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Financial Crisis, Monetary Policy, and Stock Market Volatility in China*

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This paper employs the Markov regime switching GARCH model to capture the nature of China's stock market volatility in 2003-2009. We find a significant regime shift in the volatility of the stock market when the People's Bank of China adopted an accommodative monetary policy in response to the global financial crisis of 2007-2008. After the structural change, China's stock market moved into a regime with increased volatility, which appears to be persisting into the near future. This finding suggests that the central bank of China should incorporate stock market volatility into its policy-making process.

Key Words: GARCH; Stock market; Monetary policy; Regime switching.
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1. INTRODUCTION

Since the onset of the recent global financial turbulence in 2007, China has implemented a "moderately accommodative monetary policy" to reinvigorate its economy, which leads to extraordinary growth in domestic

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credit and money supply. Following the loose monetary policy, the stock market in China appears to be manifesting signs of increasing volatility. By the end of July 2009, the China Securities Index 300 (CSI300) had nearly doubled since a positive correction commenced in November 2008[1]. However, the real challenge lies ahead as asset bubbles begin to aggregate and because of the latent risks brought by the unprecedented stimulative monetary policy which imposes much uncertainty on the stock market in the ensuing period.

These interactions between monetary policy and the stock market have attracted much attention from both academics and policy makers. As to the relationship between monetary policy and stock market volatility, an early study by Schwert (1989) finds that the volatility of inflation, money growth, and industrial production all help to predict frequent fluctuations of the stock market. In essence, his results point to a positive link between monetary policy and stock market volatility, with the direction of causality being stronger from the stock market to policy variables.

However, the model specification in Schwert (1989) does not accurately account for the persistence property of volatility and it also ignores potential downward bias induced by the use of noisy volatility proxies in that study. In the ensuing research, there have been many advances in the theoretical and empirical understanding of econometric models used for measuring time-varying volatility. In particular, a recent study by Christiano et al. (2008) calls for further investigation of the relation between monetary policy and stock market volatility. Christiano et al. (2008) find that the implementation of accommodative monetary policy can signal that a rebound of the stock market is just around the corner, and the imperfect rationality of investors can make the stock market fluctuate more frequently than is usual.

To date, the literature has come to a general consensus that stock market volatility has a negative effect on the recovery of the real economy. What remains controversial is whether monetary policy may increase stock market volatility, and therefore central banks should take this possibility into account when setting monetary policies. For example, Bernanke and Gertler (1999) and Cecchetti et al. (2000) provide distinct conclusions.

Bernanke and Gertler (1999) explore how the macro economy is affected by alternative monetary policy rules either with or without the stock market volatility being taken into account. Their results suggest that it is desirable for central banks to focus on inflationary pressures while stock market volatility becomes relevant only if it signals potential inflationary

[1]The CSI300 is composed by China Securities Index Co. Ltd, on the basis of 300 large stocks selected from A share markets of Shen Zhen and Shang Hai in China. The CSI300 is a benchmark index which reflects the general pattern of the stock market performance in China.

or deflationary forces. Therefore, monetary policy with additional focus on stock market volatility does not benefit the economy in any significant manner.

However, Cecchetti *et al.* (2000) raise several objections to Bernanke and Gertler's (1999) conclusion. Cecchetti *et al.* (2000) believe that one of the final goals of monetary policy is to maintain a stable financial system. Large fluctuations in the stock market can cause adverse shock to the real economy. Therefore, central banks should not only concentrate on inflation and real economic growth, but also set a goal to react to the stock market volatility. Filardo (2004) is sympathetic to this argument and proposes that central banks should focus solely on stock market volatility in calibrating monetary policy trade-offs. In addition, Gilchrist and Saito (2006) employs a general equilibrium model on the basis of the Real Business Cycle theory and shows that it is necessary for monetary policy to consider stock market volatility.

The contradicting conclusions in the literature come from the different assumptions they impose on the effectiveness of the capital market. Bernake and Gertler (1999) assume that the market is effective enough for asset prices to adjust automatically when there is a divergence in the prices. As long as all information is fully reflected in the stock prices, the prices will be in line with its true value in the long run. Moreover, Bernake and Gertler (1999) believe that it is difficult for central banks to distinguish the sources of stock market volatility. Consequently, any response from the central bank to stock market volatility is likely to be ineffective. However, Cecchetti et al. (2000) discard the effective market hypothesis and accentuate stock market fluctuations caused by aggressive monetary policies. So central banks should take stock market volatility into consideration in their policy-making process.

This paper incorporates new developments in the literature and focuses on the relationship between monetary policy and stock market volatility in China. To this end, we first examine the persistence characteristics of the volatility of the representative Chinese stock market price, and then investigate the causality relation between monetary policy and stock market volatility.[2] By doing so, we expect to settle the debate as to whether stock market volatility should be incorporated into the information set of the central bank of China. Such a result will also help to judge whether it is necessary for the Chinese central bank to react to the stock market volatility.

Note that to capture the possible changing nature in the volatility of the Chinese stock market, we use the Markov regime switching GARCH

[2]For more discussions on Chinese stock market, see Mei et al. (2009) and Gao and Huang (2008).

model (MRS-GARCH) in the spirit of Hamilton and Susmelb (1994) and Gray (1996). This model accounts for the possible presence of endogenous structural breaks. The main advantage of this approach is that it does not require an exogenously predetermined date as the break point. Moreover, the causality relationship is explored by using a standard vector autoregression (VAR) model based on the MRS-GARCH result.

The remainder of the paper is organized as follows. Section 2 provides a description of the MRS-GARCH model. Section 3 discusses the data for the empirical work and provides the associated results. Section 4 examines the causality relationship between monetary policy and the stock market volatility. Further discussion and implications of the baseline finding of the paper are provided in Section 5, followed by Section 6 concluding the paper.

2. MODEL SPECIFICATION

The standard MRS-GARCH model was developed by Gray (1996). In our analysis, we make two modifications to make the standard framework consistent with the reality. First, we incorporate exogenous variables (e.g. S&P 500 stock price) in the GARCH mean equation to take into account possible interactions between Chinese stock market and international stock market. Second, we assume t-distribution instead of normal distribution for the random error in each regime of the model. The use of t-distribution is motivated by the fat-tail property of the underlying stock price returns.

To use the MRS-GARCH model, we divide the time period into two distinct regimes, and in each regime, the rate of return of the stock market (r_t) follows t-distribution with different degrees of freedom, expectations, and variances. The basic idea of the MRS model is that the data generating process (DGP) of the underlying variable may be affected by a non-observable state random variable S_t. S_t represents the state that the DGP is in at time t. In our analysis, the state variable S_t differs between two volatility regimes with two values. For instance, $S_t = 1$ indicates that the DGP is in the high-volatility regime, whereas for $S_t = 2$ the DGP is in the low-volatility regime. This can be written as:

$$r_t|\zeta_{t-1} \sim \begin{cases} t_{\mu_{1t},\sigma_{1t},df_1} \\ t_{\mu_{2t},\sigma_{2t},df_2} \end{cases} \tag{1}$$

where ζ_{t-1} denotes the information set at time $t-1$. Let $pt_{it} = Pr\{S_t = i|\zeta_{t-1}\}$ denote the ex ante probability of being in regime i at time t. As such, r_t follows t distribution with mean μ_{it}, variance σ_{it}^2, and degree of freedom of df_i with the probability of pt_{it} $(i = 1, 2)$.

In the regime-dependent mean equations we explicitly take into account the possibility of first-order autocorrelation in China's stock returns (by including r_{t-1}) and the interaction between Chinese stock market and the international stock market (by including the lagged S&P500 index returns r^{sp}_{t-1}), viz.

$$r_{it} = a_{0i} + a_{1i}r_{t-1} + a_{2i}r^{sp}_{t-1} + \varepsilon_t, \quad i.i.d.\ \varepsilon_t|\zeta_{t-1} \sim t_{\mu_{it},\sigma_{it},df_i}, \ i = 1,2 \quad (2)$$

Taking conditional expectations both sides, we can draw derive the following equation

$$\mu_{it} = a_{0i} + a_{1i}r_{t-1} + a_{2i}r^{sp}_{t-1}, \ \text{for } i = 1,2. \quad (3)$$

The specification of a GARCH-process for the regime-specific variance is more difficult than the mean equation (3). The complication is caused by the so-called "path dependence" which stems from the dynamic structure of the GARCH model causes the regime-specific conditional variance to depend on the entire history $\{S_{t-1}, S_{t-2}, \ldots, S_0\}$ of the regime-indicator S_t. In our specification, we use the same collapsing procedure as in Gray (1996).

Note that GARCH(1,1) variance equation in each regime can be written as:

$$\sigma^2_{it} = b_{0i} + b_{1i}\varepsilon^2_{t-1} + b_{2i}\sigma^2_{t-1} \quad (4)$$

To obtain the variance at time t, we use MRS process. Based on t-distribution assumption, the variance of the stock return at t can be expressed as:

$$\begin{aligned}\sigma^2_t &= E[(r_t - E[r_t])^2|\zeta_{t-1}] \\ &= E[r^2_t|\zeta_{t-1}] - \{E[r_t|\zeta_{t-1}]\}^2 \\ &= pt_{1t}(\mu^2_{1t} + \sigma^2_{1t}) + (1 - pt_{1t})(\mu^2_{2t} + \sigma^2_{2t}) - [pt_{1t}\mu_{1t} + (1 - pt_{1t})\mu_{2t}]^2\end{aligned} \quad (5)$$

The quantity σ^2_{it} can be viewed as an aggregate of conditional variances from two regimes and it provides a foundation for the specification of regime-specific conditional variance $\sigma^2_{i,t+1}$ $(i = 1,2)$ in the parsimonious GARCH(1,1) model. In addition, ε_{t-1} in Equation (3) is obtained by

$$\begin{aligned}\varepsilon_{t-1} &= r_{t-1} - E[r_{t-1}|\zeta_{t-2}] \\ &= r_{t-1} - [pt_{1t-1}\mu_{1t-1} + (1 - pt_{1t-1})\mu_{2t-1}].\end{aligned} \quad (6)$$

To complete the model specification, we need to specify transition probabilities of the regime indicator S_t. For simplicity we consider a first-order

Markov process with constant transition probabilities, i.e. for $\pi_1, \pi_2 \in [0,1]$ (where π denotes probability) we define:

$$\begin{aligned} Pr\{S_t = 1|S_{t-1} = 1\} =& \pi_1,\ Pr\{S_t = 2|S_{t-1} = 1\} = 1 - \pi_1, \\ Pr\{S_t = 2|S_{t-1} = 2\} =& \pi_2,\ Pr\{S_t = 1|S_{t-1} = 2\} = 1 - \pi_2. \end{aligned} \tag{7}$$

The log-likelihood function of our MRS-GARCH(1,1) model is then written as:

$$\Lambda = \sum_{t=1}^{T} \ln\{pt_{1t} f_{1t}(r_t; \mu_{1t}, \sigma_{1t}, df_1) + (1 - pt_{1t}) f_{1t}(r_t; \mu_{2t}, \sigma_{2t}, df_2)\} \tag{8}$$

where f_{it} denotes the density function of the t-distribution with mean μ_{it}, variance σ_{it}^2, and degree of freedom of df_i. The final step of model specification is to specify the ex ante probabilities pt_{it}. According to Bayes' Formula, the whole series of ex ante probabilities can be estimated recursively by:

$$\begin{aligned} pt_{it} \;=&\; \pi_1 \frac{f_{1t-1} pt_{it-1}}{f_{1t-1} pt_{it-1} + f_{2t-1}(1 - pt_{it-1})} \\ +& \;(1 - \pi_2) \frac{f_{2t-1}(1 - pt_{it-1})}{f_{1t-1} pt_{it-1} + f_{2t-1}(1 - pt_{it-1})}. \end{aligned} \tag{9}$$

3. DATA AND EMPIRICAL RESULTS

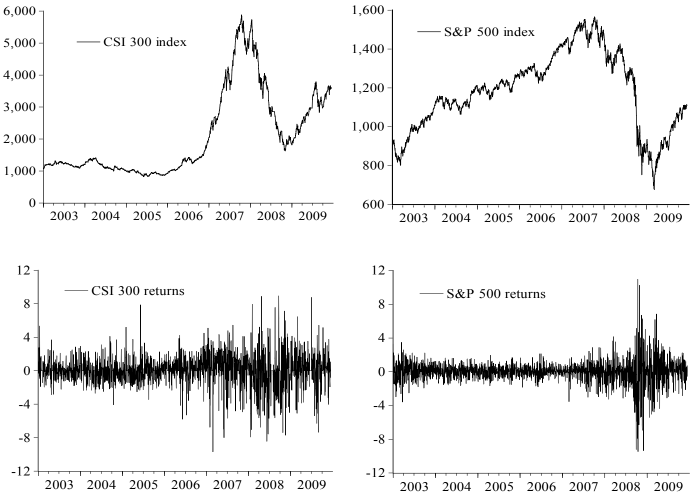
3.1. The Data

Our dataset consists of daily close prices of the CSI300 and the S&P500 covering the period between January 1st 2003 and 31st December 2009. The data are collected from Datastream. Figure 1 plots the level of the underlying stock indices and the associated daily returns (i.e. $r_t = 100 * (\ln(index_t) - \ln(index_{t-1}))$[3].

As we can see from Figure 1, the dynamic evolution of the two indices shows that China's stock market has experienced a bull market since 2006, but the index fell drastically since the outbreak of the recent financial crisis in 2007-2008. To cushion the negative shock of the financial crisis to the real economy, the Chinese government implemented a series of accommodative policies. As a result, the stock market manifested a renascence from early 2009. A similar pattern can be observed in the US stock market.

[3]Standard unit root tests (e.g., ADF test) suggest that the return series are $I(0)$ and the stock price indices are $I(1)$.

FIG. 1. The stock prices and the corresponding returns in China and the U.S.



Data source: Datastream.

These observations, to some extent, reflect both the domestic and international economic performance as well as the impact of monetary policy on the stock market in recent years. From 2003 to the first half of 2007, the world economy was continuously growing and stock markets across the world witnessed a bull market. In China, in particular, the CSI300 index tripled to as high as 6100 in 2007 from 2003. The S&P 500 also experienced a remarkable growth during the same period.

However, after the recent global financial crisis ignited by the subprime crisis in the United States, the S&P 500 index fell sharply. A drastic decline also occurred in the Chinese stock market. To counteract the negative disturbances of the new global financial crisis in 2007C2008, China implemented a four-trillion Yuan economic stimulus package to reinvigorate the economy and the PBC also reduced benchmark interest rates on deposits and loans five times and reserve ratio rate four times over four months from September 2008. In late 2008, the central bank also abolished the constraints on the credit lending of commercial banks. As a result, the CSI300 index has been increasing steadily since 2008. The volatility of the CSI300 return also manifests a notable rise during the recovery process of both the domestic and international stock markets.

3.2. The estimation results

Table 1 tabulates the maximum-likelihood estimates of the MRS-GARCH model based on Equations (1)-(9) for the stock price returns of CSI300. The model was estimated using the full dataset covering 1,829 trading days between January 1[st] 2003 and December 31[st] 2009 as described in the foregoing section.

TABLE 1.

The estimation results

	GARCH(1, 1)			MRS-GARCH		
parameter	Estimate	S.E.	p-value	Estimate	S.E.	p-value
a_{01}	0.0005*	0.0002	0.0719	0.0723	0.1033	0.4839
a_{02}				0.0521	0.0339	0.1238
a_{11}	−0.0024	0.0222	0.9116	−0.0287**	0.0492	0.0498
a_{12}				−0.0451**	0.0875	0.0427
a_{21}	0.0958***	0.0289	0.0009	0.1836***	0.0461	0.0001
a_{22}				0.0935**	0.0446	0.0362
b_{01}	0.0000**	0.0000	0.0167	0.4184*	0.2228	0.0604
b_{11}	0.0748***	0.0155	0.0000	0.0651**	0.0264	0.0137
b_{21}	0.9245***	0.0127	0.0000	0.8508***	0.0672	0.0000
b_{02}				0.0203***	0.0072	0.0048
b_{12}				0.0621***	0.0076	0.0000
b_{22}				0.9332***	0.0081	0.0000
df_1	3.0847***	0.6709	0.0000	3.0847***	0.6709	0.0000
df_2				4.0775***	0.5651	0.0000
π_1				0.9969***	0.0023	0.0001
π_2				0.9783***	0.0012	0.0000
log-likelyhood	−1414.589			−1241.196		
LRT	346.786					
Expected duration of Regime 1: 322.58 days						
Expected duration of Regime 2: 46.08 days						

Notes: S.E. denotes standard error. Sample spans Jan 1[st] 2003 to Dec 31[st] 2009. *** ,** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Note that the GARCH(1, 1) model for the daily rate of return of the CSI300 can be viewed as a benchmark effect of the MRS-GARCH process. However, the conventional likelihood ratio (LR) tests for the MRS and common GARCH models are not statistically comparable because there are 7 unknown parameters under the null hypothesis of a single regime in the GARCH model, but there are 16 unknown parameters in the MRS framework.

Therefore, we follow Hamilton and Susmel (1994) and construct an LRT statistic based on conventional LR tests[4]. The LRT statistic is to be compared with the critical values derived from the quantiles of a χ^2-distribution

[4]The LRT statistic is computed as the difference of the conventional LR statistics (multiplied by 2) pertaining to the two models. See Ang and Bekaert (2002) for a vigorous justification of this approach.

with 9 degrees of freedom, since the 'two-regime' specification has 9 more parameters than the 'single-regime' model. The critical value (at 1% level) in the current setup is 21.66. The LRT statistic reported in Table 1 (bottom panel) is 346.786 which apparently exceeds the critical value, indicating the existence of the second regime.

The results of the second model (the right panel of Table 1) show that the majority of the estimated coefficients of the mean and variance equations (3) and (4) are statistically significant at the conventional levels of significance. The autoregressive coefficients a1i for both regimes are negative and statistically significant. It is important to note that the negative autoregressive coefficients seem to be contradictory to the finding in many existing studies. The existing literature often reports a positive autoregressive structure of order 1 in stock price returns indicating non-synchronous trading (Lo and MacKinlay, 1990), and time-varying expected returns and transaction costs (Mech, 1993). The discrepancy between our result and the existing research can be explained by the different assumption about the efficiency of the stock market. The existing studies assume an efficient market while our study does not impose such an assumption because it is common to observe over-speculation and mean reverting expectation of investors in the Chinas stock market (Liu *et al.*, 2002).

The coefficients of the control variable r^{sp}_{t-1} are statistically significant at 1% level and positive in both regimes. This result suggests a strong interdependence between the stock markets in China and the United States. A further investigation of the conditional volatility reveals high volatility persistence in both regimes. The constant transition probabilities π_1 and π_2 are significantly close to unity in both regimes. Since both quantities represent the probability of the DGP in the same volatility regime during the transition from date $t-1$ to t, both volatility regimes reveal a high degree of persistence. In addition, the expected durations of the respective regimes are reported in the lower panel of Table 1. The duration describes the level of persistence of each regime and it is computed as $1/1-\pi_i$ $(i = 1, 2)$.

Moreover, we address two conditional probabilities which are of high relevance to how often and at which dates the Chinese stock market switched between high and low volatility regimes. Based on Equation (9), we can compute the ex ante probabilities of each regime (i.e. $Pr\{S_t = i|\zeta_{t-1}\}$). The ex ante probabilities are useful in forecasting one-step-ahead regimes based on the information evolving over time. In our context, the ex ante probabilities reflect current market perceptions of the one-step-ahead volatility regime and represent an adequate measure of stock market volatility sentiments. Since the estimation errors may cause abrupt jumps between the two regimes, we also computed the smoothed probability $(Pr\{S_t = i|\zeta_T\})$.

FIG. 2. The estimated probabilities of regime 1

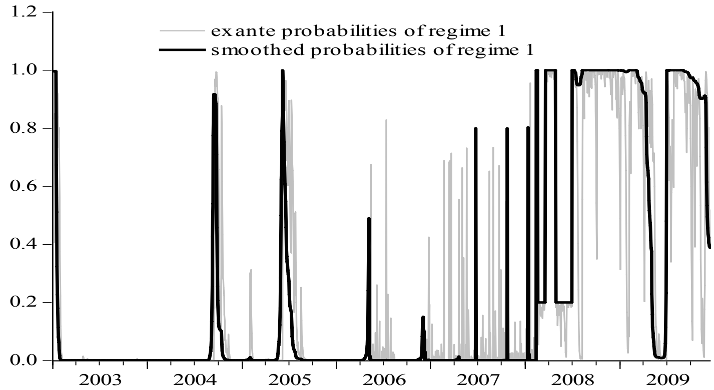
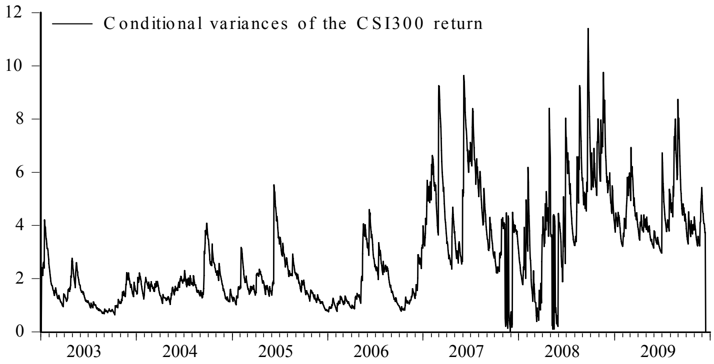


Figure 2 plots the ex ante probabilities and smoothed probabilities of regime-1 estimated for the MRS-GARCH model (depicted by a thin line and a bold line respectively). Since the ex ante probabilities are determined by an evolving (and thus smaller) information set, they exhibit more erratic behavior than the smoothed probabilities. We can also observe a notable jump from low to high volatility regime around mid-2008, which occured at the same time as the four-trillion RMB economic stimulus package initiated by the Chinese government as a response to the financial crisis. The Chinese stock market has then been in the high volatility regime since late 2008. Figure 3 provides an intuitive illustration of the regime changes of stock market volatility. The conditional variances of the stock market return plotted in Figure 3 indeed show that mid-2008 appears to be a break point after which the stock market switched to a higher volatility regime than before.

The discussion above suggests that the Chinese stock market had been in a relatively low volatility regime prior to 2008. A sudden transition from low to high volatility regime manifested itself in a similar time to the implementation of the recent extraordinary accommodative monetary policy, which pumped a large amount of liquidity into the economy. This loose monetary policy, to a large extent, encouraged the risk-preference investors to invest in capital assets and add more risks to the stock market. The infusion of excess liquidity also increased the default risk of various debts and imposed much more pressure on the banking system than would normally be the case. This chain effect from monetary policy to the stock market eventually leads to high volatility in the stock market. The following section will embark on a strict analysis of this argument (i.e. causality relationship between monetary policy and stock market volatility in China).

FIG. 3. The conditional variance of the returns (full dataset)



4. CAUSALITY ANALYSIS

In this section, we use a standard vector autoregression (VAR) model to establish a possible causality relationship between monetary policy and the stock market volatility. The baseline model is the New Keynesian-type of monetary policy analysis, discussed in Clarida *et al.* (1999), Estrella and Fuhrer (2003), Roberts (2006) and Zhang (2010). In this type of monetary policy analysis framework, a short-term interest rate and the real economic slump are often included as standard variables. One important feature of our model, however, is that the growth rate of monetary aggregate (the growth rate of M2) rather than the interest rate is used as monetary policy indicator. Although the PBOC have recently promoted the development of market-based interest rates as policy instruments, quantity-based monetary instruments remain as the main instruments of the PBOC, as explicitly stated in the periodical reports of the PBOC and shown in Burdekin and Siklos (2008) and Geiger (2008).

To consider the possible dynamic interactions between monetary policy and the stock market volatility, we extend the standard framework to incorporate the series of the conditional variance of the stock market returns in the VAR system. The real economic slump is measured by the year-on-year growth rate of real industrial production (RIGR). Therefore, our baseline VAR model incorporates monthly data for the growth rate of real industrial production, the growth rate of M2 (M2GR), and the conditional variance of the stock market returns (VOL) to capture the dynamics among real economic development, monetary policy, and the stock market volatility. The empirical sample spans January 2003 to December 2009.

To be specific, the VAR system can be written as:

$$X_t = \Phi(L)X_{t-1} + \varepsilon_t, \tag{10}$$

where X_t is a vector time series incorporating the endogenous variables$\Phi(L)$ denotes the vector polynomial of the lag operator with the optimal lag order determined by information criteria, and ε_t is a vector shock. We use the VAR model to test whether our conjecture (the causality relationship between monetary policy and the stock market volatility) is empirically true.

In the present example, VARs are estimated from each variable for the other two variables. Note that for the short-run dynamic analysis, the construction of a VAR with nonstationary data produces invalid estimates and inference because the tests used to estimate the significance of the coefficients of the VAR are invalid. To test for the stationarity of the underlying variables, standard Dickey-Fuller tests are performed on RIGR, M2GR, and VOL, and the results (not reported here) indicate that all the time series involved are stationary at conventional level of significance.

In addition, to determine the appropriate lag length of the VAR model, the AIC is implemented and the criterion suggests that a fourth order VAR model is optimal. This VAR model is then used to conduct Granger causality tests. A variable is said to Granger cause a second variable when adding past values of the variable to a dynamic model of a second variable improves the predictability of the second variable.

Wald statistics were used to test the null hypothesis of no Granger causality. Wald tests are based on measuring the extent to which the unrestricted estimates fail to satisfy the restrictions of the null hypothesis. A small probability value (i.e. p-values) of the Wald statistic rejects the null hypothesis of no feedback to the dependent variable and a large p-value implies that the null cannot be rejected.

Table 2 tabulates the results of the Granger causality tests for the three equations of the VAR system, which are VAR model tests of the joint statistical significance of the lagged values of each regressor in causing (predicting) the dependent variables. The p-value pertaining to the null hypothesis that M2GR does not Granger cause VOL is 0.035, which indicates that the stock market volatility can be explained by monetary growth occurring at earlier stages. Highlighting this result is the finding that, in the regression equation for the stock market volatility, the coefficients of the lagged M2GR are jointly significant at the 5% significance level.

An interesting finding is that the Granger causality tests in Table 2 suggest that both VOL and RIGR Granger cause the growth rate of M2. This result indicates that both the real economic performance and the stock market volatility provide significant information for future monetary

TABLE 2.

Results of Granger causality tests for the VAR model

	p-value
Dependent variable:VOL	
H_0:M2GR does not Granger cause VOL	0.035
H_0:RIGR does not Granger cause VOL	0.052
Dependent variable:RIGR	
H_0:M2GR does not Granger cause RIGR	0.158
H_0:VOL does not Granger cause RIGR	0.120
Dependent variable:M2GR	
H_0:VOL does not Granger cause M2GR	0.000
H_0:RIGR does not Granger cause M2GR	0.057

Notes: Sample spans 2003M01-2009M12 prior to lag adjustment; the optimal lag length chosen by AIC is 4.

policy. This finding also reinforces our argument that monetary authority in China should take into account the stock market volatility when setting monetary policy.

5. DISCUSSION

5.1. The recent financial crisis and monetary policy in China

During 2007, the financial crisis triggered by the subprime mortgage bubble in the United States had caused huge panic in the global financial markets and driven investors to reallocate their assets away from risky mortgage bonds and equities. This also induced a liquidity shortage which posed a grave threat to the global financial system. Additionally, with the drastic rise of the interbank interest rates, it became extremely difficult for commercial banks to obtain funds from the market, which led to a marked atrophy?of credit operations. Furthermore, a large number of bankruptcies of financial institutions deteriorated the liquidity shortage problem and imposed a negative shock on the real economy.

When the financial crisis spread to China in early 2008, the central bank of China, the People's Bank of China (PBC), attempted to use its open market operations (OMOs) to stimulate the real economy. Note that the OMOs in China differ from those of the United States. The Federal Reserve System, the central bank of the United States, generally uses the overnight repurchase agreements (repos) to adjust money supply (or reverse repos for the opposite effect). These operations in the repo markets also send a signal to modulated interest rates, which is crucial in the money market.

Unlike the Federal Reserve, there is no effective repo market in China and government bonds make up only a small proportion of the central banks balance sheet. The PBC adjusts money supply by changing benchmark (policy) interest rates and reserve requirement ratios. From September to December of 2008, the PBC has lowered the benchmark interest rates on deposits and loans five times and the reserve requirement ratio four times; see Table 3 for the timeline and details of the monetary policy adjustments. In addition, at the end of 2008, the PBC also abolished the credit quota constraints on commercial banks and urged them to expand their lending credits. As a result, the growth rate of money supply and incremental credit has been exploding since 2009[5], as is evident in Figure 4.

TABLE 3.

The timeline of the accommodative monetary policy in China in 2008

Dates	The Main Points of Monetary Policy Adjustments
16-Sep-08	The benchmark lending rates of financial institutions are lowered by 0.27%.
08-Oct-08	The reserve requirement ratio of financial institutions was cut by 0.5%, from 17.5% to 17%.
09-Oct-08	The benchmark deposit and lending rates of financial institutions are lowered by 0.27%.
22-Oct-08	The private mortgage lending rates are cut to 70% of the benchmark lending rates of commercial banks. The private mortgage lending rates of provident fund are lowered by 0.27%.
30-Oct-08	The benchmark deposit and lending rates of financial institutions are lowered by 0.27%.
26-Nov-08	The reserve requirement ratio of large financial institutions is cut by 1% and the reserve ratio of small financial institutions is cut by 2%.
27-Nov-08	The benchmark deposit and lending rates of financial institutions are lowered by 1.08%.
22-Dec-08	The reserve requirement ratio of financial institutions was cut by 0.5%.
22-Dec-08	The benchmark deposit and lending rates of financial institutions are lowered by 0.27%.

Source: The Peoples Bank of China.

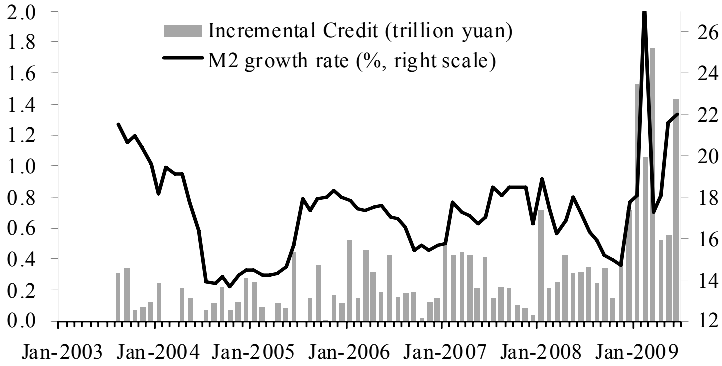
5.2. The transmission mechanism of monetary policy on stock market volatility

The foregoing discussion has not uncovered the whole story of the causal relation between monetary policy and stock market volatility in China. This sub-section discusses the transmission mechanism of the credit and money expansion on the stock market volatility. We will discuss the special feature of the administrative structure in the accommodative monetary policy implementations and show why and how monetary policy has led to rising stock market volatility since 2009.

In the standard monetary policy analysis framework (e.g Stock and Watson, 2007), an accommodative monetary policy, implemented and adminis-

[5]In 2008, Chinas government announced a stimulus package estimated at 4 trillion Yuan (about 570 billion U.S. dollars), to deal with the crisis. The money is planned to be spent over the following two years to finance 10 major areas, including low-income housing, rural infrastructure, water and electricity supply system, transportation, environmental protection, and technology innovation, among other areas.

FIG. 4. Growth rate of M2 and incremental credit in China



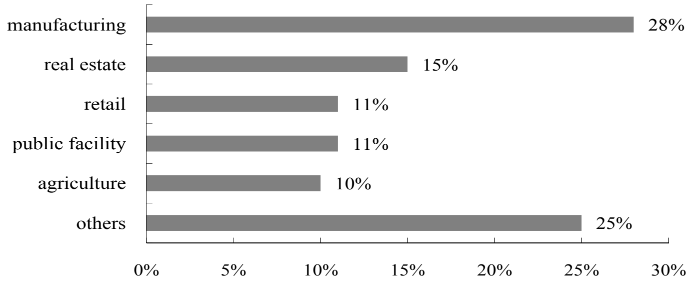
Data source: The People's Bank of China.

tered by a central bank, lowers the real cost (interest rate) of investment for the purpose of promoting real economic growth. The accommodative monetary policy implementations in 2009 in China, however, have not followed the standard process. In particular, the policy has been implemented and administered by both PBC and National Development and Reform Commission (NDRC). The PBC makes decisions on the overall monetary policy stance and administers aggregate credit supply process under the instruction and supervision of the State Council. The NDRC, however, determines the distribution and allocation of the credit supply.

Figure 5 displays percentage distribution of the incremental credit to different industries in 2009. The figure shows that the manufacturing industry was provided with the largest proportion of the incremental credit (28%), followed by the real estate sector (15%), retail sector (11%), public facility (11%), and agriculture (10%). We note that the real estate industry received 15% of the total incremental credit, which substantively helped the real estate market to boom in 2009. The prosperity of the real estate market also boosted the stock market since a sizeable amount of blue chips in the Chinese stock market are composed of real estate companies.

It should also be noted that due to their uncertain expectations on real economic recovery, the enterprises that received loans (credits) did not use the money to expand their businesses. Instead, they invested a large amount of the money into the stock market which appeared to rebound before real economy recovery. According to a report by the Macroeconomic Department of Development & Research Center of the State Council in 2009, about 20% of the total incremental credit in 2009 eventually moved to the stock market and 30% to the paper market (see Figure 6). Because it is difficult for regulation authorities to monitor the use of the funds of

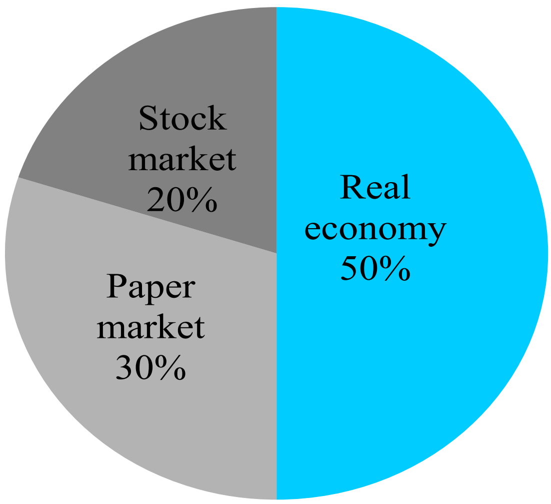
FIG. 5. The flow of incremental credit in 2009



Data source: Monetary Policy Report of the People's Bank of China in 2009.

the paper market after papers are discounted, a substantive part of the funds from the paper market has also flowed to the stock market. Most of the money which flowed to the stock market, however, is short-term and speculative in nature. Consequently, the stock market manifested growing volatility in 2009.

FIG. 6. The flows of the incremental credit to different markets in 2009



Data source: Macroeconomic Department of Development & Research Center of the State Council.

6. CONCLUSIONS

China's economic growth has rebounded quickly since the recent global financial crisis. The robust economic recovery was boosted by timely monetary policy adjustments. The accommodative monetary policy, however, may have also caused the rising volatility in Chinese stock market. Using the MARS-GARCH model and Granger causality tests, this paper finds that the year 2008 was a turning point in the stock market volatility after which China's stock market moved into a high-volatility regime. The paper also shows that there is a significant causal link between monetary policy and stock market volatility in China. We provide a comprehensive discussion on the transmission process from the accommodative monetary policy to the stock market volatility and show that a sizable amount of the stimulus money in China has moved into the stock market, which potentially leads to the rising volatility of the stock market.

These findings provide useful insight into the debate on whether the central bank should react to stock market volatility. In particular, the high level of persistence and the long expected duration of high-volatility regime in the stock market indicate a strong persistent nature of the stock market fluctuation. This also implies that it is difficult for the stock market to revert to a low-volatility regime automatically. Since monetary policy adjustments significantly influence the stock market volatility, the central bank of China should take the stock market boom-bust episodes into account when setting monetary policies.

The findings in the present paper highlight the importance of information regarding stock market volatility in the monetary policy-making process, and also warn that the stock market boom stimulated by an accommodative monetary policy may easily turn into a financial bubble. If the bubble bursts, both the financial system and the real economy will be devastated. Therefore, the side effect of an accommodative monetary policy on the stock market should draw more attention from monetary authorities. From this perspective, the conclusion of the present paper may be generalized to take into account more nations across the world.

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