Research on China's Monetary Policy and Stock Market Price-volume Relationship Based on TVP-SV-VAR Model

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Abstract. A time-varying VAR system model of monetary policy and stock market is established in this paper for analyzing the dynamic correlation and response mechanism between monetary policy variables and stock market variables. It is found that the influence of interest rate on stock price has experienced a period of "irrelevance, positive correlation and negative correlation" in 20 years. According to the uniformly-spaced impulse response, it is found that China's monetary policy has real effect in the short term, but lacks long-term sustainability. The stock reform in 2005 can be regarded as an important time node to change the relationship of stock market price-volume in the past two decades. For most of the period after the stock reform, stock prices have a positive impact on stock market turnover and stock market returns.

1. Introduction
China stock market has constituted an integral part of the economic system with more than 20 years of development and accumulation. The stock market has made important contributions to the financing of enterprises, the optimization of resources and the diversification of market risks. At the same time, we should also clearly see that China stock market has been established for a short time, compared with the western stock market, so that its foundation is not strong, and there are still many problems. The People's Bank of China lacks enough experience in the process of formulating monetary policy and grasps the economic situation inaccurately. Accordingly, it is often difficult to achieve the expected effect of monetary policy. This makes it difficult for monetary policy to play an effective role. We should not only fully grasp the pulse of the macro economy, but also fully consider the transmission on the stock market and the price-volume relationship in the process of making monetary policy. Only in this way can we stabilize the stock price and promote the healthy and stable development of the real economy at the same time.

Previous studies show that most scholars use linear VAR model to study the monetary policy transmission on stock market, but the parameters of such model do not change with time. However, the study of this kind of problem generally has a long sample period. Under different economic cycles, great changes would take place in economic factors and policy preferences. Traditional models can not reflect these changes. At the same time, most scholars only studied the impact of monetary policy on stock prices, but did not further study the impact on stock market turnover and Volume-price relationship. Therefore, this paper establishes a time-varying VAR system model of monetary policy transmission on stock market under the framework of time-varying system model, and analyzes the
dynamic correlation and response mechanism between monetary policy variables and stock market variables in the system through time-varying parameter vector autoregressive model (TVP-SV-VAR).

2. Setting of time-varying VAR system for monetary policy and stock market price-volume relationship

2.1. Selection of variables
The monetary volume and interest rate are selected as proxy variables of monetary policy in this paper. The monthly data of the month-on-month growth rate of M2 are selected for the monetary volume, which is denoted as LM2 in this paper, and the data are obtained from the CEInet Statistics Database. Because of seasonal fluctuation of M2, the original data of M2 are first adjusted seasonally in this paper, and Census X12 method of EViews8 is used to complete the first-order differential processing of adjusted data in order to eliminate unit root. There are many kinds of interest rates in the financial market. Selected benchmark interest rate is characterized by high marketization, complete term structure and strong timeliness. Therefore, according to the selection principle of interest rate indicators, the selected interest rate indicators are monthly data of one-year deposit benchmark interest rate, which is recorded as OYR in this paper.

Shanghai composite index is selected as the proxy variable of stock price in this paper. In order to eliminate the unit root, the original data is processed by logarithmic difference, which is recorded as SPR. The original data is obtained from the CEInet Statistics Database. The monthly data of total turnover of Shanghai Stock Exchange is selected to represent the stock market turnover, processed by logarithmic difference, which is recorded as STO. Weighted average monthly market yield of stock market is selected as the yield of stock market, expressed by SYR in this paper, and the data are from RESSET Financial Database. ADF unit root test results show that there is no unit root in the above data or the processed data. Considering the limitation of some models on sample size, 248 groups of monthly data from January 1997 to August 2017 are studied for more than 20 years, in order to ensure the integrity of the data in the whole empirical analysis interval.

2.2. Setting of TVP-SV-VAR model
The SVAR model set by Sims is described as follows:

\[ Ay_t = F_1 y_{t-1} + L + F_s y_{t-s} + \mu_t, \quad t = s + 1, \ldots, n \]  

Where, \( y_t \) represents the \( k \times 1 \) dimensional observation vector, \( A \) means \( k \times k \) dimensional simultaneous parameter matrix, \( F_1, \ldots, F_s \) expresses the \( k \times k \) dimensional coefficient matrix, and \( \mu_t \) is perturbation term of \( k \times 1 \) dimensional structural impact. If \( \mu_t \sim N(0, \Sigma) \), then:

\[
\Sigma = \begin{bmatrix}
\sigma_1 & 0 & L & 0 \\
0 & O & O & M \\
M & O & O & 0 \\
0 & L & 0 & \sigma_k
\end{bmatrix}
\]

Assuming that the simultaneous relationship of structural impact is the relationship of recursive identification, that is, \( A \) model is a lower triangular matrix:
Thus, Equation (1) can be abbreviated as the following VAR model:

$$y_t = B_0y_{t-1} + L + B_1y_{t-s} + A^{-1}\Sigma_1\epsilon_t, \quad \epsilon_t \sim N(0, I_s)$$

(2)

$$B_i = A^{-1}F_i, \quad i = 1, ..., s$$

(3)

Each row elements of $B$ in Formula (3) is expressed by $k^2s \times 1$ dimensional column vector $\beta$. If $X_t = I_s \otimes (y_{t-1}, ..., y_{t-s})$, where $\otimes$ represents kronecker product, then the model is rewritten as follows:

$$y_t = X_t\beta + A^{-1}\Sigma_1\epsilon_t$$

(4)

The model is set in this paper in reference to methods of Primiceri (2005) [1] and Jouchi Nakajima (2011) [2]. Firstly, $A_i$ is set as a lower triangular matrix, which is consistent with the basic idea of VAR model recognition. The lower triangular matrix makes estimation easier. Then the model can be extended to model TVP-SV-VAR, so that all parameters and coefficients of the system can change with time, as shown below:

$$y_t = X_t\beta_t + A_t^{-1}\Sigma_t\epsilon_t, \quad t = s + 1, ..., n$$

(5)

Set the simultaneous parametric matrix $A_t$, coefficient matrix $\beta_t$ and covariance matrix $\Sigma_t$, rewrite either 0 or 1 element in lower triangular matrix $A_t$, and set them to be time-varying at the same time, that is, $a_t = (a_{21}, a_{31}, a_{32}, a_{41}, ..., a_{k,k-1})$. Given $h_t = (h_{t1}, ..., h_{tk})$, where $h_{ti} = \log \sigma_{ii}^2, \quad i = 1, ..., k$, $t = s + 1, ..., n$. In addition, in order to reduce the parameters to be estimated and facilitate empirical analysis, it is assumed that the parameters in Equation (4) follow a random walk process, which is more conducive to discovering the dynamic time-varying of the conduction system:

$$\begin{align*}
\beta_{t+1} &= \beta_t + \mu_{\beta_t} \\
\alpha_{t+1} &= \alpha_t + \mu_{\alpha_t} \\
\mu_{t+1} &= \mu_t + \mu_{\mu_t} \\
\Sigma_{t+1} &= \Sigma_t + \Sigma_\mu 
\end{align*}$$

$$: N\left(\begin{pmatrix} I & O & O & O \\ O & \Sigma_\beta & O & O \\ O & O & \Sigma_a & O \\ O & O & O & \Sigma_h \end{pmatrix}\right), \quad t = s + 1, ..., n$$

(6)

Where $\beta_{s+1} : N(\mu_{\beta_0}, \Sigma_{\beta_0}), \alpha_{s+1} : N(\mu_{\alpha_0}, \Sigma_{\alpha_0}), h_{s+1} : N(\mu_{h_0}, \Sigma_{h_0})$

Assuming that all parameters are subject to the random walk process, a priori value under Bayes framework needs to be set specially, in reference to methods of setting the monotone prior value by Nakajima (2013) [3] artificially. Given that the priori values of parameters $\beta$, $a$ and $h$ follow the
normal distribution, then the mean value is $\mu_{ah} = \mu_{ah} = \mu_{ah} = 0$, and covariance matrix is $\Sigma_{ah} = \Sigma_{ah} = 10 \times I$, respectively. Prior distribution value of the $i$th diagonal element of covariance matrix is set as follows: $(\Sigma_{ah})_{i}^{-2} : \text{Gamma}(40, 0.02)$, $(\Sigma_{ah})_{i}^{-2} : \text{Gamma}(40, 0.02)$ and $(\Sigma_{ah})_{i}^{-2} : \text{Gamma}(40, 0.02)$.

The basic algorithm of TVP-SV-VAR model described in this paper is a algorithm under Bayes estimation framework. Firstly, the prior distribution is set. The generated samples of algorithm are from the high-dimensional posterior distribution including the parameters of potential variables. At the same time, the joint sampling [4] is carried out based on the residual parameters, i.e. $\beta = \{\beta_{1}\}_{t=1}^{n}$, $a = \{a_{t}\}_{t=1}^{n}$ and $h = \{h_{t}\}_{t=1}^{n}$. The specific algorithm is as follows: firstly, set the initial value $\beta, a, h, \alpha, \beta, h, \Sigma_{a}, y$; secondly, sample the $\beta | a, h, \Sigma_{a}, y$; thirdly, sample the $\Sigma_{a} | \beta$; fourthly, sample the $a | \beta, h, \Sigma_{a}, y$; fifthly, sample the $\Sigma_{a} | a$; sixthly, sample the $h | \beta, a, \Sigma_{a}, y$; seventhly, sample the $\Sigma_{a} | h$; eighthly, repeat the second step.

2.3. MCMC simulation results
In this paper, the posterior estimation of parameters in TVP-SV-VAR model is calculated by 50000 times of MCMC simulations. The simulation process is completed by OxMetrics6 programming. The estimated results of system parameters are described in Table 1. The simulation effect of MCMC is judged by inefficiency factor (IF) and Geweke statistic. Whether the MCMC chain obtained by pre-simulation converges in posterior distribution is judged by Geweke statistic. The ratio of the posterior sample mean and the sample mean of uncorrelated sequence is judged by inefficiency factor [5].

| Table 1. Parameter Estimation Results of MCMC Simulation Method |
|---------------------------------------------------------------|
| **Parameter**        | **MEAN** | **S.D.** | **95.U.** | **95.L.** | **Gew** | **I.F.** |
|----------------------|----------|----------|-----------|-----------|---------|---------|
| $(\Sigma_{\beta})_{i}$ | 0.0336   | 0.0036   | 0.0393    | 0.0117    | 0.224   | 11.72   |
| $(\Sigma_{\beta})_{2}$ | 0.0208   | 0.0020   | 0.0173    | 0.0253    | 0.240   | 7.25    |
| $(\Sigma_{\omega})_{i}$ | 0.1232   | 0.0623   | 0.0497    | 0.2859    | 0.431   | 50.64   |
| $(\Sigma_{\omega})_{2}$ | 0.0566   | 0.0125   | 0.0373    | 0.0871    | 0.370   | 36.61   |
| $(\Sigma_{h})_{i}$ | 0.4157   | 0.0850   | 0.2736    | 0.6069    | 0.160   | 33.35   |
| $(\Sigma_{h})_{2}$ | 0.3295   | 0.0871   | 0.1881    | 0.5363    | 0.122   | 70.48   |

The judgment of MCMC chain simulation effect refers to Geweke value and inefficiency factor. As shown in Table 1, the Geweke values of parameter test are all within 1.96 (5% critical value), and the mean values of all parameters fall between 95% upper bound and 95% lower bound, indicating that MCMC sampling is effective. Sampling effect is negatively correlated with the value of inefficiency impact factor. The highest inefficiency factor is 70.48 in all parameters of the model, while the other inefficiency factors are not significant, showing that at least 709 irrelevant samples (50 000/70.48) can be obtained, which is sufficient for posterior inference [6].
Notes: columns 1-3 represent the autocorrelation coefficient of samples, sample path of MCMC sampling (5000 times) and posterior distribution of samples, respectively

Figure 1. MCMC Simulation Parameter Distribution

Dynamic simulation paths of variables \((\Sigma_\beta)_1, (\Sigma_\beta)_2, (\Sigma_a)_1, (\Sigma_a)_2, (\Sigma_h)_1\) and \((\Sigma_h)_2\) are shown in Figure 1. At the same time, the posterior distribution density graph shows that after 50000 times of MCMC sampling, the estimators of parameters present good convergence and fluctuation clustering [7]. It is proved that the simulation validity of the model can be further analyzed by TVP-SV-VAR model.

3. Analysis of time-varying impulse response of the system

3.1. Analysis on time-varying characteristics of impulse response of monetary policy to stock price and stock market turnover in different periods

It can been seen from Figure 2 that only the short-term impact of money supply on interest rate is not significant, while there is positive impact in long-term and medium-term, and the short-term impact effect on interaction between other variables is significant. Lag 1 effects on relationship between most of variables are significant, and the impact of money supply on interest rate approached 0 value before 2010, while it shows a slight negative impact relationship from 2010 to 2013. Money supply before 2013 showed a less positive impact on stock prices, while it showed a slight negative impact after 2013. Generally speaking, during the past twenty years, the influence of interest rate on stock price has experienced a period of "irrelevance, positive correlation, and negative correlation", and the reform of interest rate marketization makes the transmission channel of interest rate to stock market smoother, producing a substitution effect on the transmission of money volume to a certain extent. In terms of the influence of stock prices on stock market turnover, the influencing coefficients are all larger than 1.5 in the past 20 years, but it becomes lower around 2007 and 2017 and is periodic. Interest rate in both periods also keeps in lower level in the past decade, so it is concluded that the stock prices have a small influence on stock market turnover when the interest rate keeps in lower level.
With the extension of the lag period, the intensity of stock market variables affected by the impulse response of monetary policy will decline constantly. On the whole, the intensity of lag 6 and 12 is basically same, approaching 0 value at most of the time. It is proved that the Chinese monetary policy only has a short-term effect on stock market, but not sustainable. Monetary policy has not long-term effect on stock market.

3.2. Analysis on time-varying characteristics of impulse response of monetary policy to stock market returns in different periods

The impulse response functions of money volume to stock market returns ($\varepsilon_{LM2} \uparrow \rightarrow SYR$), interest rate to stock market returns ($\varepsilon_{OIR} \uparrow \rightarrow SYR$), stock price to stock market returns ($\varepsilon_{SPR} \uparrow \rightarrow SYR$), and stock market turnover to stock market returns ($\varepsilon_{STO} \uparrow \rightarrow SYR$) in different time lags are described in Figure 3 and similarly, the impulse response of lag 1 is significant. The influence of stock prices on stock market returns approached 0 value before 2005, while the influencing coefficients became larger after 2005 and showed periodic variation. In terms of the influence of stock market turnover on stock market returns, the influencing coefficients approached 0 before 2005, while the influence was characterized by periodic positive correlation, irrelevance, and negative correlation after 2006. At the same time, it can be seen that three variables have a significant short-term influence on stock market returns, while medium-term and long-term influence are not significant.
Note: Structural impact response state of lag 1, 6, and 12 are represented by solid line, long dotted line, and short dotted line respectively.

Figure 3. Impulse Response Function in Different Periods (II)

4. Conclusion
It is found from research that the monetary volume had a small positive impact on stock prices from 1997 to 2013 and it began to change into the non-negative impacts from 2013. The impact of interest rates on stock prices experienced an irrelevant → positive correlation → negative correlation in 20 years. Taking 2013 as the node, the reform of interest rate marketization has made the conduction channel of interest rate to the stock market smooth, which has certain substitution effect on the conduction of monetary volume. The equally spaced impulse response function generally reflect that the impacts of monetary policy on the stock market and the volume-price relationship of the stock market are significant at the short term, the impulse response strength of each variable is significant in the first three periods, but tends to converge after the lag period 3, and the impulse response at the lag period 6 and 12 is close to zero. This shows that monetary policy has the real effect in the short term and lacks long-term sustainable effects.

The impact factor of stock market turnover on stock market return rate is close to 0 before 2005 and the impact relationship shows the positive correlation → irrelevant → negative correlation periodic characteristics after 2016. The stock price has a positive impact on the stock market return rate during most of the period after the share reform. The stock price is positively correlated with the real earnings. In 2009, due to the excessive currency growth after the financial crisis and the strong volatility of stock market in 2015, the stock market’s real earnings is not positively correlated the stock price. This shows that the stock price has a negative impact on the stock market return rate when the strong volatility of stock market leads to the stock market disasters. The share reform in 2015 can be an important time node for changing the price-volume relationship of stock market in the past two decades. The stock price has a positive impact on stock market turnover and stock market return rate in most periods after the share reform.

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