volatility, investor sentiment, and agricultural loan market volatility into a single TVP-SV-VAR model for analysis. The data frequency is quarterly, collected from the CSMAR database, covering the period from the first quarter of 2011 to the first quarter of 2024.

#### 3.2.1. Measuring volatility in the capital market and agricultural loan market

The stock market volatility is defined in this study as the standard deviation of the logarithmic returns, which is one of the most common methodological approaches used in finance to quantify the fluctuation of asset prices over time. This is advantageous in the stock market because of its high frequency and ease in obtaining the necessary data; this directly measures the changes in price. In contrast, the variation in the agricultural loan market is not clear as straightforward as the stock market because agricultural loans are not traded as frequently as stocks and the data are not characterized by high frequency. Therefore, the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model is used to estimate the conditional variance for loan market volatility because it captures time-varying volatility in financial time series data characterized by low frequency trading and long-lasting shocks (Bollerslev, 1986).

The reason for employing different methods for the two markets is based on the nature of the data of stock prices and agricultural loan balances. Stock prices have high frequency data and it is easy to identify daily changes, therefore simple standard deviation is effective for short-term fluctuations. However, agricultural loan data are less variable than the daily data and the model like GARCH is required to capture the persistence and volatility clustering in the data.

#### 3.2.2. Robustness check and alternative estimation methods

In order to avoid some concerns that may arise regarding the reliability of the volatility estimation techniques, further sensitivity analyses were conducted using the GARCH model on stock market volatility. In addition, the Garman-Klass estimator of volatility, which makes use of both opening and closing prices as well as the intraday price ranges to measure volatility was also used. Comparing both the GARCH model and the Garman-Klass estimator to the standard deviation method used initially, the results are consistent, substantiating the findings.

**Table 2.** Volatility estimates comparison (Stock market and agricultural loan market).

| Market | Estimation Method | Volatility Measure | Conclusion |
|---|---|---|---|
| Stock Market | Standard Deviation | 5.12% | Consistent |
| Stock Market | GARCH | 5.15% | Consistent |
| Stock Market | Garman-Klass Estimator | 5.08% | Consistent |
| Agricultural Loan Market | GARCH | 3.45% | Consistent |

**Table 2** shows the comparison of volatility estimates of both stock and agricultural loan market using various techniques. The findings show that, although the different approaches generate somewhat different levels of volatility, the trends and conclusions are similar, thus supporting the approach employed in this research.

#### 3.2.3. Stock market volatility

Stock market volatility is an important indicator reflecting the fluctuations of the stock market. In this study, the constituent stocks of the CSI 300 Index are used as the measure of China’s stock market volatility (Stock), based on two main considerations. First, past empirical literature typically uses representative indices or their constituent stocks to assess overall market volatility. For example, Schwert (1989) employed the S&P 500 Index to evaluate U.S. stock market volatility, while Xie and Mo (2014), Xu (2018), Yang (2016), and Yu (2013) used the CSI 300 Index to study stock market volatility in China. Second, the CSI 300 Index tracks the 300 constituent stocks, which represent 70%–80% of the total market capitalization of the A-share market during the sample period, so it can well reflect the overall volatility of the A-share market.

Closing price method is one of the most common and traditional ways adopted for computing volatility. Volatility as one of the most used variables to measure the size of movements in asset prices is often operationalized as the standard deviation of the natural logarithm of returns. Yang (2016) measures the monthly volatility by the closing price method in the CSI 300 Index while Liu (2020) measures the historical volatility by the standard deviation of the logarithmic returns for the stock market. In this paper, daily closing indices of CSI 300 Index are employed, while the standard deviation of daily logarithmic return is applied to measure the stock market risk which is later converted into quarterly data.

#### 3.2.4. Investor sentiment

Today, there are many numerous and profound academic works on the measurement of investor sentiment, and its various and broad approaches and ideas. The primary methods for measuring investor sentiment can be categorized into two main approaches: Research has classified them as direct measurement (Guo et al., 2024; Jiang et al., 2021) and indirect measurement (Baker and Wurgler, 2006; Huang et al., 2015; Lee et al., 1991). Because of the problems associated with the direct measurement approach, which include sample bias, subjectivity, and inaccuracy of responses, the indirect measurement approach adopted in this study is the single-indicator method to measure investor sentiment. Following the methodology of Xue (2005) and Li et al. (2023), we use the Consumer Confidence Index (CCI) as a proxy for investor sentiment, calculating the monthly logarithmic return of the CCI as $It = \ln Xt - \ln Xt-1$, and then convert it into quarterly returns.

#### 3.2.5. Agricultural loan market volatility

The "Agricultural Loan Balance" refers to the total amount of loans extended by financial institutions to the agricultural sector that have not yet been repaid, as published by the People's Bank of China under short-term loans, and the broader "Agricultural-Related Loans" quarterly indicators since 2010. The term "Agricultural Loan Balance" will be used to refer to both types of data. This balance reflects the level of financial support provided to agriculture and the debt situation in the agricultural sector. As a point-in-time metric, it is closely related to the volume of agricultural loans issued and repaid, and serves as a crucial indicator for analyzing trends and potential risks in agricultural economic development. The agricultural loan market primarily supports agricultural production and rural economies, with relatively stable loan conditions and interest rates. However, the agricultural loan balance is a dynamic indicator that fluctuates with the issuance and repayment of loans. Its volatility is influenced by various factors, including agricultural production and market demand, policy environment, credit policies of financial institutions, farmers' income and repayment ability, and risks in the agricultural sector. The agricultural loan balance is a significant indicator of the overall condition of the agricultural loan market. Luo and Hu (2023) use the agricultural-related loan balance to measure agricultural credit; therefore, this study uses the agricultural loan balance as the proxy variable for the agricultural loan market.

Khan et al. (2023) studied the market volatility and asymmetric behavior of Bitcoin, the Euro, the S&P 500 index, gold, crude oil, and sugar during the COVID-19 pandemic. Their results showed that each GARCH model was capable of adequately simulating the volatility behaviors of these six financial markets. Following Luo and Hu (2023), and considering both the representativeness of the variables and the availability of data, this study uses quarterly data on China's agricultural-related loan balance. To eliminate seasonal trends, the data was adjusted for seasonality using Census X-12 software in EViews 13.0. Next, GARCH model was estimated and the conditional variance was used as measure of volatility to establish the volatility in agricultural loan market.

**Table 3.** Variables in the model, measurement basis, and supporting literature.

| Variable | Symbol | Measurement Basis | Relevant Research Literature |
|---|---|---|---|
| Stock Market Volatility | Stock | Standard Deviation of Daily Returns of the CSI 300 Index | Schwert (1989), Xie and Mo (2014), Xu (2018), Yang (2016), Yu (2013) |
| Investor Sentiment | Senti | Consumer Confidence Index | Li et al., (2023), Xue (2005) |
| Agricultural Loan Market Volatility | Loan | Based on quarterly data of China's agricultural loan balances, the GARCH model is used to calculate | Khan et al., (2023), Luo and Hu (2023) |

Source: Compiled by this study.

**Table 3** shows the three variables in the model and the basis of measurement, to avoid the effects of seasonality, it becomes appropriate to use Census X-12 seasonal adjustment on all three series and perform stationarity test.

### 3.3. Empirical method

With the development of Chinese stock market and the constant reform, the agricultural loan market is also in the process of changing. Thus, the relationship between the stock market volatility and the agricultural loan market can be time-varying and not accurately measured by conventional VAR models that do not consider the clustering of the stock market volatility. To compare with the traditional VAR model more flexibly and accurately and take into account factors including time-varying characteristics and stochastic volatility in this study, a TVP-SV-VAR model is built to dynamically examine the relationship between stock market and agricultural loan market volatilities. TVP-SV-VAR model not only enables the estimation of the time-varying contemporaneous correlations between variables, but also handles potential heteroskedasticity problem through time-varying volatility (Lü et al., 2023).

The traditional VAR model can be specified as follows:

$$Ay_t = F_1 y_{t-1} + \cdots + F_s y_{t-s} + u_t \ t = s+1, \ \cdots, \ n \tag{1}$$

In this context, $\sum = \begin{bmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_k \end{bmatrix}$, $A = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ a_{21} & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ a_{k1} & a_{k2} & \cdots & 1 \end{bmatrix}$.

Assuming $B_i = A^{-1}F_i$ ($i = 1, \ \cdots, \ s$), multiplying both sides of Equation (1) by $A^{-1}$on the left, we obtain:

$$y_t = B_1 y_{t-1} + \cdots + B_s y_{t-s} + A^{-1} \sum \varepsilon_t \qquad \varepsilon_t \sim N(0, I_k) \tag{2}$$

Further, following Primiceri (2005), let $X_i = I_k \otimes (y'_{t-1}, \cdots, y'_{t-s})$, where $\otimes$ denotes the Kronecker product.

$$y_t = X_{\mathrm{t}}\beta + A^{-1} \sum \varepsilon_t \tag{3}$$

Incorporating time-varying factors, the TVP-SV-VAR model is:

$$y_t = X_{\mathrm{t}}\beta_t + A_t^{-1} \sum\nolimits_t \varepsilon_t \quad \varepsilon_t \sim N(0, I_k), \ t = s+1, \ \cdots, \ n \tag{4}$$

Based on this, let $\alpha_t$ be the stacked vector of the lower triangular elements of matrix $A_t$, and $h_t = (h_{1t}, \ \cdots, \ h_{kt})^T$ represents the log-volatility matrix (SV), and for all $j = 1, \cdots, k$ and $t = s+1, \cdots, n$, $h_{jt} = \ln \sigma_{jt}^2$. In Equation (4), all parameters follow a first-order random walk process:

$$\begin{aligned} \beta_{t+1} &= \beta_t + \mu_{\beta_t} \\ a_{t+1} &= a_t + \mu_{a_t}, \\ h_{t+1} &= h_t + \mu_{h_t} \end{aligned} \begin{pmatrix} \varepsilon_t \\ \mu_{\beta_t} \\ \mu_{a_t} \\ \mu_{h_t} \end{pmatrix} \sim N\left(0, \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & \sum_\beta & 0 & 0 \\ 0 & 0 & \sum_a & 0 \\ 0 & 0 & 0 & \sum_h \end{pmatrix}\right)$$

where $\boldsymbol{\beta_{t+1}} \sim N(\mu_{\beta 0}, \sum_{\beta 0})$, $\boldsymbol{a_{t+1}} \sim N(\mu_{a0}, \sum_{a0})$, and $\boldsymbol{h_{t+1}} \sim N(\mu_{h0}, \sum_{h0})$.

Although stochastic volatility increases the flexibility of the model, it also complicates parameter estimation. Traditional SVAR model estimation methods, such as least squares or maximum likelihood, may face issues with model parameter overidentification. Therefore, this study follows Nakajima (2011) and employs the widely used Markov Chain Monte Carlo (MCMC) method from Bayesian analysis to estimate the model. Furthermore, impulse response functions are used to delve deeper into the interactions between variables, enhancing the precision and reliability of the empirical results.

When using the impulse response functions of the TVP-SV-VAR model to analyze the interactions between different variables and their lagged effects, one faces the issue of error terms within the model system generally exhibiting correlation. When error terms are correlated, no specific variable can effectively identify the common components. Introducing the Cholesky decomposition method helps orthogonalize the error terms and effectively identify the common components. The dynamic response process is essentially a process of Cholesky decomposition, where the order of variables in the model affects the decomposition results. If the variable order is later, there will inevitably be some degree of endogeneity within the system. This is because variables preceding the selected variable generally also exhibit endogeneity (Hu, 2018). Therefore, the order of variables in the model affects the empirical results, necessitating the specification of the sequence in which variables enter the system (Li et al., 2017; Hu, 2018; Qian et al., 2021).

Given that stock market volatility is largely exogenous to the agricultural loan market variables, and since the model is constructed to explore the impact of stock market volatility on the agricultural loan market, the stock market volatility indicator is placed before the agricultural loan market variables. The order of variables is as follows: stock market volatility, investor sentiment, and agricultural loan market volatility. Thus, the composition of $y_t$ is:

$$y_t = (Stock_{\mathrm{t}}, \quad Senti_{\mathrm{t}}, \quad Loan_{\mathrm{t}}) \tag{5}$$

## 4. Findings and discussions

Based on data availability, the empirical analysis in this study covers the sample period from Q1 2011 to Q1 2024. First, three variables are tested for stationarity. Second, parameter estimation is performed using the MCMC technique under Bayesian model. Last of all, impulse response functions are discussed.

Before performing the analysis, it was necessary to test for stationarity of all variables included in the model and check whether they meet the requirements for the model; stock market volatility, investor sentiment, as well as agricultural loan volatility all passed this test. This makes the analysis proceed with eased confidence since non-stationary data may distort the results obtained.

### 4.1. Data testing and model specification

To overcome the problem of spurious regression as a result of using TVP-SV-VAR model, unit root test was conducted on each variable. The augmented dickey fuller unit root test results show that all variables are stationary and therefore ruling out the problem of spurious regression in the later analysis. Moreover, while testing for the TVP-SV-VAR model, there is the need to choose appropriate lag length for the variables in the model. This is typically done using the optimal lag length criteria from a general VAR model. **Table 4** shows the *FPE*, *AIC*, *HQIC*, and *SBIC* values for lag lengths ranging from 1 to 4. Based on the principle of minimizing information criteria, the optimal lag length for each variable in the model is determined to be 1.

**Table 4.** Lag length diagnostics.

| Lag | LL | LR | *FPE* | *AIC* | *HQIC* | *SBIC* |
|---|---|---|---|---|---|---|
| 0 | 384.459 | | 3.5e−11 | −15.5698 | −15.5258* | −15.4539* |
| 1 | 395.122 | 21.327 | 3.2e−11* | −15.6376* | −15.4619 | −15.1743 |
| 2 | 399.898 | 9.5509 | 3.9e−11 | −15.4652 | −15.1576 | −14.6544 |
| 3 | 403.992 | 8.1881 | 4.8e−11 | −15.265 | −14.8255 | −14.1067 |
| 4 | 417.065 | 26.146* | 4.1e−11 | −15.4312 | −14.86 | −13.9255 |

Note: * indicates the optimal lag length according to various criteria.

### 4.2. Parameter estimation and model diagnostics

Based on the theoretical model analysis, this study establishes a three-variable TVP-SV-VAR model with the variable entry order of Stock, Senti, and Loan. Parameter estimation is conducted using the Monte Carlo simulation algorithm (MCMC), with the simulation implemented using OxMetrics 6.0 software. Following the methodology of Nakajima (2011), the MCMC algorithm is used to sample estimates from the posterior distribution. A total of 20,000 samples are drawn, with the first 2000 samples discarded as “burn-in” to ensure the validity of the sampling.

**Table 5.** Parameter estimates and diagnostic results.

| Parameter | Posterior Mean | Posterior Stdev | 95% Confidence Interval | Geweke | Inef. |
|---|---|---|---|---|---|
| sb1 | 0.0229 | 0.0027 | [0.0184, 0.0288] | 0.105 | 4.13 |
| sb2 | 0.0228 | 0.0026 | [0.0184, 0.0288] | 0.346 | 4.38 |
| sa1 | 0.0780 | 0.0289 | [0.0410, 0.1528] | 0.150 | 23.94 |
| sa2 | 0.0521 | 0.0126 | [0.0336, 0.0818] | 0.428 | 13.52 |
| sh1 | 0.3503 | 0.1562 | [0.0944, 0.6887] | 0.891 | 54.60 |
| sh2 | 0.3696 | 0.1539 | [0.1577, 0.7562] | 0.197 | 30.61 |

Note: sb1, sb2, sa1, sa2, sh1, and sh2 represent the estimated results of the first two diagonal elements of the posterior distribution.

**Table 5** reports the posterior distribution means, standard deviations, 95% confidence intervals, Geweke convergence diagnostic values, and inefficiency factors for the model parameters. The Geweke convergence test assesses the null hypothesis that the posterior distribution has converged; if the MCMC sampling sequence is stationary, the Geweke statistic should converge to a standard normal distribution. The inefficiency factor is used to evaluate the effectiveness of the MCMC random sampling. The results show that the posterior distribution means of all parameters fall within the 95% confidence intervals. The Geweke convergence diagnostic values did not exceed the 5% critical value of 1.96, indicating that the estimated parameters cannot reject the null hypothesis of convergence to the posterior distribution, suggesting that the pre-sampling iterations allow the Markov chain to concentrate. Additionally, the inefficiency factors, which reflect the number of samples needed to achieve uncorrelated samples, are generally low, with the highest inefficiency factor being 54.60. This means that from a total of 20,000 MCMC samples, approximately 20,000/54.60 ≈ 366.3 uncorrelated sample observations can be obtained, indicating that the posterior mean can approximate the true parameter values. Based on the Geweke convergence diagnostics and inefficiency factor results, it can be concluded that the Markov chain simulation performs well.

Based on **Figure 3**, which presents the sample autocorrelation coefficients, sample paths, and posterior distribution density functions for the three variables—stock market volatility, investor sentiment, and agricultural loan market volatility—it can be concluded that the parameters are robust. The first row of **Figure 3** shows the sample autocorrelation coefficients, which decline steadily and converge towards zero. The second row shows the value paths, which fluctuate around the mean in a stable manner. The third row shows that the sample posterior distribution density functions generally exhibit normal distribution characteristics, indicating the validity of the sampling values. Thus, these diagnostic checks support the subsequent inferences based on the TVP-SV-VAR model.

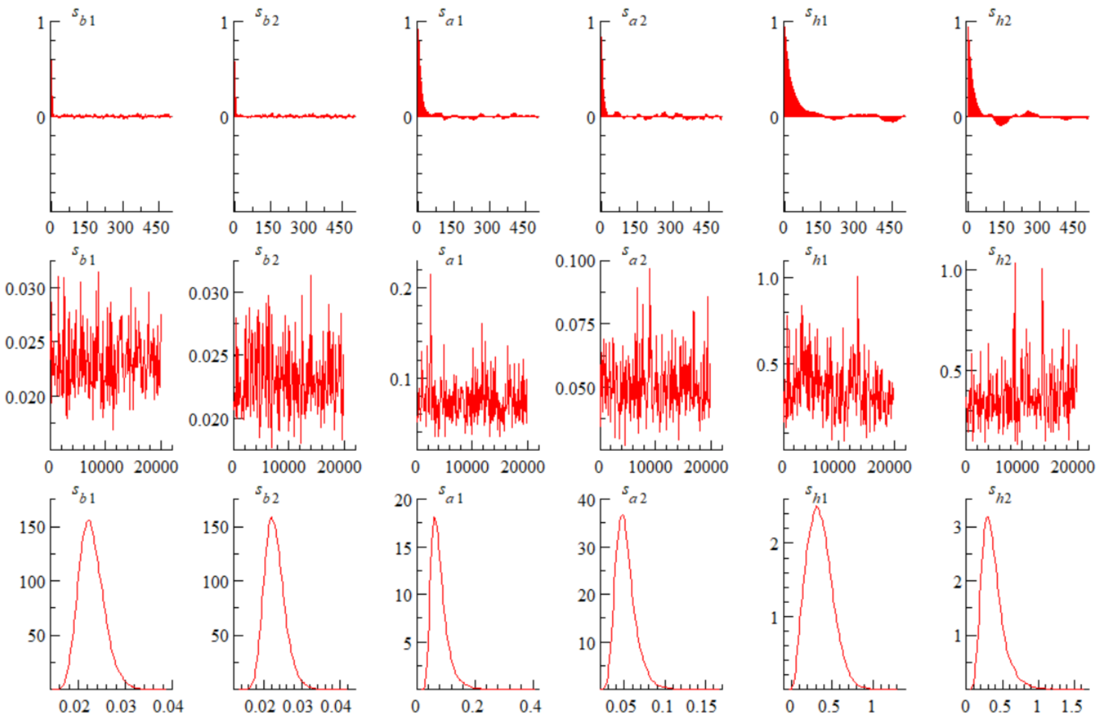

**Figure 3.** Sample autocorrelation coefficients, sample paths, and posterior distributions.

### 4.3. Time-varying impulse response analysis

The dynamic impulse response analysis among stock market volatility, investor sentiment, and agricultural loan market volatility can be effectively depicted using the TVP-SV-VAR model. This model captures dynamic responses over different periods, including both interval-based impulse responses and point-in-time impulse responses.

#### 4.3.1. Interval-based impulse response analysis

Interval-based impulse response refers to the impact of the current value of one parameter on other parameters over a fixed number of lags. This approach effectively captures the lagged effects of stock market volatility on investor sentiment and agricultural loan market volatility. Here, the effects of stock market volatility on investor sentiment and agricultural loan market volatility are analyzed over short-term (2-period), medium-term (4-period), and long-term (8-period) horizons.

**Figure 4** shows the response of stock market volatility (Stock) to a one-standard-deviation shock to itself. The solid line represents the response function with a 2-period lag, while the long dashed line and short dashed line represent the response functions with 4-period and 8-period lags, respectively. The figure indicates that the interval-based impulse response functions of various variables are relatively consistent across different lags, suggesting that the model is relatively robust. Specifically, the short-term impulse response shows that stock market volatility reacts quickly and significantly to its own shocks in the short term. The impulse response of stock market volatility to itself exhibits a decaying trend, with the effect becoming very weak after 8 periods, which aligns with the typical behavior of stock market volatility.

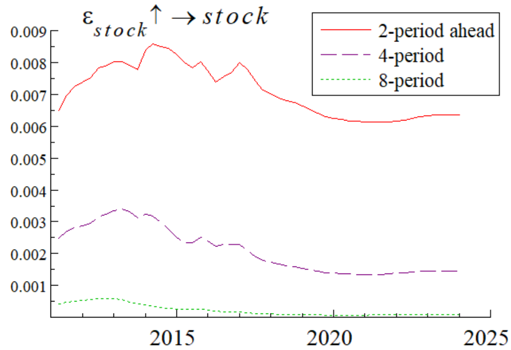


**Figure 4.** Interval-based impulse response of stock market volatility to itself.

**Figure 5** indicates that stock market volatility has time-varying effects on agricultural loan market volatility. Given a unit positive shock to stock market volatility during the sample period, the impulse response values of stock market volatility to agricultural loan volatility are all above zero. This suggests that overall, stock market volatility has a significant positive impact on agricultural loan volatility, which supports Hypothesis 1 of this study. Specifically, increases in stock market volatility lead to corresponding increases in agricultural loan volatility. Generally, the time-varying impact is most pronounced between 2011 and 2017. After 2017, the impact effect stabilizes and remains at a lower level. This may be explained by the fact that from 2011 to 2017, the stock market had a more substantial impact on the agricultural loan market due to economic restructuring, de-leveraging policies, and higher financial market uncertainty. However, after 2017, with the stabilization of the economy, enhanced financial regulation, and the maturation of the capital markets, stock market volatility decreased and agricultural loan market volatility also stabilized. The policy support for the agricultural loan market and its relative independence further weakened the impact of stock market volatility, leading to a gradual reduction in the correlation between the two, and resulting in a stable and low level of impact of stock market volatility on the agricultural loan market after 2017.

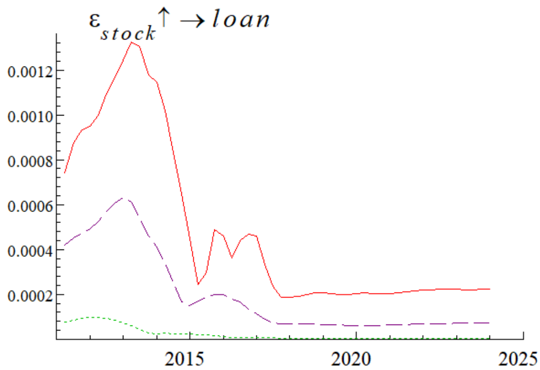


**Figure 5.** Interval-based impulse response of stock market volatility to agricultural loan market volatility.

In the short and medium term, the time-varying impulse response values show the following trend: from 2011 to 2012, they rose sharply in a straight line, followed by a significant straight-line decline from 2013 to 2014, creating an inverted “V” shape. Subsequently, from 2015 to 2016, the response values exhibited slight fluctuations and an upward trend, with a minor decrease in 2017 before stabilizing. The potential mechanism behind these results can be described as follows: from 2011 to 2012, the Chinese economy was in the recovery phase following the global financial crisis. The government implemented a series of stimulus policies to promote economic growth, including lowering interest rates and increasing fiscal spending. These policies probably raised stock market volatility, which in turn probably led to a rise in agricultural loan volatility and overall response of agricultural loan volatility to stock market volatility.

Starting from 2013 to 2014, China shifted its policy towards economic restructuring and de-leveraging. Specifically, in 2013, the government began to implement a series of economic structural reform, for example, the so-called, "new normal" economy, which stressed the quality of economic development instead of quantity. Together with market fluctuation in 2013 and 2014, such as the "cash crunch" in 2013, this could have raised the volatility of the stock market while lowering the response of agricultural loan balances due to policy tightening or market risk, hence, resulting in sharply reduced values of impulse response. In 2015–2016, Chinese stock market have seen fluctuations, for example: stock market crash in August 2015. In this respect, stock market volatility rose and balances of agricultural loans might have moved responding to market fluctuations and thus slightly increasing impulse response figures.

In fact, as the stock market gradually stabilized, especially after 2017, the Chinese economy has reached relatively stable growth, and the policies have become more stable and predictable. This may have reduced the extent of fluctuations in stock market performance affecting the balances of agricultural loans which slightly declined. Since the beginning of 2017, China's economy has officially entered a more stable stage and the policy environment and market are becoming more stable. This stability likely reduced and stabilized the impact of stock market volatility on agricultural loan volatility, with the impulse response showing a small positive effect. In the long term, the impulse response values remained stable and slightly positive, reflecting that the long-term impact of stock market volatility on agricultural loan volatility is minimal and stable.

In **Figure 6**, the dynamic impulse response functions of stock market volatility to investor sentiment across three different periods all show negative values. This indicates that an increase in stock market volatility generally leads to a decline in investor sentiment, reflecting a cautious attitude among Chinese investors when faced with stock market fluctuations. The rising uncertainty in the stock market heightens concerns about future economic prospects. From the perspective of varying impact across periods, the impact of stock market volatility on investor sentiment is predominantly observed in the short term, suggesting that investors are most sensitive to stock market fluctuations in the short run. In terms of temporal evolution, before 2017, the negative impact of stock market volatility on investor sentiment shows a clear expansion trend, which then diminishes and stabilizes after 2017. This can be explained by the rapid economic growth in China from 2011 to 2017, which was accompanied by uncertainty and volatility, such as the unusual stock market fluctuations in 2015 and frequent government interventions. These factors led to an increased sensitivity of investor sentiment to stock market volatility. After 2017, with the implementation of economic structural adjustments and deleveraging policies, market volatility gradually decreased, and its impact on investor sentiment also weakened. In the medium term, the impact significantly reduces and becomes more stable, indicating that investor sentiment's response to stock market volatility diminishes as investors gradually adapt to fluctuations and sentiment stabilizes. In the long term, the impact is weakly negative and stable, showing that the effect of stock market volatility on investor sentiment has become minimal and essentially unchanged.

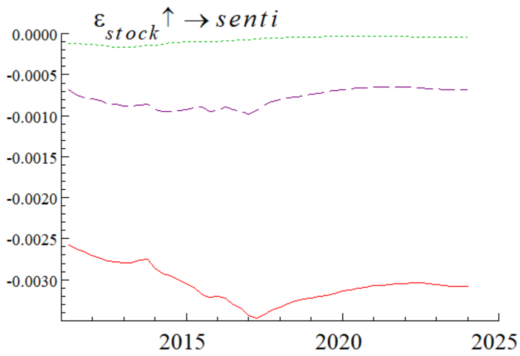


**Figure 6.** Interval impulse response of stock market volatility to investor sentiment.

**Figure 7** presents the impulse response functions of investor sentiment to agricultural loan volatility. From the impact effects observed across different periods, the influence of investor sentiment on agricultural loan volatility is primarily seen in the short term. In the short term, from early 2011 to mid-2012, the impact effect shifts from positive to negative and rapidly decreases in a linear manner. After this period, it fluctuates upward and turns positive by mid-2017, eventually stabilizing after two years of fluctuations. A possible explanation is that during early 2011 to mid-2012, China was in the economic recovery phase following the financial crisis, with the government implementing a series of economic stimulus policies. In the early recovery stage, when investor sentiment received a positive shock, market confidence had not yet fully recovered, leading to increased volatility in the agricultural loan market.

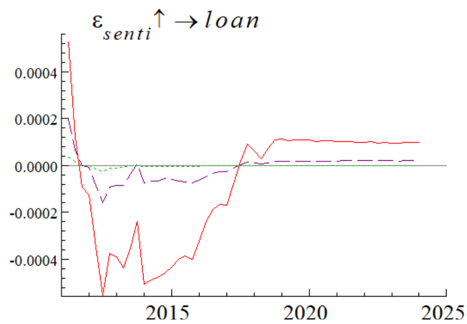


**Figure 7.** Interval impulse response of investor sentiment to agricultural loan market volatility.

However, after some time, with the policies' impact emerging and market expectations shifting, pro-market sentiment contributed to a fast decline in agricultural loan variability. Later on, the relationship between investor sentiment and the volatility of agricultural loans increased, which proved that the negative shock effect of policy changes and economic fluctuations was gradually alleviated. Thereafter, starting from the second quarter of 2017, the impact effect became positive and stabilised due to the increased pace of economic structural adjustment and debt reduction measures by the Chinese authority. This stabilization of sentiment together with the enhanced capability of the agricultural loan market to respond to these changes led to only a slight and gradual rise in agricultural loans volatileness as the sentiment improved and demanded growth in the agricultural loan.

In the medium to long term, the impact effects follow a similar trend to the short term, but with a significantly reduced magnitude in the medium term and a very weak impulse response in the long term. This indicates that over time, the agricultural loan market has gradually adapted to policy changes and economic adjustments. In the medium term, the stability and continuity of policies have lessened the agricultural loan market's sensitivity to changes in investor sentiment. In the long term, the impact of investor sentiment on agricultural loan volatility has become very weak, and the market's response to changes in investor sentiment has stabilized.

Overall, **Figures 6** and **7** show that the impact of stock market volatility on investor sentiment is negative, while the effect of investor sentiment on agricultural loan market volatility exhibits time-varying characteristics, stabilizing after mid-2017. Both effects are primarily significant in the short term. This indicates that stock market volatility affects agricultural loan market volatility through investor sentiment as an intermediary variable, with the most pronounced effect occurring before 2017. This finding supports the second hypothesis of the study, which posits that investor sentiment is a crucial channel for effect transmission.

#### 4.3.2. Point-in-time impulse response analysis

This study sets specific point-in-time shocks based on key landmark events and variable fluctuations to characterize the time-varying heterogeneity and impact pathways of investor sentiment and agricultural loan market volatility induced by stock market volatility. For the period from Q1 2011 to Q1 2024, three representative impulse points are selected for analysis.

First, in 2015, the Chinese stock market experienced abnormal volatility, particularly during the summer stock market crash, which resulted in a massive evaporation of market value and significantly impacted investors. Therefore, Q3 2015 is chosen as the first specific shock point. Second, in 2018, the escalating US-China trade tensions led to the imposition of three rounds of tariffs by the United States on China, with China responding with targeted countermeasures. This had a significant impact on the Chinese economy and financial markets, so Q4 2018, when the US implemented the third round of tariffs, is selected as the second specific shock point. Finally, in the first half of 2020, the outbreak of the COVID-19 pandemic was met with a strong policy response from the Chinese government, including a comprehensive "six stabilities and six guarantees" package. This support enabled the Chinese economy to recover from the pandemic's impact, with GDP growth rebounding to 3.2% in Q2 2020, marking a V-shaped recovery and a transition to normalized pandemic control. Therefore, Q2 2020 is selected as the third shock point.

Overall, the impulse responses at different specific points converge to zero. The impacts of key event shocks initially exhibit either positive or negative correlations, but over time, these effects gradually diminish until reaching zero, which is consistent with economic principles.

**Figure 8** shows that the impact of stock market volatility on itself remains relatively consistent across the three different time points. The response to shocks quickly diminishes from the first quarter, indicating that at significant event points, stock market volatility can adjust relatively flexibly, and the inertia mechanism of its own volatility is relatively low, leading to minimal sustained effects on its future volatility. **Figure 9** illustrates the impact of stock market volatility on agricultural loan market volatility at different points in time. During the summer of the 2015 stock market crash, the impulse response coefficient is negative in the first period, quickly turns positive in the second period, reaches the maximum positive impact in the third period, and then starts to decline, reaching zero by the tenth period. The shock effects at the other two time points are somewhat diminished but still follow a similar pattern. The underlying mechanism can be summarized as follows: During the summer stock market crash, market uncertainty and risk significantly increase, leading to persistently low investor sentiment and greater volatility in the agricultural loan market. In response to significant event impacts, when stock market volatility experiences a positive shock, the central bank rapidly implements various measures to stabilize the market in the short term, reducing agricultural loan market volatility. However, the impact on lending entities, investors, and commercial banks quickly becomes apparent, leading to an increase in agricultural loan market volatility. Over time, as the shock effects diminish, the response of the agricultural loan market volatility gradually decreases.

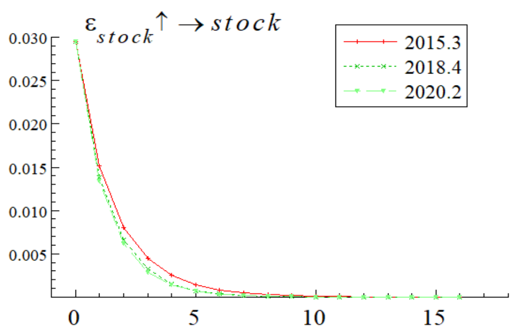


**Figure 8.** Point-in-time impulse response of stock market volatility to itself.

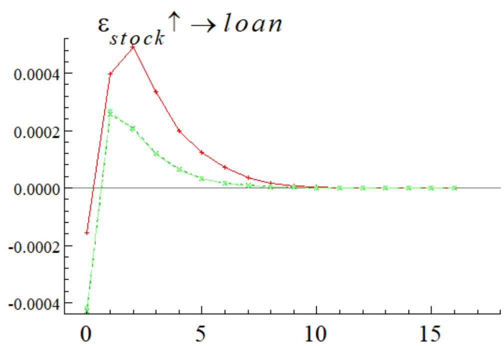


**Figure 9.** Point-in-time impulse response of stock market volatility to agricultural loan market volatility.

Furthermore, in **Figure 10**, the impact of stock market volatility on investor sentiment shows a generally consistent trend across different significant event points, demonstrating an inverse "hump" shape with an initial decrease followed by an increase. Specifically, when stock market volatility experiences a one-unit positive shock, the immediate response of investor sentiment is negative, indicating that an increase in stock market volatility leads to a negative reaction in investor sentiment, reflecting a pessimistic outlook on the future market and a decline in confidence. This negative impact reaches its minimum at the second period, then begins to decay, eventually diminishing to zero after the tenth period. The underlying mechanism can be summarized as follows: When significant events increase stock market volatility, investor sentiment initially suffers and reaches its peak quickly. Over time, the reaction of investor sentiment gradually declines until it becomes negligible, suggesting that the impact of stock market volatility on investor sentiment has a certain degree of persistence.

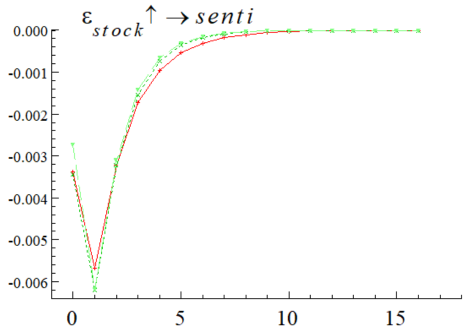


**Figure 10.** Point-in-time impulse response of stock market volatility on investor sentiment.

**Figure 11** illustrates the impact of investor sentiment on agricultural loan market volatility. During the major event of the summer stock market crash in the third quarter of 2015, when investor sentiment faced an external shock, the response coefficient of agricultural loan market volatility was negative, reaching its maximum negative value at the first period and then diminishing to zero by the eighth period. This indicates that when investor sentiment receives a one-unit positive shock, implying a surge in investor sentiment, market uncertainty and risk significantly increase, leading to more funds flowing into commercial banks. The central bank's policy measures also greatly stabilized the agricultural loan market, but the effect weakened over time, with the impact gradually diminishing. For the third quarter of 2018, during the escalation of the US-China trade friction, and the second quarter of 2020, when COVID-19 pandemic control measures shifted to a normalized state, the impulse response curves are quite similar. The shock effect initially shows a maximum negative value at the first period, turns positive by the second period, and then decays to zero by the eighth period. This can be understood as follows: Unlike the 2015 summer stock market crash, which was solely a major economic event, the US-China trade friction and the normalization of COVID-19 control were significant political and economic events. The Chinese government promptly introduced a series of policy measures to stabilize market sentiment and the economic fundamentals, ensuring stability in the agricultural loan market and reducing volatility. With the implementation of stabilization policies and increased support for agriculture loans, agricultural loan market volatility experienced a slight increase, and the impact gradually diminished afterward.

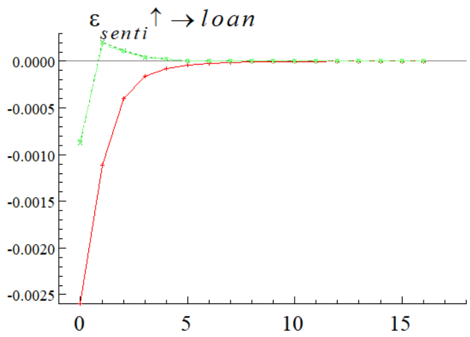


**Figure 11.** Point-in-time impulse response of investor sentiment on agricultural loan market volatility.

### 4.4. Robustness test

In essence, robustness testing is a very important process that helps check the reliability and robustness of the research findings. The selection of the variables and methods of data processing may affect the final empirical analysis results in the VAR models (Qian et al., 2021). The type of robustness check that most scholars who use the TVP-SV-VAR model perform involves either reordering of the variables (Gu and Wang, 2023; Song and Zhang, 2023) or replacing them (Cui and Zhao, 2023; Tang and Liu, 2023; Wang et al., 2023; Zhang et al., 2022). This study also employs these two methods.

(1) Adjusting the Order of Variables

Since the order of variables in the TVP-SV-VAR model can affect the results, robustness checks were conducted by swapping the positions of the stock market volatility (Stock) and agricultural loan market volatility (Loan) variables. Accordingly, the expression for $y_t$ in the TVP-SV-VAR model was modified to:

$$y_t = (Loan_t,\ Senti_t,\ Stock_t) \tag{6}$$

When comparing the interval impulse response analysis results after changing the variable order with those of the original model, it was found that the results are generally similar, with the main differences being that the impulse response of stock market volatility to agricultural loan market volatility shows some variations in the direction of the impact in the short to medium term. Overall, the direction of stock market volatility's effect during the sample period and the transmission path through the investor sentiment channel are consistent with the original model's results. This indicates that altering the variable order did not affect the core conclusions of the experimental results, thus confirming their robustness.

(2) Variable Substitution

To further ensure the robustness of variable and indicator selection, this study replaces the original proxy variable for investor sentiment (Senti) with the investor sentiment index (CICSI) in the model. The model is then re-examined with this substitution. Comparing the interval impulse responses and point-in-time impulse responses before and after the variable substitution reveals that the main characteristics and transmission paths remain consistent with those of the original model. This indicates that the results of the original model are robust.

## 5. Conclusion and policy recommendations

### 5.1. Conclusion

This paper reviews existing literature and its limitations, and innovatively investigates the time-varying impact of stock market volatility on agricultural loan market volatility and the transmission mechanism of investor sentiment, based on behavioral finance theory and the theory of the relationship between monetary policy and the credit market. Using the Time-Varying Parameter Stochastic Volatility Vector Autoregression (TVP-SV-VAR) model, the following main conclusions are drawn:

Firstly, the impact of stock market volatility on agricultural loan market volatility exhibits time-varying characteristics, with a predominantly positive effect. This impact is most pronounced before 2017 and is primarily observed in the short and medium terms (short term refers to 2 quarters or 6 months, medium term refers to 4 quarters or 1 year), with the short-term effects being the most significant, followed by medium-term effects, while long-term effects are minimal. This impact has notably decreased and stabilized after 2017. This is largely due to China's economic structural adjustments, de-leveraging policies, and high financial market uncertainty from 2011 to 2017, which led to a significant impact of stock market volatility on the agricultural loan market. However, after 2017, with economic stabilization, strengthened financial regulation, matured capital markets, and policy support for the agricultural loan market, the connection between the two has weakened, resulting in a lower and more stable level of impact.

Secondly, the transmission process of stock market volatility affecting agricultural loan market volatility through investor sentiment is significant in the short term, while the medium and long-term transmission mechanisms are not significant. This impact also shows certain time-varying characteristics, particularly before 2017, where the negative impact of stock market volatility on investor sentiment expanded, while the effect of investor sentiment on agricultural loan market volatility showed considerable fluctuations. This indicates that investor sentiment is an important channel for effect transmission.

Thirdly, compared to political and economic events, substantial stock market fluctuations (such as the summer 2015 stock market crash) can significantly undermine investor confidence, leading to greater volatility in the agricultural loan market. Under the influence of various major events, increased stock market volatility significantly dampens investor sentiment with a certain degree of persistence, which then gradually diminishes. The central bank's responses to unconventional events help mitigate the impact of investor sentiment and stabilize the agricultural loan market.

## 5.2. Policy remarks

Based on the findings of this study, the following policy implications can be drawn:

(1) Ensure Market Stability: Financial authorities in China should implement measures to ensure the stable operation of the stock market and minimize unforeseen fluctuations caused by uncertainty. Such volatility not only negatively affects investor sentiment but may also exacerbate agricultural loan market fluctuations through the transmission mechanism. Therefore, financial regulatory agencies should enhance the financial market system, strengthen market expectation management, and improve risk monitoring to prevent and control potential sources of market volatility.

(2) Timely Policy Interventions: In the face of unforeseen market fluctuations, the government should promptly introduce specific policy measures to boost investor confidence and establish flexible agricultural loan conditions to mitigate adverse impacts on the agricultural loan market. For example, timely monetary policy interventions, such as lowering interest rates or increasing liquidity supply, can effectively reduce market panic, stabilize financial markets, and indirectly support the smooth functioning of the agricultural loan market.

(3) Manage Investor Sentiment: Stock market volatility can have a "cumulative" effect on agricultural loan market fluctuations through its impact on investor sentiment, creating a "domino effect" of negative feedback. To prevent investor confidence from being undermined, regulatory agencies and financial media should provide timely and transparent information to reduce market uncertainty and prevent rumors and false information from causing panic. It is crucial to enhance the interpretation of market dynamics, guide investors to view market fluctuations rationally, and prevent the spread of emotional volatility.

(4) Develop Agricultural Credit Systems: As the agricultural loan market's operating mechanisms evolve and investors continuously adapt to stock market fluctuations, the impact on the agricultural loan market tends to become more moderate. Therefore, it is fundamental to build a robust agricultural credit system to withstand market uncertainties. Financial institutions should improve information disclosure, enhance the credit information system for farmers and agricultural enterprises, develop diversified financial products and services tailored to the agricultural sector, expand credit coverage, and establish a mature and stable agricultural credit operating mechanism.

## 5.3. Limitations and future directions

This study, which uses the TVP-SV-VAR model to assess the impact of stock market volatility on the agricultural loan market in China, has several limitations. First, the research is confined to China, which somewhat limits its applicability to emerging market countries. Although using "agricultural loan balance volatility" as a proxy for "agricultural loan market volatility" reflects market fluctuations to some extent, it represents only one important aspect of the agricultural loan market. More refined and systematic proxy variables could be explored. Moreover, government policies play a critical role in regulating the agricultural loan market, so future research could enhance policy relevance by incorporating variables such as policy uncertainty indexes.

Additionally, conducting similar studies in emerging market countries would also help develop a more comprehensive understanding of the topic.

**Author contributions:** Conceptualization, KY and HY; methodology, HY; software, KY; validation, KY and HY; formal analysis, HY; investigation, KY; resources, HY; data curation, KY; writing—original draft preparation, KY; writing—review and editing, KY and HY; visualization, KY; supervision, HY; project administration, HY; funding acquisition, HY. All authors have read and agreed to the published version of the manuscript.

**Conflict of interest:** The authors declare no conflict of interest.

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