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Impact of Margin Trading and Short Selling on the Volatility of the Shanghai Composite Index: A GARCH Analysis

Yiguo Li *

School of Economics and Management, Nanjing University of Science and Technology, Nanjing, China

* **Corresponding author**

Abstract: China launched a pilot margin trading and securities lending program on 31 March 2010, ending the stock market's single-sided trading regime. The program now has a material effect on stock price volatility, yet the price discovery function of margin trading and short selling has not been fully realized. This paper examines the effect of these activities on the volatility of the Shanghai Composite Index through theoretical and empirical analysis. It first explains the channels through which margin financing and securities lending affect stock market volatility, then fits volatility with a GARCH model and applies Granger causality tests and impulse response analysis. The results indicate that both margin financing and securities lending help st abilize stock market volatility. The paper recommends gradually expanding the range of eligible securities, improving the securities lending and refinancing mechanism, strengthening investor education on market risk, and enhancing risk controls for margin trading and short selling.

Keywords: Margin trading and short selling, Stock price volatility, GARCH model.

1. Introduction

1.1. Research Background and Significance

Margin trading and securities lending play a central role in the securities market and support its core functions. They encourage trading activity, improve market liquidity, and provide another channel for price formation, thereby increasing the efficiency of price discovery and improving the overall functioning of the market.

These activities also contribute to a multi-tier securities market system. First, they increase the turnover of existing funds and securities, enliven trading, raise trading volume, and improve liquidity. Second, by improving the long-short structure, discouraging improper arbitrage, and rebalancing the interests of different investor groups, they support countercyclical adjustment. Third, they bring new funds into the market, improve capital utilization, and increase trading activity. Margin financing and securities lending also create interest-income sources for securities firms and expand their revenue base. At the same time, securities lending helps dampen market swings and encourages more balanced use of financing and lending tools. By meeting institutional investors' different needs to borrow or lend securities, these activities promote business innovation and deepen the market.

Margin trading and securities lending give investors both long and short options and make the market more flexible. Unlike single-sided trading, these instruments allow investors to hedge through purchases or sales, which can reduce exposure to risk and alleviate information asymmetry. From this perspective, they may curb excess volatility and improve price discovery. As leveraged instruments, however, they can also amplify price swings. Because of the margin requirement, investors can control a much larger position with a small amount of capital, magnifying both gains and losses. These activities are therefore a double-edged sword: they energize the market but can also encourage blind speculation, increase volatility, and expose investors to losses. Theory alone does not provide a definitive account of their net effect on stock market volatility.

In 2010, the China Securities Regulatory Commission announced the launch of a pilot margin trading and securities lending program, marking the beginning of the formal pilot stage. Since the program began on 31 March 2010, the eligible-securities list has been expanded repeatedly, from an initial scale of zero to about RMB 833.9 billion and 1,600 eligible securities across the Shanghai and Shenzhen stock exchanges, substantially increasing market participation and flexibility.

1.2. Literature Review

International and Chinese studies have focused mainly on changes to the margin-trading regime and have paid comparatively little attention to margin balances. Three views dominate the literature on the effect of margin trading and short selling on stock price volatility. The first holds that these mechanisms reduce volatility and stabilize the stock market. Xiao and Kong (2014) find that margin trading and securities lending reduce the idiosyncratic volatility of eligible stocks [1]. Li et al. (2015) report that these activities effectively reduce the volatility and amplitude of eligible stocks and contribute to the stability of China's stock market [2]. Yang and Jiang (2021), using a parametric vector autoregressive model, find a significant volatility-reducing effect in the short run that weakens over time [3]. Deng and Yao (2022), using a difference-in-differences model, find that relaxing both margin financing and securities lending reduces price volatility. The overall effect is modest, however, and the stabilizing effect of relaxing margin financing is more pronounced than that of relaxing securities lending [4].

The second view holds that margin trading and securities lending may trigger sharp price swings. Chu and Fang (2016), using a difference-in-differences design, find that the mechanism did not mitigate stock price crash risk as expected and may even have increased it [5]. Ba and Zhu (2016) argue

that excessive leverage combined with inadequate risk controls can encourage irrational investors to speculate, increase sensitivity to sentiment, and destabilize the market [6]. Zhang et al. (2016), using a TGARCH event model, find that excessive speculation became more frequent after the eligible-securities expansion and raised stock market volatility [7]. An et al. (2018) find that margin trading and securities lending can exert a negative shock on volatility under some market conditions, although their stabilizing function is limited [8]. Liu et al. (2019), using a VAR model, confirm that these activities amplified stock market volatility; the effect of securities lending was smaller than that of margin financing [9]. Zhang and Li (2021) apply ADF tests, a VAR model, stability tests, Granger causality tests, and impulse response analysis to show that margin trading and securities lending increased volatility during periods of economic downturns [10].

The third view finds no clear relationship between these mechanisms and stock price volatility and concludes that the effects of leveraged trading and short selling are not statistically significant. Tang (2012) finds no marked difference between volatility before and after the introduction of margin trading and securities lending in China [11]. Liu et al. (2016) compare the effect of information shocks before and after the policy and find that, although the probability of large price movements did not change significantly, the asymmetry between sharp rises and sharp falls increased [12]. Liu and Cao (2021) find that the effect of margin trading and securities lending on stock prices is not significant and that volatility is driven mainly by the external environment and stock-specific factors [13].

Overall, no consensus has emerged. The difference-in-differences results of Chu and Fang capture the direct association between the policy change and volatility, but the estimated effect may also reflect time effects. This paper therefore uses a GARCH framework, which is well suited to time-series analysis, to investigate the actual effect of China's margin trading and securities lending activities on stock price volatility. This approach provides a more comprehensive assessment of the policy and a stronger basis for future financial market policy.

1.3. Research Methods and Structure

The paper is organized into five sections.

Section 1 introduces the background and significance of the research, reviews the literature on margin trading, securities lending, and stock price volatility, identifies the starting point and contribution of this study, and outlines the research methods and structure.

Section 2 presents the theoretical analysis, including the theoretical foundations and the mechanisms through which margin trading and securities lending affect stock price volatility.

Section 3 describes the empirical design and data analysis, including the data source, variable selection, descriptive statistics, normality tests, and stationarity tests.

Section 4 reports the empirical analysis. It draws conclusions from Granger causality tests and impulse response analysis, and uses a GARCH model to forecast volatility in the Shanghai Composite Index.

Section 5 presents the conclusions and recommendations. Drawing on the empirical results and relevant evidence, it proposes targeted measures in three areas: optimizing the investor structure, improving the margin system, and strengthening regulatory oversight.

The study combines theoretical and empirical analysis. It explains how the introduction of margin trading and securities lending can affect stock market volatility through the range of eligible securities, the margin ratio, and the investor structure. It then constructs a GARCH model using daily margin financing and securities lending balances from the Shanghai Stock Exchange and the daily high and low prices of the Shanghai Composite Index from 2015 to 2024. The growth rates of the financing and lending balances and the daily stock price volatility are calculated and examined empirically.

2. Theoretical Analysis of Margin Trading, Short Selling, and Stock Price Volatility

2.1. Theoretical Foundations of Stock Price Volatility

Traditional stock trading relies mainly on investors' own funds and existing holdings, so supply and demand are relatively fixed and inelastic. Margin trading and securities lending allow market participants to adjust supply and demand more flexibly in line with their expectations about future prices. Investors can quickly increase or reduce demand for shares through margin financing and increase or reduce supply through securities lending. As a result, supply and demand respond more rapidly to information and expectations, making stock prices more sensitive to new developments. For example, after an unexpected negative industry announcement, eligible investors can immediately borrow and sell the relevant shares, amplifying the decline more quickly and sharply than in a market without securities lending.

The scale and direction of margin trading and securities lending also convey information and shape other investors' expectations. A rising securities lending balance, for example, suggests that more investors expect the stock price to fall. Other participants may revise their views, adjust their strategies, sell, or at least postpone purchases. These changes in expectations feed back into prices through investor behavior and can amplify volatility. Similarly, a rapid increase in the margin financing balance signals that a stock is viewed favorably, attracts additional capital, and can push the price upward.

The feedback mechanism emphasized in behavioral finance is particularly visible in margin trading and securities lending. Once a transaction-driven price trend emerges, investor sentiment and behavior can reinforce it. Consider a price rise driven by margin purchases. The rise generates paper profits for margin buyers, strengthens their confidence, and may encourage them to borrow more and buy additional shares. Other investors may follow, pushing the price higher and creating a positive feedback loop that leads to overpricing. The reverse occurs after securities lending and selling push prices down. Falling prices convince short sellers that their judgment was correct, encouraging further borrowing and selling. Holders may panic and sell, accelerating the decline and creating a negative feedback loop that increases volatility.

The theoretical foundations of stock price volatility therefore span market sentiment, macroeconomic indicators, investor behavior, and specific theoretical models. Together, these forces produce the complex dynamic balance and changing conditions observed in stock markets.

2.2. Mechanisms Linking Margin Trading and Short Selling to Volatility

2.2.1. Mechanism of Margin Financing

When investors expect a stock's intrinsic value to exceed its market price, they can post margin, borrow funds, and invest in the security. The resulting signal is that the stock is undervalued, and other investors may follow. Demand for the stock rises above supply, and the resulting imbalance pushes the price higher. Continued margin purchases reinforce the cycle and can drive the price above intrinsic value. Investors then sell to realize the difference. Selling changes the supply-demand balance, increases supply, and signals that the stock may be overvalued. Other investors may follow and sell, pushing the price lower. As supply increases further, the price continues to fall until it is below intrinsic value, at which point investors buy again and the cycle repeats. Along this path, margin financing can reduce stock market fluctuations and move prices toward intrinsic value.

2.2.2. Mechanism of Securities Lending

Securities lending affects volatility through a broadly similar path. When investors expect intrinsic value to be below the market price, they can borrow and sell securities. The resulting signal is that the stock is overvalued, and other investors may follow.

Supply then exceeds demand, pushing the price lower. Investors continue to borrow and sell until the price falls below intrinsic value. At that point, rational investors buy the stock, changing the demand relationship and signaling that it is undervalued. Other investors follow, pushing the price and demand higher until the price exceeds intrinsic value. Investors then sell, and the cycle repeats. Securities lending can therefore also reduce fluctuations and move prices toward intrinsic value.

In summary, margin trading and securities lending affect volatility mainly by changing the supply of and demand for securities. Whether the market price is above or below intrinsic value, long and short mechanisms can help bring the two into balance. Because investors must post a margin, however, while the borrowed funds or securities can be several times the margin, these transactions are leveraged and can generate large market swings. Theory supports a stabilizing role, but the required conditions are difficult to satisfy in practice. Capital markets remain underdeveloped in some respects, information is asymmetric, and regulatory policies and management may be inefficient. These factors can weaken the positive effect of margin trading and securities lending on market stability. For this reason, many researchers conclude that the introduction of these mechanisms can increase stock market volatility.

3. Empirical Research Design

3.1. Data

China's A-share market has grown steadily since the pilot program began in 2010 and has undergone seven rounds of expansion. In the expansion of 12 December 2016, the number of eligible stocks rose from 873 to 950. The number of eligible stocks on the Shanghai Stock Exchange increased from 485 to 525, and the number on the Shenzhen Stock Exchange increased from 388 to 425. The newly eligible stocks generally had lower price-to-earnings ratios, larger free-float market capitalizations, more active trading, and more stable market performance. To investigate the effect of margin trading and securities lending on stock market volatility, this study examines the Shanghai Composite Index and the Shanghai Stock Exchange over the period from 23 July 2015 to 25 December 2024. The sample contains 2,292 observations and includes the eligible-securities expansion of 12 December 2016, allowing a more precise assessment of the volatility effect.

3.2. Variable Selection

The dependent variable is stock price volatility.

This study examines the effect of margin trading and securities lending on stock price volatility, so volatility is used as the dependent variable. Existing studies offer several measures. This study uses the ratio of the daily price range of the Shanghai Composite Index to the average of its daily high and low, as shown in Eq. (1):

$$VOL=\frac{P_H-P_L}{(P_H+P_L)/2} \tag{1}$$

Where P_H is the daily high of the Shanghai Composite Index and P_L is the daily low.

The explanatory variables are the margin financing and securities lending variables.

The margin financing variable is the daily growth rate of the margin financing balance on the Shanghai Stock Exchange, as shown in Eq. (2). The margin financing balance is the total amount borrowed through margin transactions to purchase securities that remains outstanding at a given time. An increase in the balance usually indicates greater optimism and stronger purchase demand for specific securities.

$$RZ_t=\frac{R_t-R_{t-1}}{R_{t-1}} \tag{2}$$

Where R_t is the margin financing balance on day t and R_{t-1} is the balance on day $t-1$.

The securities lending variable is the daily growth rate of the securities lending balance on the Shanghai Stock Exchange, as shown in Eq. (3). The securities lending balance is the amount of securities borrowed and sold through securities lending that has not yet been returned. A higher balance may indicate that market participants expect the security's price to fall.

$$RQ_t=\frac{Q_t-Q_{t-1}}{Q_{t-1}} \tag{3}$$

Where Q_t is the securities lending balance on day t and Q_{t-1} is the balance on day $t-1$.

3.3. Descriptive Statistics

Table 1 reports the descriptive statistics. Stock price volatility (VOL) averages 1.341, with a maximum of 8.577, a minimum of 0.252, and a standard deviation of 0.912, indicating substantial variation during the sample period. The mean values of margin financing (RZ) and securities lending (RQ) are 0.000 and 0.001, respectively, while their ranges and standard deviations also differ considerably. These patterns show pronounced variation in the scale and intensity of margin trading and securities lending. The skewness and kurtosis values indicate that all three variables depart substantially from normality. VOL and RQ are right-skewed, RZ is left-skewed, and all three series are strongly leptokurtic, suggesting that the sample contains many extreme observations.

Table 1. Descriptive statistics of the sample

Variable	Obs.	Mean	Maximum	Minimum	Std. dev.	Skewness	Kurtosis
VOL	2,292	1.341	8.577	0.252	0.912	2.810	14.652
RZ	2,292	0.000	0.074	-0.070	0.006	-1.107	33.701
RQ	2,292	0.001	0.224	-0.179	0.032	0.388	7.838

3.4. Normality Tests

Financial time series are often nonstationary and exhibit leptokurtosis and fat tails, which differ markedly from the standard normal distribution. Unconditional variance alone is therefore not sufficient to describe market volatility. A normality test is important for the accuracy of the subsequent analysis.

Table 2. Normality test results

Variable	SW W	SW V	SW z	Prob. > z	JB
VOL	0.7436	344.120	14.932	0.000	16,000
RZ	0.7677	311.738	14.679	0.000	90,000
RQ	0.9412	78.955	11.168	0.000	2,292

The Shapiro-Wilk (SW) and Jarque-Bera (JB) tests are both applied. The W statistics for VOL and RZ are 0.7436 and 0.7677, respectively, indicating clear departures from normality. The W statistic of 0.9412 for RQ is closer to a normal distribution but may still reflect some deviation. All p-values are 0.000, so the null hypothesis of normality is rejected at any reasonable significance level. The JB statistics are very large for all three variables, which also points to non-normal distributions.

3.5. Stationarity Tests

A stationarity test is a key step in time-series analysis because it establishes whether a series has stable statistical properties. The test helps ensure the accuracy and reliability of subsequent modeling and forecasting.

To reduce the bias caused by nonstationary series, the study uses Stata to perform augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit-root tests before estimating the GARCH model. A series without a unit root is stationary. The ADF results are reported in Table 3.

Table 3. ADF unit-root tests

Variable	ADF statistic	p-value	1% critical value	5% critical value	10% critical value
VOL	-15.801	0.000	-3.439243	-2.865355	-2.568858
RZ	-17.910	0.000	-3.439255	-2.865360	-2.568861
RQ	-23.654	0.000	-3.439205	-2.865338	-2.568849

All three ADF p-values are 0.000, so the null hypothesis of a unit root is rejected. Daily stock price volatility, margin financing, and securities lending are therefore stationary.

Table 4. PP unit-root tests

Variable	Test	PP statistic	p-value	1% critical value	5% critical value	10% critical value
VOL	Z(rho)	-1,379.116	0.000	-29.500	-21.800	-18.300
VOL	Z(t)	-28.728	0.000	-3.960	-3.410	-3.120
RZ	Z(rho)	-1,496.127	0.000	-29.500	-21.800	-18.300
RZ	Z(t)	-30.791	0.000	-3.960	-3.410	-3.120
RQ	Z(rho)	-2,655.477	0.000	-29.500	-21.800	-18.300
RQ	Z(t)	-53.423	0.000	-3.960	-3.410	-3.120

The PP tests reject the null hypothesis for all variables, both when the statistics are compared with their critical values and when their p-values are examined. All series are therefore stationary and suitable for GARCH modeling.

4. Empirical Analysis of the Volatility of the Shanghai Composite Index

4.1. Autocorrelation Test

In a multiple regression model of the form $y = \beta_0 + \beta_1 x_1 + ... + \beta_k x_k + \varepsilon$, the residuals ε may be autocorrelated. Autocorrelation refers to correlation between observations in a time series at different lags. When autocorrelation is present, ordinary least squares estimates remain unbiased but are no longer efficient and do not have minimum variance. Standard errors may be underestimated, t-statistics may be overstated, and insignificant variables may appear significant. Testing for autocorrelation is therefore important. Common tests include the Durbin-Watson and Breusch-Godfrey tests. This study uses the Breusch-Godfrey (BG) test, which is better suited to multiple regression. It is based on the Lagrange multiplier principle, can detect higher-order autocorrelation, and is unaffected by the number of regressors. The results are reported in Table 5.

Table 5. Breusch-Godfrey autocorrelation test

Lag (p)	Chi-square statistic	df	Prob. > chi-square
1	645.410	1	0.000
2	759.024	2	0.000

At lag 1, the chi-square statistic is 645.410 and the p-value is 0.000. At lag 2, the statistic is 759.024 and the p-value is again 0.000. The null hypothesis is therefore rejected in both Breusch-Godfrey LM tests at any reasonable significance level. The residuals from the regression are autocorrelated.

4.2. ARCH Effect Test

Cross-sectional data often exhibit heteroskedasticity, while

time-series data often exhibit autocorrelation. Engle (1982) showed that time-series data can also exhibit a special form of heteroskedasticity known as autoregressive conditional heteroskedasticity (ARCH). Stata is used to conduct an LM test for ARCH effects, and the results are reported in Table 6.

Table 6. ARCH LM test

Lag order	LM statistic	p-value	ARCH effect
1	35.080	0.0000	Yes
2	53.506	0.0000	Yes
3	92.415	0.0000	Yes
4	104.124	0.0000	Yes
5	111.739	0.0000	Yes
6	133.748	0.0000	Yes
7	134.259	0.0000	Yes
8	139.344	0.0000	Yes
9	139.889	0.0000	Yes
10	146.188	0.0000	Yes

The p-values are below 0.01 for lags 1 through 10, so the null hypothesis of no ARCH effect is rejected. Heteroskedasticity is present. The GARCH model is therefore used to examine the effect of margin trading and securities lending on the volatility of the Shanghai Composite Index.

4.3. GARCH Model Construction

The GARCH model describes changes in the volatility of financial time series. It extends the ARCH model by modeling the variance of the error term and is well suited to series with heteroskedasticity. It consists of a conditional mean equation and a conditional variance equation.

The mean equation is specified first.

The conditional mean equation usually takes an autoregressive moving-average (ARMA) form. For a time series y_t, the conditional mean can be written as Eq. (4):

$$y_t=\mu+\sum_{i=1}^{p}\varphi_i y_{t-i}+\sum_{j=i}^{q}\theta_j \epsilon_{t-j}+\varepsilon_t \quad (4)$$

The autocorrelation test shows that the residuals are autocorrelated. The ARMA model combines autoregressive (AR) and moving-average (MA) components, is suitable for forecasting stationary series, and can remove residual autocorrelation so that the model captures heteroskedasticity. The autocorrelation function (ACF) and partial autocorrelation function (PACF) are used to select an appropriate specification and lag order, as shown in Figs. 1 and 2.

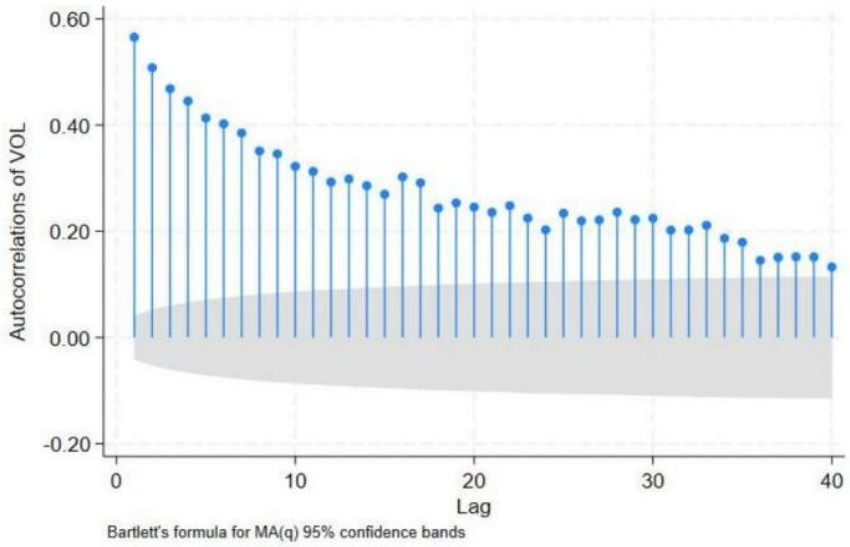


Figure 1. Autocorrelation function of stock price volatility.

In Fig. 1, the autocorrelation coefficients decline as the lag increases. Although the coefficients are small at higher lags such as 10 and 20, they remain outside the confidence band shaded in gray. The ACF therefore exhibits a slowly decaying tail.

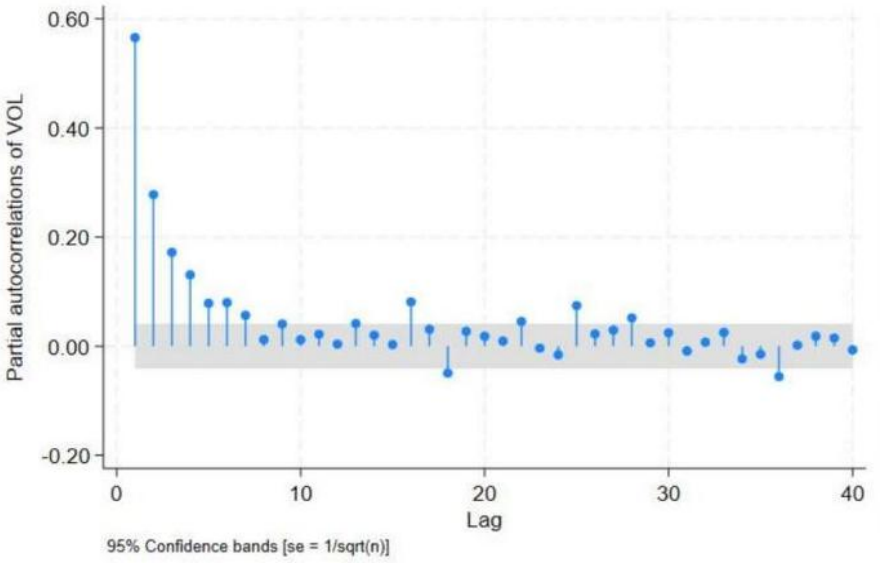


Figure 2. Partial autocorrelation function of stock price volatility.

In Fig.2, the partial autocorrelation coefficients fluctuate after lag 1, then fall quickly inside the 95% confidence band after low lags such as 2 and 3. The PACF cuts off rapidly, so an AR(1) specification is appropriate.

Table 7. ARIMA(1,0,0) estimation results

Variable	Coefficient (t-statistic)
VOL, constant	1.341*** (26.77)
ARMA, L.ar	0.566*** (48.54)
Sigma, constant	0.752*** (127.21)

*** denotes significance at the 1% level.

The estimated model is shown in Eq. (5):

$$VOL_t = 1.341 + 0.566 VOL_{t-1} + \epsilon_t \quad (5)$$

Where VOL_t is the daily stock price volatility of the Shanghai Composite Index on day t, VOL_{t-1} is the value on day $t-1$, and ε_t is the error term. The estimated standard deviation is 0.752.

The ARIMA regression results show that all coefficients are highly significant and that the model fits well. The constant and the ARMA autoregressive term have clear estimates and confidence intervals, and the error standard deviation is also reasonably estimated. These results can be used to analyze and forecast VOL, as shown in Fig. 3. The figure displays observed volatility and the one-step forecast from 2015 through 2025; the blue line is observed volatility and the red line is the forecast.

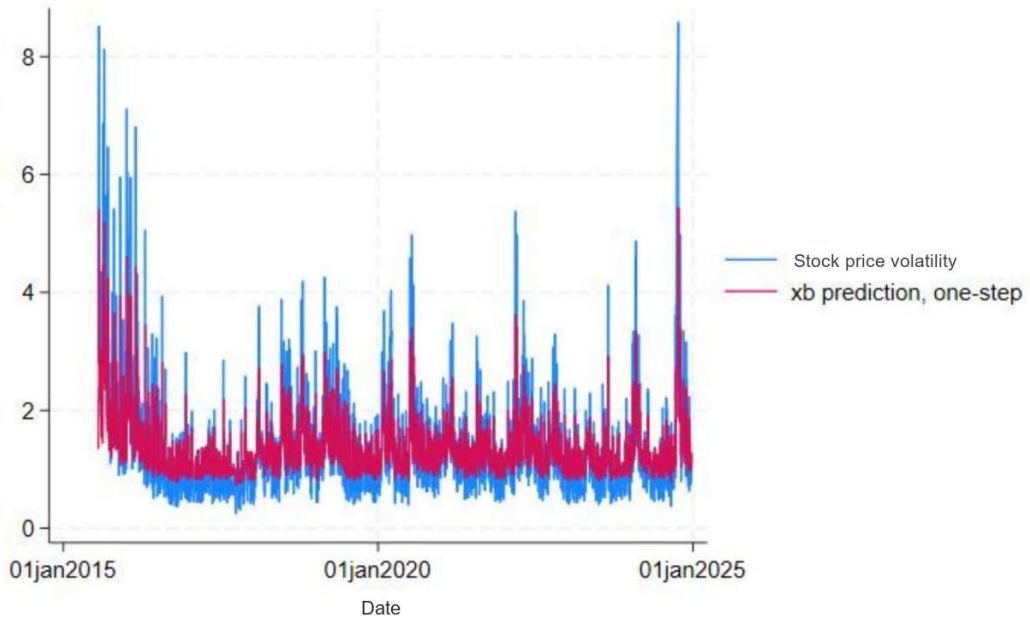


Figure 3. Observed and predicted volatility of the Shanghai Composite Index.

The variance equation is specified next. The basic variance equation of the GARCH model is Eq. (6):

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \quad (6)$$

Where σ_t^2 is the conditional variance; ω is greater than 0; α_i and β_j are nonnegative; and the usual non-negativity and stationarity conditions apply. Alternative ARCH and GARCH orders are compared using the AIC and BIC, and GARCH(1,1) is selected as the optimal specification. Table 8 reports the

estimation results.

Table 8. GARCH (1, 1) estimation results

Variable	(1) VOL	(2) Variance equation
L.arch	--	0.117*** (0.00562)
L.garch	--	0.862*** (0.00395)
Constant	1.076*** (0.0132)	0.0164*** (0.00132)
Observations	2,292	2,292

*** denotes significance at the 1% level.

Using these coefficient estimates, the GARCH (1, 1) variance equation is Eq. (7):

$$\sigma_t^2=0.0164+0.117\epsilon_{t-1}^2+0.862\sigma_{t-1}^2 \quad (7)$$

4.4. Granger Causality Test

Granger causality is used to assess whether past values of one variable improve the forecast of another beyond what can be achieved with the second variable's own past values. In other words, the past of X contains information that helps explain future changes in Y. Granger causality tests require stationary variables. The stationarity results above show that VOL, RZ, and RQ satisfy this condition. The test results are reported in Table 9.

Table 9. Granger causality tests for VOL, RZ, and RQ

Null hypothesis	p-value
RZ does not Granger-cause VOL	1.174509e-05
VOL does not Granger-cause RZ	6.162999e-12
RQ does not Granger-cause VOL	0.00443367
VOL does not Granger-cause RQ	0.00258937

The lag order is selected using information criteria. In the standard output, the optimal order for each criterion is marked with an asterisk, and the order with the most asterisks is chosen. At the 1% significance level, all null hypotheses are rejected. VOL is therefore Granger-caused by RZ and RQ, and RZ and RQ are in turn Granger-caused by VOL; the relationships are bidirectional.

4.5. Impulse Response Analysis

An impulse response function shows how a one-standard-deviation shock to one endogenous variable affects the other endogenous variables in the system, both contemporaneously and in later periods. Consider a simple two-variable VAR model:

$$Y_{1t} = a_{11}Y_{1t-1} + a_{12}Y_{2t-1} + \varepsilon_{1t} \quad (8)$$

$$Y_{2t} = a_{21}Y_{2t-1} + a_{22}Y_{2t-1} + \varepsilon_{2t} \quad (9)$$

In this model, ε_{1t} is a random disturbance. If ε_{1t} receives a one-standard-deviation external shock, the shock has an immediate effect on Y_{1t}. Through lagged effects, changes in Y_{2t} can then affect Y_{1t} in later periods. As the effect propagates, the shock spreads through the system and its influence may strengthen before it eventually fades. Impulse responses generally produce either persistent or transitory effects. A persistent effect remains at a stable level after the initial shock. A transitory effect expands at first but then diminishes and eventually disappears.

Impulse response analysis is conducted using the two VAR models, with one-standard-deviation shocks to VOL, RZ, and RQ. The horizontal axis represents the lag period and the vertical axis represents the cumulative response. If the response eventually returns to zero, the effect is transitory. If the response converges to a nonzero value, the effect is persistent. The main focus is the effect of margin trading and securities lending on the volatility of the Shanghai Composite Index. Fig. 4 presents the pairwise impulse responses for VOL, RZ, and RQ.

A positive one-standard-deviation shock to financing intensity affects stock price volatility. The shock initially reduces volatility, reaches its maximum effect in period 2, and then weakens over periods 2 and 3. In period 5, the response becomes positive and increases volatility, after which it declines and stabilizes. The results indicate that a change in financing intensity first reduces volatility, then fluctuates for several periods before the effect fades.

A positive one-standard-deviation shock to securities lending intensity also affects stock price volatility. The effect initially reduces volatility, peaks in period 1, and then weakens. In period 4, the response becomes positive and increases volatility, after which it declines and stabilizes. The results show that a change in securities lending intensity first reduces volatility, then increases it, with the effect disappearing as the lag order rises.

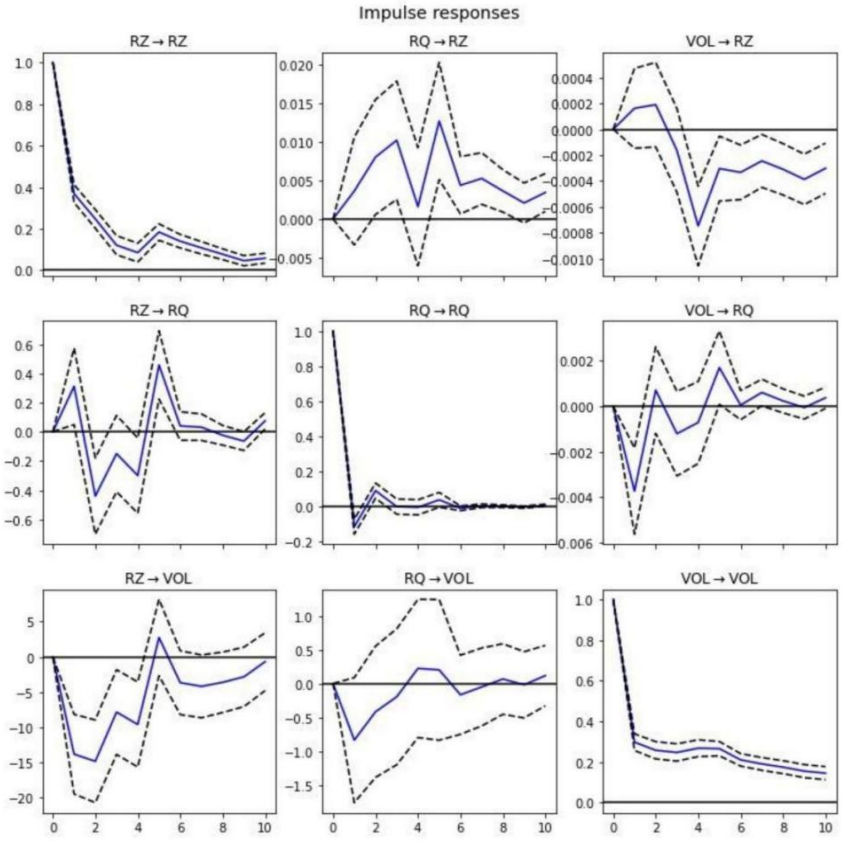


Figure 4. Impulse responses among VOL, RZ, and RQ.

5. Conclusions and Recommendations

This study combines theoretical and empirical analysis. It explains the factors that affect stock market volatility and constructs a GARCH model using margin financing and securities lending balances from the Shanghai Stock Exchange and daily high and low prices of the Shanghai Composite Index from 2015 to 2024. The growth rates of the balances and daily stock price volatility are calculated and examined empirically. The results show that both margin financing and securities lending help stabilize stock market volatility, although the effect weakens as the lag order increases.

The paper makes the following recommendations.

5.1. Optimize the Investor Structure

Individual investors account for a large share of China's margin trading and securities lending credit accounts, while institutional investors account for a relatively small share. This imbalance may undermine market stability. A moderate increase in institutional participation can improve market activity, increase the supply of lendable securities, and help balance the mix of margin financing and securities lending. Such a change would support a healthier and more stable securities market.

Investor education is also essential. The China Securities Regulatory Commission has proposed incorporating investor education into the national education system and addressing the "four shortcomings" facing small and medium-sized investors: an incomplete trading system, an imperfect market system, an unsuitable regulatory system, and immature investors. Improving financial knowledge and risk awareness can raise the quality of investment decisions and reduce investment risk.

A sound investor suitability system is another important protection. Optimizing the return mechanism and safeguarding investors' lawful rights can create a safer and more reasonable investment environment. Specific measures include training and exchange sessions on investor education and protection, strict enforcement of delisting rules, and simpler procedures and lower costs for small and medium-sized investors seeking legal remedies. Together, these measures form a comprehensive strategy for strengthening investor management through better market supervision, investor education and protection, and suitability requirements.

5.2. Improve the Margin System

The margin system is central to risk management in derivatives markets. It must be continuously improved to adapt to changing market conditions and risk-control needs. A reasonable margin ratio is particularly important: it supports the healthy development of margin trading and securities lending while limiting risk. The ratio controls risk by limiting the amount of leverage available to investors, and exchanges and market institutions must set it with multiple factors in mind. When the economy overheats or inflation rises, an exchange can raise the margin ratio to reduce excessive investment, lower stock market liquidity, and cool the economy. When investment activity is too low, the ratio can be lowered to reduce financing costs, encourage investment, and increase liquidity. Margin-ratio adjustments should therefore be made prudently and in a timely manner to maintain orderly trading and support macroeconomic objectives.

5.3. Strengthen Regulatory Oversight

First, information-disclosure rules for margin trading and securities lending should be established and improved so that market participants can obtain timely and accurate

information and the market becomes more transparent and fair. The Implementation Rules for Margin Trading and Securities Lending should be revised to expand the range of eligible securities and remove the uniform minimum maintenance guarantee ratio. Securities firms should be allowed to agree on the ratio with clients according to the client's credit, the quality of collateral, and the firm's risk tolerance.

Second, the reporting time for market-based agreed securities refinancing should be adjusted from same-day availability to next-day availability, and lending of restricted shares should be fully suspended. These steps would limit the efficiency of short selling, reduce the possibility of market manipulation, and stabilize price fluctuations. Supervision should also be strengthened across the inquiry, pricing, and allotment stages of initial public offerings; overpricing, excessive fundraising, and coordinated bid suppression should be addressed; disclosure for fundraising projects should be tightened; and capital should be guided toward healthy development through look-through supervision and regulatory coordination.

Finally, supervision of securities firms should be strengthened. Firms should improve the management of client trading and prohibit improper transactions involving securities lending. Enforcement should follow a zero-tolerance approach and protect the bottom line against risk. Regulators should focus more effectively on their core responsibilities and act more swiftly against fraudulent issuance, financial misstatement, insider trading, and other violations. Investor-protection mechanisms such as advance compensation, ordered repurchase, and class actions should be used fully. Continued innovation in regulatory methods, better coordination, and greater use of regulatory technology can further improve the effectiveness of capital market supervision.

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