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The Impact of Volatility Index on China's Stock Market

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Abstract

As global economic integration quickens its pace, economies and trades between China and the United States grow more interactive, resulting in a clear impact on China's stock market. The Chicago Board Options Exchange Market Volatility Index (VIX) reflects stock market volatility in the United States and represents investors' expectation of the stock market by its American counterpart. Different from prior studies of stock markets in China and the United States, this paper focuses on the VIX to determine its impact on the CSI 300 Index. Our purpose is twofold: to determine whether the VIX influences the volatility of the CSI 300 index and to analyze the extent to which the VIX influences the rate of return of the Chinese stock market. Using a GARCH model, we find that the VIX is positively correlated with the volatility of the Chinese stock markets and that a leverage effect exists between them. A vector autoregression model shows that the VIX exerts negative impact on the CSI300 index. The capital asset pricing model shows that the VIX rises with the decline of the rate of return of individual shares in the hi-tech industries. The results provide both a better management of China stock market vitality and strategic suggestions regarding investment.

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1. Introduction

Financial liquidity on the global scale has increased due to the accelerated integration of international financial market and economies in the twenty-first century. Within this context, assets of similar risk structure in different regions of the world undergo price fluctuations even when one marketplace is influenced. The rapid development of communication technology facilitated by the internet makes possible the immediate delivery of any news to any corner of the globe, and hence the share price is an immediate reflection of new messages. In addition, the boom of international trade and investments from multinational corporations promote this interconnectedness of international stock markets.

The U.S. subprime crisis in 2008 triggered the stagnation of the global economy. The situation was made worse by the following European debt crisis, resulting in the decline of global financial market, turmoil within stock markets, and the loss of investors' confidence. Risk management became a top priority in all regulatory bodies and a heated topic among scholars. An important variant in contemporary finance research, volatility plays an integral role in risk management. The increasing openness of the financial market makes it impossible for China stock market to maintain its own business without regard to outside volatility. Given these global conditions, the importance of studying the influence of international stock market volatility on the Chinese stock market is clear and bears practical significance for both investors and administrators. Such a study can, through effective estimation and projection of volatility, introduce a correct market expectation, provide recommendations for effective supervision of the financial market, and encourage the maintenance of a healthy Chinese stock market.

The most commonly used volatility index is the Chicago Board Options Exchange Market Volatility Index (VIX), a measure of implied volatility based on past volatility. Also referred to as the investor fear gauge, it represents one measure of the market's expectation of stock market volatility. The fear index surged after the 2008 U.S. subprime crisis and has remained high ever since. Numerous studies show that the VIX is negatively correlated with stock market yield rate. The VIX has become a benchmark measure of U.S. stock market volatility. The U.S. stock market, as the world's most important market, serves as a predictor for stocks all around the world. Its influence on the Chinese stock market cannot be underestimated, especially as both countries grow more interdependent economically.

This paper employs generalized autoregressive conditional heteroskedasticity (GARCH) models and adds the VIX as an exogenous variable to examine the influence of U.S. stock market volatility on the Chinese stock market, namely, the CSI 300. Our purpose is twofold: to determine whether the VIX influences the CSI 300 Index and, if so, to examine the extent to which the VIX influences the rate of return of the Chinese stock market.

This study provides two new points of research. First, while studying Chinese stock market volatility, scholars stress the leverage effect and GARCH model-based volatility spillover effect. However, few studies address the international stock market's influence on Chinese stock markets; most treat the Dow Jones, S&P500, or NASDAQ indexes as subjects. Different from prior research, we investigate the U.S. stock market's influence on the Chinese stock market by introducing VIX, a measure of implied volatility of index options. Second, scholars who study the VIX focus on its influence on the U.S. stock price yield rate. This investigation, which has reached maturity, shows that the VIX is negatively correlated with the U.S. stock market yield rate. However, associated research concerning the VIX and burgeoning capital markets remain to be perfected. In addition, few VIX-based domestic studies exist because China has yet to launch option transactions, and researchers must still compute Chinese stock market volatility with the help of the VIX. Thus, another contribution of this paper is to fill up the gap in the research concerning VIX. In addition, we provide theoretical reference to ensuing studies because China is likely to engage in stock index option trading in the future.

2. Literature Review

Engle (1982) finds time-varying volatility clustering in economic time series by means of autoregressive conditional heteroskedasticity (ARCH) models. Engle and Ng (1993) show the asymmetry information curve and provide evidence of the leverage effect, that is, the asymmetric effect that is a result of the financial market. Chen and Yang (2011) find a weak leverage effect for the U.S. stock markets on the Chinese stock market. Using GARCH-M models, Guo (2006) analyzes the relation of the volatility of the Shanghai and the Shenzhen composite indexes and finds that messages can be exchanged effectively between the two markets with a two-way volatility spillover effect characterized by clustering and asymmetry. Zhao (2013) examines volatility in the Chinese market after the 2008 financial crisis and finds that the exponential GARCH (EGARCH) model is better than threshold GARCH (TGARCH) model to capture the leverage effect of Chinese stock market. Zhang, Fan, and Li (2010) analyze the correlation between the Chinese and U.S. stock market using the Shanghai composite index and Dow Jones index, respectively, as samples. The results show that China's stock market provides little guidance to its U.S. counterpart in price and volatility spillover whereas the U.S. stock market guides the Chinese stock market after the Qualified Domestic Institutional Investor scheme came into effect in 2006.

Using a volatility index, Whaley (1993) finds that the VIX and S&P 100 indexes are negatively correlated, which suggest a risk aversion effect of derivatives undergoing the VIX secondary agent and that the VIX can effectively avoid investment portfolio risk without regard to other risk parameters. Copeland (1999) finds that the VIX can serve as a leading indicator of the stock market. When the VIX increases noticeably, remuneration realization of large-scale investment portfolios are better than those of small-scale portfolios, and vice versa. Simon and Wiggins (2001) use a market sentiment index including the VIX, put–call ratio, and a trading index to conduct mock trading to determine whether the purchase of S&P500 futures on a high fear index results in abnormal returns. They find that the VIX, put–call ratio, and the trading index are useful contrary indicators. Huang and Zheng (2009) use data from the Hang Seng index option market to determine whether a historical data-based GARCH model or implied volatility model is more effective. They find that over a short (long) forecast period the GARCH (implied volatility) model performs better. Guo (2011) finds a negative correlation between the VIX and the price fluctuation of nonferrous metals in futures market. Xia (2013) uses the historical volatility method to forecast volatility by applying a GARCH model to analyze the CSI 300 index. Wang (2009) finds that the GJR-GARCH-M can catch the fluctuation in various countries' stock markets in Asia. As the VIX rises, the volatility of Asian stock markets increases correspondingly.

3. Empirical Method

3.1 Data Specification

The CSI 300 Index, China's A-share stock market index, was co-developed by the Shanghai and Shenzhen stock exchanges. It replicates the performance of more than 10 leading enterprises within industries that include banking, iron and steel, petroleum, electricity, coal, household appliance, machinery, textile，food, brewing, chemical fiber, nonferrous metals, transportation, electron devices, commercial department stores, biological pharmacy, hotel tourism, and real estate. It is composed of mainstream investment stocks of strong representativeness and liquidity that reflects the overall trend of A-share stock markets. The constituent stocks in the CSI 300 Index are issued and modulated by exchanges with an established reputation of being impartial and authoritative. Therefore, we use the CSI 300 Index as representative of price fluctuation of China stock markets to conduct our empirical analysis.

The VIX is a popular measure of the implied volatility of the S&P500

index option. Since its introduction in 1993, the VIX has been considered by many to be the world's premier barometer of investor sentiment and market volatility. Often referred to as the fear index or the fear gauge, it represents one measure of the market's expectation of stock market volatility over the next 30 days.

3.2 The Family of GARCH Models

Conventional econometric models assume that the variance of the disturbance term is constant. However, in the real world, many economic time series exhibit periods of unusually large volatility, followed by periods of relative tranquility. In such circumstances, the assumption of a constant variance is inappropriate. To characterize and model observed time series more precisely, Engle (1982) uses ARCH models. ARCH models assume that the variance of the current error term or innovation is a function of the actual sizes of the previous time periods' error terms. Often the variance is related to the squares of the previous innovations. ARCH models are commonly employed to model stationary time series that exhibit time-varying volatility clustering. Time series analysis is based on the stationarity hypothesis. We use the augmented Dickey–Fuller (ADF) unit root test to check the stationary of time series. See Appendix A for details.

3.2.1 GARCH Model

Extending Engle's (1982) original work, Bollerslev (1986) develops a technique that allows the conditional variance to be an autoregressive moving average (ARMA) process, known as a GARCH model. The GARCH model is more flexible in the setting of the conditional heteroskedasticity function than the ARCH model. The GARCH model is expressed as:

$$y_t = \alpha_0 + \beta x_t + \varepsilon_t \tag{1}$$

$$\varepsilon_t = \nu_t \cdot \sqrt{h_t} \tag{2}$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_i h_{i-1} \tag{3}$$

Equation (1) is called the mean function, and x_t is an ARMA process of order (p^m, q^m). In addition, x_t can contain exogenous variables. Equation (2) is the error process. ε_t represents the information shock during period t. The conditional variance of ε_t is the ARMA process given by the expression h_t in Equation (3); therefore, Equation (3) is called the conditional heteroskedasticity function.

3.2.2 TGARCH Model

Glosten, Jaganathan, and Runkle (1993) show that the effects of good and bad news have different effects on volatility. Specifically, $\varepsilon_{t-1} = 0$ is a threshold such that shocks greater than the threshold have different effects than shocks below the threshold. Formally, the TGARCH (p, q) model is expressed as

$$h_t = c + \beta_0 h_{t-1} + \beta_1 \varepsilon_{t-1}^2 + \gamma d_{t-1} \varepsilon_{t-1}^2, \tag{4}$$

where d_{t-1} is a dummy variable that equals 1 (zero) if $\varepsilon_{t-1} < 0$ ($\varepsilon_{t-1} \geq 0$) and γ is the asymmetry coefficient. The intuition behind the TGARCH model is that positive values of ε_{t-1} are associated with a zero value of d_{t-1}. Therefore, if $\varepsilon_{t-1} \geq 0$, the effect of a ε_{t-1} shock on h_t is $\beta_1 \varepsilon_{t-1}^2$. When $\varepsilon_{t-1} < 0$, d_{t-1}=1, and the effect of an ε_{t-1} shock on h_t is $(\beta_1 + \lambda)\varepsilon_{t-1}^2$. If $\gamma > 0$, negative shocks will have larger effects than positive shocks on volatility.

3.2.3 EGARCH Model

Another model that allows for the asymmetric effect of news is the

EGARCH model. One problem with a standard GARCH model is that all of the estimated coefficients must be positive. Nelson (1991) proposes a specification that does not require non-negativity constraints. The equation for conditional variance is in the log-linear form. The EGARCH process is

$$\ln(h_t^2) = \alpha_0 + \alpha_1 \ln(h_{t-1}^2) + \beta\left|\varepsilon_{t-1}/h_{t-1}\right| + \lambda(\varepsilon_{t-1}/h_{t-1}) \tag{5}$$

In the EGARCH model, if $\varepsilon_{t-1}/h_{t-1}$ is positive, the effect of the shock on the log of the conditional variance is $\beta + \lambda$. If $\varepsilon_{t-1}/h_{t-1}$ and is negative, the effect of the shock on the log of the conditional variance is $\beta - \lambda$. We add an exogenous variable, the VIX, to the family of GARCH models. Our empirical models of mean function, modified GARCH, modified TGARCH, and modified EGARCH are therefore expressed, respectively, as

$$R_t = \alpha_1 R_{t-1} + \varepsilon_t + \varphi_1 \varepsilon_{t-1} \quad \varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t) \tag{6}$$

$$h_t = c + \beta_0 h_{t-1} + \beta_1 \varepsilon_{t-1}^2 + \delta_1 VIX_{t-1} + \delta_2 D * VIX_{t-1} \tag{7}$$

$$h_t = c + \beta_0 h_{t-1} + \beta_1 \varepsilon_{t-1}^2 + \gamma d_{t-1} \varepsilon_{t-1}^2 + \delta_1 VIX_{t-1} + \delta_2 D * VIX_{t-1} \tag{8}$$

$$\ln(h_t^2) = c + \lambda_1 \ln(h_{t-1}^2) + \theta_1 \left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \theta_2 \frac{\varepsilon_{t-1}}{h_{t-1}} + \delta_1 VIX_{t-1} + \delta_2 D * VIX_{t-1} \tag{9}$$

where R_t denotes the return ratio of CSI 300; VIX_t presents the new series after the first order logarithmic difference method; *D* is a dummy variable that equals 1 when today's VIX_t goes up compared to yesterday's VIX_{t-1}, so that the impact of the VIX equals $(\delta_1 + \delta_2)VIX_{t-1}$, and zero when VIX_t drops, so that the impact of VIX on R_t is $\delta_1 * VIX_{t-1}$; and δ_1 and δ_2 are coefficients that are expected to be estimated.

3.4 VAR Model

The VAR model describes the evolution of a set of k variables (called endogenous variables) over the same sample period as a linear function of only their past values. All variables in a VAR are treated symmetrically in a structural sense, and each variable has an equation explaining its evolution based on its own lags and the lags of the other model variables. A *p*th order VAR, denoted VAR(*p*) is

$$Y_t = c + A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \varepsilon_t \tag{10}$$

where the one-period back observation Y_{t-1} is called the first lag of Y; c is a k × 1 vector of constants (intercepts); A_i is a time-invariant k × k matrix; and ε_t is a k × 1 vector of error terms, which satisfies the following conditions: every error term has mean zero, the contemporaneous covariance matrix of error terms is Ω (a k × k positive-semidefinite matrix), and for any non-zero k no correlation across time exists.

3.5 Capital Asset Pricing Model (CAPM)

The CAPM is a model for pricing an individual security or portfolio. For individual securities, we make use of the security market line and its relation to expected returns and systematic risk (beta) to show how the market must price individual securities in relation to their security risk class. The formula of the CAPM is

$$E(R_i) - R_f = \beta_i \left(E\left(R_m \right) - R_f \right) \tag{11}$$

where $\mathrm{E}(R_i)$ is the expected return on the capital asset; R_f is the risk-free rate of interest such as interest arising from government bonds; β_i is the sensitivity of the expected excess asset returns to the expected excess market returns; $\mathrm{E}(R_m)$ is the expected return of the market; $\mathrm{E}(R_i) - R_f$ is the risk premium; and $E(R_m) - R_f$ is the market premium. Based on the original CAPM, we add the VIX as a new risk factor. Therefore, the modified model is:

$$R_{i,t} - R_f = \alpha + \beta_1 (R_m - R_f) + \beta_2 VIX_m + \varepsilon_t \tag{12}$$

where $R_{i,t}$ refers to the monthly rate of return of each individual share; R_f refers to the risk-free interest rate; R_m represents the monthly return rate of market portfolio; VIX_m represent the series of VIX-adjusted monthly close price after the first-order logarithmic difference method; ε_t is an error term, which represent the influence of variables that are not explicitly included in the model; and α, β_1, and β_2 are the estimated coefficients.

4. Empirical Analysis

4.1 The VIX's Impact on the Volatility of Chinese Stock Market

We select the VIX and CSI 300 indexes as sample data from the Chinese stock software Great Wisdom 365. The data set covers January, 2005 to December, 2013. In light of the different holiday and festival dates in mainland China and the United States, the VIX takes precedence; that is, if the U.S. stock market is closed on a day that the VIX is closed for trading, volatility in the correspondent country is not taken into consideration. In other words, the VIX is included in the sample data only when both the VIX and its correspondent country provide an opening quotation on the same day. Due to the time differences between the countries, U.S market trends do not influence the Chinese market until one day later; therefore, when sample matching, we match the VIX to the CSI 300 index one day earlier. Data collected through this method provide 2,019 observations including both the VIX and CIS 300 indexes.

We process the sample data with the first-order logarithmic difference method to obtain R_t (daily rate of return of the CSI 300 index) and VIX_t (a new series that is the closing daily price of the VIX after the first-order logarithmic difference method). Table 1 provides the descriptive statistics of R_t and VIX_t. The results show that R_t has negative skewness, which means that we can reject the null hypothesis that the mean of R_t=0. However, VIX_t has positive skewness. R_t and VIX_t have high kurtosis and their Jacque–Bera statistics are more than 3, p-values equal 0.0000. Clearly R_t and VIX_t do not follow normal distributions. High kurtosis and fat tail are the distinctive features of R_t, figures 1 and 2 show volatility clustering phenomenon in R_t and VIX_t .

Table 1
Descriptive Statistics of R_t and VIX_t

	Mean	Max	Mini	Std. Dev.	Skewness	Kurtosis	JB	Prob.
R_t	0.000378	0.0893	-0.0969	0.0186	-0.3281	5.8778	765.6261	0.0000
VIX_t	–0.000001	0.4960	-0.3596	0.0699	0.7110	7.2744	1783.2290	0.0000

Notes: This table reports the descriptive statistics of R_t and VIX_t. R_t stands for daily return rate of CSI 300 index and VIX_t stands for the new series that the daily closing price of VIX after first-order logarithmic difference method. p-value is for the Jargue–Bera test of normality.

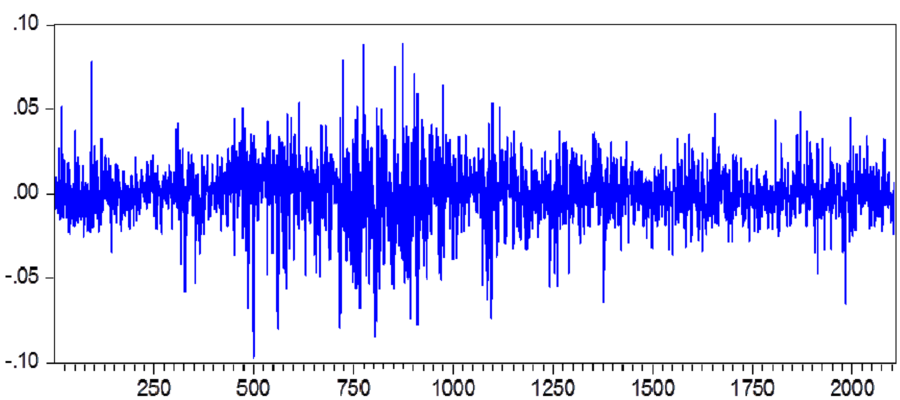

Fig. 1 The Daily Return Rates of CSI 300 Index. This figure reports the daily return rate of the CSI 300 Index. The daily return rate of the CSI 300 Index fluctuates up and down around the mean, which stands for the stationary of the series. In addition, there is a clustering effect among the series.

The ADF unit root test on R_t and VIX_t is important because all time-series analysis is based on the stationarity hypothesis. In Table 2, the p-value of the ADF statistic of R_t (VIX_t) is 0.0001 (0.0000). Thus, we can reject the null hypothesis where series R_t and VIX_t have a unit root. In other words, both of them are stationary.

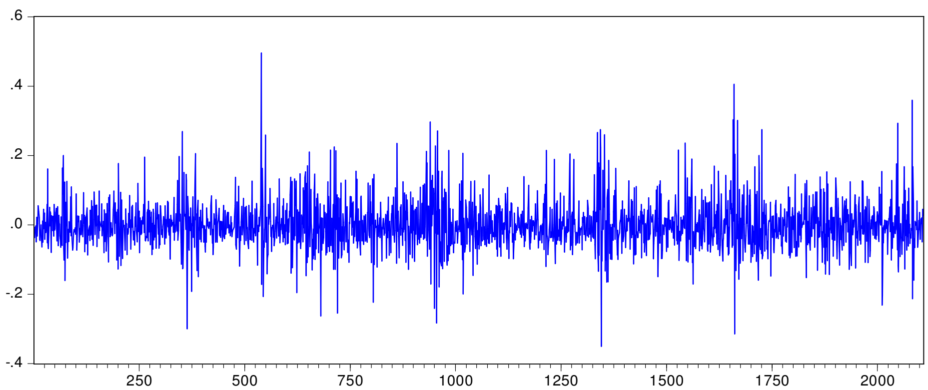

Fig. 2 Series of VIXt. This figure reports the new series that the daily closing price of VIX after the first-order logarithmic difference method. The new series fluctuates up and down around the mean, which shows the stationary of the series.

Table 2
Augmented Dickey-Fuller Unit Root Test on R_t and VIX_t

Variables	ADF Statistics	1% level	5% level	10% level	Prob.
R_t	–45.8485	3.4333	–2.8627	–2.5674	0.0001
VIX_t	–37.5625	3.4332	–2.8627	–2.5674	0.0000

Notes: This table reports the augmented Dickey–Fuller (ADF) unit root test on series R_t and series VIX_t.. The null hypothesis of ADF test is that the series has unit root. We reject the null hypothesis at 1%, 5%, and 10% level. p-value is for the ADF test of stationarity. Both R_t and VIX_t are stationary.

Based on the analysis of the descriptive statistics, R_t clearly has a time-varying variance characteristic. Before setting up the GARCH model, we need to confirm whether the R_t series has a clustered volatility called the ARCH effect. First, we must establish the ARMA model of the R_t series. We use the Alaike information criterion and Schwartz Bayesian criterion to select the best lag phase for the ARMA model. Going through many times trials by software, we finally obtain the best fitted model, the ARMA (1, 1). Using the ordinary least squares method to estimate coefficients, we obtain

$$R_t = -0.9069 R_t + \varepsilon_t + 0.9801 \varepsilon_{t-1} \tag{13}$$

$$t = (-35.9675) \quad (43.9176)$$

Then, we take the serial correlation Lagrangian multiplier (LM) test of the residuals in that model. Table 3 shows that when q=10 the p-value of LM statistics is 0.0474 at less than the 5 percent significance level. In other words, the residuals have a high order of ARCH effect.

Table 3
Breusch-Godfrey Serial Correlation LM Test

F-statistic	1.9375	Prob. F(10,2096)	0.0364
Obs*R-squared	18.4763	Prob. Chi-Square(10)	0.0474

Notes: This table reports the Breusch-Godfrey serial correlation LM test on the residuals in that model: $R_t = -0.9069 R_t + \varepsilon_t + 0.9801 \varepsilon_{t-1}$
The null hypothesis of the LM test is that the residuals series is not auto-correlative at given lagged values (represented by q). When q=10, the p-value of LM statistics is 0.0474 at less than the 5% significance level. In other word, the residuals have high order of ARCH effect.

Table 4 show estimated results of the three models. In general, when the VIX goes up, its impact can be measured by the coefficients of $\delta_1 + \delta_2$. When the VIX drops, its impact is captured by the coefficients of δ_1. Table 5 show that in three models the coefficients of $\delta_1 + \delta_2$ are positive, which means that the volatility of the CSI 300 goes up along with the VIX. The coefficients of δ_1 are negative in the three models. When the VIX falls, the volatility of the CSI 300 index declines. The empirical results are the same as the theoretical assumption that the VIX is positively correlated with Chinese stock market volatility in all the three GARCH models.

Table 4
Parameter Estimation for the GARCH Family Models

Parameters	GARCH Model	T-GARCH Model	E-GARCH Model
α_1	0.9413***	–0.9634***	0.9374***
φ_1	–0.9333***	0.9774***	–0.9257***
c	0.0000***	0.0000**	–0.1743***
β_0	0.9533***	0.9488***	×
β_1	0.0392***	0.0351***	×
γ	×	0.0139*	×
λ_1	×	×	0.1094***
θ_1	×	×	–0.0155*
θ_2	×	×	0.9886***
δ_1	–0.000101**	–0.0000918*	–0.2366
δ_2	0.000165***	0.00155**	0.4944*

Notes: This table reports the estimation results for the following regressions:

$$R_t = \alpha_1 R_{t-1} + \varepsilon_t + \varphi_1 \varepsilon_{t-1} \quad \varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t)$$

$$h_t = c + \beta_0 h_{t-1} + \beta_1 \varepsilon_{t-1}^2 + \delta_1 VIX_{t-1} + \delta_2 D * VIX_{t-1}$$

$$h_t = c + \beta_0 h_{t-1} + \beta_1 \varepsilon_{t-1}^2 + \gamma d_{t-1} \varepsilon_{t-1}^2 + \delta_1 VIX_{t-1} + \delta_2 D * VIX_{t-1}$$

$$\ln(h_t^2) = c + \lambda_1 \ln(h_{t-1}^2) + \theta_1 \left| \frac{\varepsilon_{t-1}}{h_{t-1}} \right| + \theta_2 \frac{\varepsilon_{t-1}}{h_{t-1}} + \delta_1 VIX_{t-1} + \delta_2 D * VIX_{t-1}$$

***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5
The Impact of VIX on the Three Models

Model	When VIX grows up: $\delta_1 + \delta_2$	When VIX drops down : δ_1
GARCH	0.000064	–0.000101
TGARCH	0.0000632	–0.0000918
EGARCH	0.2578	–0.2366

Notes: This table reports the impact of VIX on the volatility of R_t among three models. We calculate the sum of δ_1 and δ_2 in the three GARCH models. The result is explicit that the VIX has a positive effect on the volatility of R_t.

Table 6 shows the VIX's leverage effect. The leverage effect is the tendency for bad news to have a more pronounced effect on volatility than good news does. $|\delta_1|$ ($|\delta_1+\delta_2|$) denotes good news (bad new). Comparing the different information shocks, we find that only the TGARCH and EGARCH models explain the leverage effect well. However, in the GARCH model, the impact of good news is larger than that of bad news. The GARCH model's effect extraordinarily because the TGARCH and EGARCH models are specially designed for asymmetric phenomena in the endogenous variables. In other words, when the exogenous variable VIX is excluded, the GARCH model neglects the volatility's own leverage effect. Therefore, one reasonable explanation is that in the GARCH model the endogenous leverage effect influences the VIX's leverage effect.

Table 6
Leverage Effect in the Three Models

Model	Comparison of the shock	Dose the model have VIX's leverage effect?
GARCH	$\lvert\delta_1+\delta_2\rvert < \lvert\delta_1\rvert$	No
TGARCH	$\lvert\delta_1+\delta_2\rvert > \lvert\delta_1\rvert$	Yes
EGARCH	$\lvert\delta_1+\delta_2\rvert > \lvert\delta_1\rvert$	Yes

Notes: This table reports the leverage effect in the three models. $|\delta_1|$ denotes good news, and $|\delta_1+\delta_2|$ denotes bad news. Comparing the different information shocks, we find that only the TGARCH and EGARCH models can explain the leverage effect well.

4.2 The VIX's Impact on the Rate of Return of Chinese Stock Market

The empirical analysis thus far explores the influence of VIX on the CSI 300 index in terms of volatility. The close relation between volatility and stock prices convince us that the VIX exerts an influence not only on the volatility but also rate of return of the Chinese stock market. Thus in the following discussion we investigate how the VIX influences stock prices from the perspective of the Chinese stock market and individual shares.

In this part, we use a VAR model and select the monthly exchange data of the VIX and CSI 300 indexes between January 2005 and December 2013.

We use Y_t to denote the monthly rate of return of the CSI 300 index and X_t to denote the new series after the first-order logarithmic difference. According to Table 7, series Y_t and X_t are stationary. Then we find out that the fittest lag length is 1. In other words, we choose to set up a VAR (1) model. Because the VAR model is structural rather than simplified, all of its variables are explained variables, and the estimated value of a single parameter may be biased. Therefore, it is pointless to work out the estimated value of any single parameter. In sum, we now drop the parameter estimation of the model and base the subsequent analysis on the VAR model, for example, Granger causality analysis, impulse response, and variance decomposition.

Table 7
Augmented Dickey-Fuller Unit Root Test on CSI and VIX

Variables	ADF Statistics	1% level	5% level	10% level	Prob.
Y_t	–9.1091	–3.4925	–2.8889	–2.5813	0.0000
X_t	–10.7114	–3.4925	–2.8887	–2.5813	0.0000

Notes: This table reports the augmented Dickey–Fuller (ADF) unit root test on series Y_t and series X_t. We use Y_t to denote monthly rate of return of the CSI 300 index and X_t to denote the new series after the first-order logarithmic difference. The null hypothesis of ADF test is that the series has a unit root. We can reject the null hypothesis at the 1%, 5% and 10% level. P-value is for the ADF test of stationarity. Both Y_t and X_t are stationary.

Table 8 provides the results of Granger causality analysis. The results show that VIX is the Granger reason of the CSI 300 index while the CSI 300 index is not the Granger reason of the VIX. Table 9 shows the variance decomposition of two variables. The CSI 300 index does little to the volatility of the VIX with a negligible 0.8 percent contribution. In contrast, the VIX's contribution to the CSI 300 index reaches 5.18 percent in period 2 and remains around 5.19 percent from the fourth lagged period. Thus, the VIX can in part explain the rate of return of the CSI 300 index. As for impulse response, Figure 3 shows a continuous negative impact on the rate of return of the CSI 300 index by the VIX, which reaches a high period 2 but it does not last long and converges to zero after period 4.

Table 8
Granger Causality Tests of Y_t and X_t

Null Hypothesis	F-Statistic	Prob.
X_t does not Granger Cause Y_t	5.6916	0.0189*
Y_t does not Granger Cause X_t	0.0626	0.8029

Notes: This table reports the Granger causality tests of Y_t and X_t, where Y_t denotes monthly return rate of the CSI 300 index and X_t denotes the new series after the first-order logarithmic difference. * denotes significance at 10% confidence level.

Table 9
VAR Variance Decomposition of VIX & CSI 300

Period	S.E.	CSI 300	VIX
Panel A : Variance Decomposition of VIX			
1	0.193167	0.746952	99.25305
2	0.193519	0.824897	99.17510
3	0.193520	0.825084	99.17492
4	0.193520	0.825084	99.17492
5	0.193520	0.825084	99.17492
6	0.193520	0.825084	99.17492
7	0.193520	0.825084	99.17492
8	0.193520	0.825084	99.17492
9	0.193520	0.825084	99.17492
10	0.193520	0.825084	99.17492
Panel B : Variance Decomposition of CSI 300			
1	0.096255	100.0000	0.000000
2	0.099588	94.81936	5.180640
3	0.099596	94.80792	5.192081
4	0.099596	94.80790	5.192104
5	0.099596	94.80790	5.192104
6	0.099596	94.80790	5.192104
7	0.099596	94.80790	5.192104
8	0.099596	94.80790	5.192104
9	0.099596	94.80790	5.192104
10	0.099596	94.80790	5.192104

Notes: This table reports the variance decomposition of the VIX and CSI 300 in the VAR (1, 1) model. Panel A is the variance decomposition of the VIX. The CSI 300 index does little to the volatility of VIX with a negligible 0.8% contribution. Panel B is the variance decomposition of CSI 300. The VIX's contribution to CSI 300 index reaches 5.18% in period 2 and remains around 5.19% from the fourth lagged period.

We draw the following conclusions from the empirical analysis. First, the

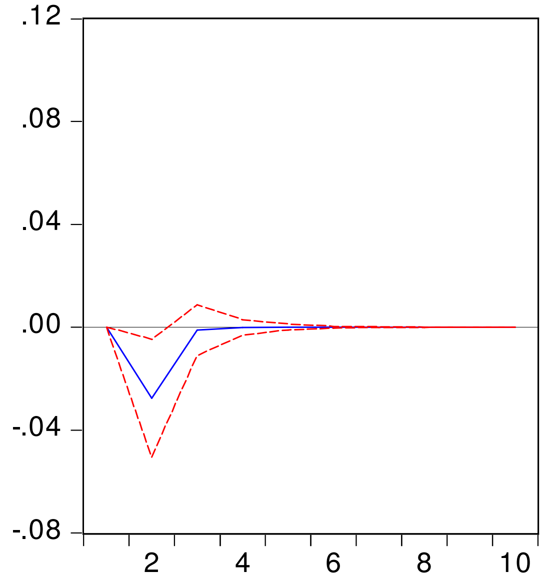

Fig. 3 The Impulse Response of the CSI 300 to the VIX. This figure reports the impulse response of the CSI 300 to the VIX. The X-axis is the time that the impulse response will continue. The Y-axis represents the fluctuation triggered by a unit impulse. The fluctuation is measured by percentage. The impulse response is mainly negative in the figure and maximized at period 2.

VIX provides a unidirectional impact on the rate of return of the CSI 300 index. In other words, the volatility of the VIX influences the rate of return of the CSI 300 index, whereas the CSI 300 index fails to influence the VIX. Second, the VIX's impulse response to the CSl 300 index is mainly negative, but the impulse response is temporary and disappears in four periods.

4.3 The VIX's Impact on the Rate of Return of the Hi-Tech Individual Shares

Taking into consideration the high-risk, volatility, and sensibility of hi-tech industries, we use computer industry stocks in the Shanghai and Shenzhen a-share market as our research sample. After excluding unqualified individual shares with discontinued data, we collect monthly data of 20 individual stocks from January 2005 to December 2013. The number of total panel (balanced) observations in the CAPM is 2,160. Appendix B provides the stock codes[1]. The calculation of the rate of return of individual shares, which is different from that of the stock market and must consider incomes such as dividends, is calculated as

$$R_t = \frac{P_{t+1} - P_t + D_t}{P} \tag{14}$$

where, P_{t+1} and P_t refer to the closing price in period t+1 and period t, respectively; and D_t refers to the dividends in period t.

We use the CSI 300 index as the market portfolio. Regarding the risk-free interest rate, scholars usually take short-term Treasury rates (three months by definition) as the research sample, but this method does not work in China. In contrast to the large portion of institutional investors abroad, individual investors dominate the Chinese market and deposits make up a large share of investments. Therefore, we use the three-month fixed-term deposit rate (compound interest) as the risk-free interest rate. Besides, compound interest is expressed in the form of annual interest rate whereas we need the monthly interest rate. The conversion formula is

$$(1 + R_m)^{12} = (1 + \frac{R_q}{4})^4 \tag{15}$$

where R_q (R_m) refer to the annual interest rate of three-month (one-month) fixed-term deposits. From 2005 to 2013, three-month fixed-term deposits are adjusted many times due to the government's monetary policies especially after the 2008 financial crisis. Therefore, the risk-free interest rate is worked out in three stages using a weighted mean method in terms of different monthly interest rates. The result is 0.2203 percent.

[1] A list of the stock codes is available from the authors on request.

Table 10 shows that β_1 in all 20 stocks are positive as expected and significant at the 1 percent level. The results are consistent with classical CAPM theory. However, of major interest relevant to this study is how the VIX acts on the rate of return of individual stock. β_2 is -0.0409 and significant at the 1 percent level. The *p*-value of the F-statistics reject the null hypothesis at the 1 percent confidence level, which means that the linear relation between the dependent variable and independent variables is significant. However, the adjusted *R*-squared is 0.3432, because some variables that affect the rate of return of individual stock are not considered in this model (e.g., price–earnings ratio, earnings per share, asset–liability ratio, liquidity ratio). In general, if the VIX moves upward, the market panics, and the rate of return of 20 hi-tech stocks falls.

Table 10
The Cross-Section Regression Results for the CAPM

Variable	**Coefficient**	**Std. Error**	***t*-statistic**	**Prob.**
α	0.0067	0.0029	2.3376	0.0195*
$R_m - R_f$	0.9799	0.0293	33.4297	0.0000***
VIX_t	–0.0409	0.0150	–2.7221	0.0065***
R^2	0.3438			
$\overline{R}^2$	0.3432			
F-statistic	565.1204***			

Notes: This table reports the estimation cross-section results for the following CAPM regressions:

$$R_{i,t} - R_f = \alpha + \beta_1(R_m - R_f) + \beta_2 VIX_t + \varepsilon_t$$

*** and * denote significance at the 1% and 10% levels, respectively.

5. Conclusion

Our empirical analyses show that the VIX is positively correlated with China's stock market volatility in all the three GARCH model fittings; that is, for all the three models, when the VIX rises, the coefficient $\delta_1 + \delta_2$ is always positive and when VIX declines, the coefficient δ_1 is always negative. Furthermore, the VIX's leverage effect on China's stock market volatility demonstrates high significance in the TGARCH and EGARCH models, but the GARCH model has an adverse leverage effect. Finally, the VIX is negatively correlated to the rate of return of the Chinese stock market, especially for hi-tech industries.

These findings generate some recommendations for Chinese investors and supervisory authorities. First, Chinese investors should be rational. We show that the CSI index is heavily influenced by the VIX and that leverage effects exist between the two. The result suggests Chinese investors' lack of judgment and their susceptibility to outside information. Chinese investors need to improve their judgment, increase their knowledge about investing, establish a commitment to investing independently, and avoid following suit. Second, the different exchange hours as a result of the different time zones provide an opportunity to use the VIX to predict the Chinese stock markets. According to the negative correlation between the VIX and the rate of return of the Chinese stock market, Chinese investors may view the VIX as an indicator in their stock trading, especially for the investors who invest in the hi-tech industries. Third, China's financial supervisory authorities can make use of our empirical analyses for a better general understanding of volatility in China's stock markets and to facilitate Chinese Securities Regulatory Commission's supervision on stock markets. The co-movement in China and the U.S. stock markets can be very helpful for China's financial regulators to deal with the volatility in foreign markets and to reduce risk outside the domestic markets. In addition, the act of importing the VIX helps to depict the volatility in domestic markets and implies the volatility index's important role in the healthy development of the country's stock markets. Currently, capital markets in many developed countries have their own volatility index. Due to the lack of option trading and strict financial supervision from the government, the Chinese financial market has failed to set up its own volatility index. Therefore, China's financial regulators should take an active part to further reform and readjust its rigid policies to secure a more stable and healthy development of the Chinese stock markets.

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Appendix A: Augmented Dickey–Fuller (ADF) Unit Root Test

In econometrics and statistics, a stationary process is a stochastic process whose joint probability distribution does not change when shifted in time. Consequently, parameters such as the mean and variance, if they are present, also do not change over time and do not follow any trends. Stationarity has played an important role in time series analysis, where the raw data are often transformed to become stationary. Otherwise, if the raw data is a non-stationarity process, the subsequent studies will be in vain. Several methods check the stationary of time series, such as the Dickey–Fuller test, ADF test, KPSS test, and P-P test. This paper chooses the augmented Dickey–Fuller (ADF) unit root test.

The testing procedure for the ADF test is the same to the Dickey–Fuller test, but it applies different critical tables. The three main versions of the test, analogous to the Dickey–Fuller test, are the test for unit root, test for unit root with drift, and test for a unit root drift and deterministic time trend, respectively, as follows:

$$\Delta y_t = \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t \,, \qquad \text{(A.1)}$$

$$\Delta y_t = \alpha + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t \qquad \text{(A.2)}$$

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t \quad \text{(A.3)}$$

where α is a constant, β the coefficient on a time trend, and p the lag order of the autoregressive process. Imposing the constraints $\alpha = 0$ and $\beta = 0$ corresponds to modeling a random walk, and using the constraint $\beta = 0$ corresponds to modeling a random walk with a drift. Each version of the test has its own critical value that depends on the size of the sample. In each case, the null hypothesis is that the unit root, $\gamma = 0$, exists.

Appendix B: List of the 20 Hi-Tech Individual Stocks

This appendix reports the list of 20 hi-tech individual stocks that are traded in the Shanghai Stock Exchange and Shenzhen Stock Exchange. The screening criteria of these stocks are based on its industry prospect, innovation capability in technology, and continuity of transaction data during study period.

Stock Code	Stock Code	Stock Code	Stock Code
000021	600343	600536	600756
000063	600410	600570	600770
000725	600446	600588	600797
002202	600476	600601	600804
600037	600498	600637	600850