The Interaction between Interest Rates and Stock Returns:

--- A Comparison between China and US

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Abstract

The relationship between monetary policy and stock market has been discussed since 1970s, but it is still one of the hot topics due to the changing market condition over time among different countries and the development of empirical methodologies. Owing to the fact that the stock market of China has involved in the fast-growing of Chinese economy, identifying the relationship between interest rates and stock returns in China becomes more attractive. This paper estimates the interaction between interest rates and stock returns in China by employing the structural vector autoregressive (SVAR) models with a long-run restriction, and the interaction in US is analyzed as a comparison. By analyzing the impulse responses and variance decompositions which are generated from the SVAR models, we confirm the interaction between interest rates and stock returns in China. However, compared to that in US, the magnitude of interaction in China is much smaller, showing that the effectiveness of interest rates as a monetary policy tool is still low.

Keywords: interest rates, stock returns, structural VAR models

Acknowledgements

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1   Introduction

The relationship between monetary policy and stock market has been discussed frequently. It is still worth researching owing to the fact that market conditions are not static over time among different countries and new empirical methodologies are proposed to study this topic.

Since the significant economic reforms initiated in 1978, Chinese economy has experienced rapid development and has gone through some smooth transitions. One significant transition is that Chinese economy gradually changes from a command economy to a more market-oriented one. In tandem with the development of socialist market economy, Chinese stock market also has evolved. The rate of stock market capitalization to gross domestic product (GDP) in general trend has increased since the re-open of the stock markets in China, showing the developing importance of stock markets.

According to Mishkin (2004), stock prices can affect macro economy through Tobin's q theory, wealth effects, balance sheet channel and household liquidity effects. In Tobin's q theory, q refers to the market value of firms divided by the replacement cost of capital. When q is high, it means that new plant and equipment capital is cheap relative to the market value of firms. So companies can buy new investment goods at a relatively low cost compared to the price they can get through issuing stocks. The relation between monetary policy and stock prices through this channel is that expansionary monetary policy will give rise to the money that people can spend and one place to spend money is stock market. Increasing demand for stocks will raise their prices and consequently lead to a higher q and higher investment. The wealth effects illustrates that it is the lifetime resources of consumers that determines consumption spending rather than just today's income. Therefore, when stock prices rise, the value of wealth will increase and then consumption will rise. As for the balance sheet channel, a rise in stock prices will lead to the decrease in adverse selection and moral hazard problems. Then lending will increase and further results in higher investment spending. Household liquidity effect is another credit channel besides the balance sheet channel, but in a consumer spending view. Financial assets are much more liquid than consumer durables and

housing and consumers would prefer to hold more liquid financial assets when they expect a higher likelihood of experiencing financial distress. Considering the liquidity effects, if stock prices increase, the value of financial assets will rise as well; more secure financial position would reduce the likelihood of financial distress and then lead to the higher desire of consumers to spend money on consumer durable and housing.

Central banks are commonly accepted that they have clear macroeconomic objectives for their monetary policies. The ultimate goals of the monetary policy in China are high employment, economic growth, price stability and equilibrium in the balance of payments. Since the economy can be influenced by stock markets through so many channels and stock markets are playing an increasing important role, the monetary policymakers may use stock prices as indicators for whether the current monetary policy is appropriate and have incentives to take stock markets into account when implement monetary policy.

In developed countries, the most important control instrument of central bank is the short-term interest rate (Allsopp and Vines, 2000). Interest rate is also an important instrument of monetary policy in China. The research of Liao and Tapsoba (2014) underscores the importance of China's monetary policy to move toward a more price-based target. In recent years, interest rate system reform has been put forward and the central bank of China now is better able to guide the market interest rate with the use of monetary policy instruments. Therefore, in our paper, we will focus on interest rates as proxy variables of monetary policy.

It is commonly believed that monetary policy can influence private-sector decision making. Monetary policy is likely to impact stock prices through interest rate channel. Modern financial theory posits that stock price is equal to the present value of expected future cash flow discounted by an appropriate discount rate. Keran (1971) refers that interest rate is used to determine the present value of expected future cash flow in this discounting procedure. Thus, the increase in interest rate which indicates the higher discount rate could cut the stock price directly. It other words, contractionary monetary policy, which implies the increase of interest rate in general, would lead to the fall of stock price. In the meanwhile, the rising of cost of financing caused by the contractionary monetary policy also could decrease the expected future cash flow. Furthermore, the research of Bernanke and Kuttner (2003) shows that monetary policy affects stock prices mostly by influencing the perceived riskiness of stocks. A tightening monetary policy can lead investors to view stocks as riskier investments

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and thus demand a higher return. All of the above explanations give the same implication that stock prices react negatively to the changes in interest rates.

Many empirical methods have been used to analyze this issue, including event study, GARCH models etc. Since Sims (1980) proposed vector autoregressive (VAR) models, it has been widely used for empirical research in macroeconomics. In VAR models, there is no need to specify endogenous and exogenous variables and flexible dynamics are allowed. Such merits make the model suitable for analyzing the macroeconomic variables which are usually interrelated and dynamic. However, the model cannot be used to analyze the simultaneous interdependence among variables. Ruling out the simultaneous relations by predetermined assumptions may have impact on the results we finally get. Therefore, we choose to follow Bjornland and Leitemo (2009) to employ structural vector autoregressive (SVAR) models which allow for simultaneity between monetary policy and financial markets by using a long-run restriction rather than a short-run restriction. Impulse response functions and variance decompositions are used to interpret the model.

Usually, market conditions are different between developing and developed countries. For example, the efficiency of emerging stock markets may differ from that of the developed markets. So when our paper focuses on China, we will analyze the interaction between interest rates and stock returns in US at the same time as a comparison to see whether there are some differences in the way of interaction and if exist, what the reasons for the differences are. Ultimately, with the help of comparison, we can better understand the conclusions obtained from the empirical study.

With the research, we hope to see whether there are simultaneous interdependence between interest rates and stock returns in China. We also want to see the degree of the interactions and try to explain it. The research conclusions may help monetary policymakers, especially the monetary policymakers in China, to formulate effective policy decisions. Besides, from the perspective of market participants, the study may help them with more accurate estimates of the responsiveness of the stock prices to monetary policy and then more effective investment and risk management decisions can be made.

The rest of this paper is organized as follows. The literature review is shown in section 2, which provides a review of the previous researches that study the relationship between monetary policy and stock market over time with different methodologies. Section 3 presents

the theory of SVAR models and the identification scheme used in our model. The basic diagnostic tests for time series variables, the methods of interpretation and the choice of variables and data will be explained in section 3 as well. Section 4 presents empirical results and the analysis of the results. In section 5, we will come to conclusion and give some suggestions.

2   Literature Review

A great number of empirical studies have been done to analyze how monetary policy influence stock market and the effects of monetary policy shocks on stock returns have been identified. The empirical results that stock returns react negatively to contractionary monetary policy and positively to expansionary monetary policy are concluded as a fairly robust result over countries and time period by Sellin (2001). Based on single equation regressions, almost all early studies use changes in money supply to represent monetary policy shocks when dealing with the relationship between stock returns and monetary policy. Some studies (Cooper, 1974; Rozeff, 1974) point out that stock prices are affected by changes in money supply. Nonetheless, as Sellin (2001) state, the regression results are hard to interpret due to the endogenous problem of money supply. In this case, the event study approach is performed. Based on this methodology, the variables for measuring monetary policy are not only money supply but also interest rate instrument (Pearce and Roley, 1985; Hafer, 1986). It is indicated that contractionary monetary policy leads to the fall of equity prices by using interest rate instrument. For instance, Pearce and Roley (1985) and Hafer (1986) provide the evidence that equity prices react negatively to changes in discount rate for US, and the research of Thorbecke (1997) proves that expansionary money policy increases subsequent stock prices by employing event study approach. With the same methodology, the strong negative impact of interest rates on stock returns in Pakistani is identified by Rahman and Mohsin (2011). The methodology has been employed in China as well. Some researches (Wang and Deng, 1999; Li and Fan, 2000) attribute the weak impact of interest rates shock on stock returns to the inefficiency of Chinese stock market and monetary market at that time.

Besides event study approach, some other methodologies have been applied to model the relationship between monetary policy and stock returns worldwide. In US, Lee (1997) uses market-timing models to analyze the impact of short-term interest rate on stock market, and concludes that the relationship changes from significantly negative to no relationship over time. Based on Robust MM weighted least squares estimates, Kontonikas et.al (2013) examine the impact of interest rates on stock returns over 1989 to 2012. They prove the

negative effect of interest rates on stock returns outside the financial crisis period as pervious researches. Nevertheless, they find that stock returns do not react positively to the cut of interest rates during the financial crisis. The behavior of stock investors changes owing to the worsening market condition. In UK, Dinenis and Staikouras (1998) study the effect of interest rates changes on stock returns by applying two-index model. The result reveals a strong negative relationship between changes in interest rates and stock returns. By using the smooth transition regression and GARCH models, the nonlinear and negative correlation between interest rates and stock prices in Bogota is confirmed by Arango (2002). Based on GARCH-M model, Wang and Deng (1999) examine the relationship among interbank interest rate, securities' trading volume and securities' returns in China. They point out that both interbank interest rate and securities' trading volume have influences on securities' returns. The dissertation of Wang (2003) shows that stock returns are negatively correlated with interbank interest rates in the long term by applying Engle-Granger approach to Chinese market. Based on error correction model and cointegration model, Liu (2005) and Luo (2009) also prove that stock prices react negatively to interest rates shock in China. Moreover, they find that stock prices and interest rates share not only the common trend in long run but also the common volatility in short run. By using the monthly data from 1988 to 2003, Alam and Uddin (2009) test the relationship for fifteen developed and developing countries (for example, Australia, Canada, Germany, South Africa, Chile and etc.) based on random walk model. They confirm the negative correlation between interest rates and stock prices for all countries. Moreover, for Bangladesh, Colombia, Italy, Japan, Malaysia and South Africa, it is proved that the changes of interest rates have negative relations with changes of stock prices.

Compared to the above studies that focus on the effect of monetary policy on stock returns, there are relatively few literatures building models to analyze the interdependence relationship between monetary policy and stock returns. Granger causality test is used by Hashemzadeh and Taylor (1988) and they point out that interest rates Granger cause the changes of stock prices in financial market of US while the opposite is not true. Furthermore, since Sims (1980) put forward vector autoregressive (VAR) analysis, which treats all variables as endogenous in VAR models and estimates each variable according to its own lags and lags of other variables, the methodology has been applied to examine the interaction between monetary policy and stock returns worldwide. By using long-horizon regression and short-horizon VAR model, the research of Patelis (1997) indicates that interest rate and monetary

supply are important predictors of future stock prices in US. He also concludes that tighter monetary shocks lead stock returns to decrease initially, but increase thereafter. Thorbecke (1997) finds that the increases in stock prices are strongly associating with the negative shocks to federal funds rate according to the analysis of VAR model. Specially, he states that the equity prices of small firms react strongest to the monetary tightening. Bernanke and Kuttner (2005) apply the methodology according to Campbell and Ammer. It is identified that an unexpected 25 basis point reduce in federal funds rate results in stock market index increases by 1.3 percent. Based on the similar methodology, Ehrmann et al. (2004) observe the prominent effects of monetary policy announcement on stock prices as well. They conclude that an unexpected tightening of 50 basis points in federal funds rate leads to about 3 percent decline in stock prices. Cao (2004) tests the relationship between monetary policy and stock returns in China. The result shows that one-year deposit rate exerts a powerful effect on stock returns from year 1998 to 2003. This is consistent with the result of Yu (2007) who uses the Granger Causality test to deal with the relationship between interest rates and stock returns in China. Cao (2004) further proves that expanding monetary policy has positive impacts on stock returns whereas contractionary monetary policy has negative effects on stock returns.

The empirical studies mentioned above have made great contributions to revealing the relationship between interest rates and stock returns. However, they measure the correlation between interest rates and stock returns without taking the issue of contemptuous interdependence between them into account. Some different models are established to solve the simultaneity problem. Rigobon and Sack (2003) use an identification technique based on the heteroscedasticity of stocks. They find that short-term interest rates are affected by the stock market shocks significantly, changing in the same direction as the variation of stock returns. With the same method, Rigobon and Sack (2004) prove that stock returns decline significantly when short-term interest rates are raised by Federal Reserve System. To be specific, they conclude that a 25 basis points increase in short-term interest rates causes stock index to drop by 1.9 percent. Obviously, the impact is higher than the result found by Bernanke and Kuttner (2005). What's more, Rigobon and Sack (2004) indicate that the heterscedasticity-basis method generates a greater negative effect of monetary policy on the stock market than event-study approach.

Bjornland and Leitemo (2009) offer another methodology to solve the simultaneity problem, that is, structural vector autoregressive (SVAR) model with a combination of short-run and long-run restrictions. The strong interdependence between interest rates and real stock prices is proved in US. More specific, they suggest that the monetary policy shock which raises federal funds rate by 100 basis points leads to an immediate fall on stock prices by 7 percent to 9 percent and a one percent increase in stock prices caused by a stock prices shock results in a rise in the interest rate by 4 basis points. The study of Iglesias and Haughton (2013) examines the interaction between interest rates and stock returns in Caribbean countries by applying the same model as Bjornland and Leitemo (2009). The research gives similar results as the study of Bjornland and Leitemo (2009) about US in terms of the sign of the correlation: stock returns react negatively to tightening monetary policy shocks while the positive stock returns shock lead to the increase of interest rate in all Caribbean countries. However, their study shows different results from the perspective of the magnitude of effects. They indicate that compared to that in US, the interactions in these countries are weaker due to that the less efficient information channel and the smaller size of economy. Neri (2004) uses SVAR models to analyze the case of G-7 countries and Spain. The effects of short-term interest rates on stock market indices are negative but small and temporary. The persistence, magnitude and timing of the influences differ significantly among countries. In China, Zhang et al. (2013) test the interaction relationship between monetary policy and stock market by applying SVAR model with a short-term restriction. They prove the interdependent relationship between Shanghai interbank offered rate and Shanghai composite index, but show that the impact of interest rates on stock prices is not strong.

In this paper, we choose to build SVAR models with a long-run restriction to solve the simultaneity problem when testing the interdependence between interest rates and stock returns in the financial markets of China and US. The long-term constraint we set follows Bjornland and Leitemo (2009), assuming that shocks to interest rates do not affect the level of real stock prices in the long run.

3   Methodology

3.1   Structural VAR model [1]

The unrestricted vector autoregressive (VAR) models measure the interdependencies among multiple time series based on a hybrid of univariate autoregressive models. All the variables are endogenous in the model and each variable can be estimated according to its own lags and lags of other variables. The matrix notation of unrestricted VAR models with k variables and p lags is as follow,

$$\boldsymbol{y}_t = \boldsymbol{A}_1 \boldsymbol{y}_{t-1} + \cdots + \boldsymbol{A}_p \boldsymbol{y}_{t-p} + \boldsymbol{\varepsilon}_t, \qquad t = 1,2,\dots,T \tag{1}$$

Where $\boldsymbol{y}_t, \boldsymbol{y}_{t-1}, \dots, \boldsymbol{y}_{t-p}$ and $\boldsymbol{\varepsilon}_t$ are all $(k \times 1)$ vetocrs and $\boldsymbol{A}_1, \dots, \boldsymbol{A}_p$ are all $(k \times k)$ vectors, the unobservable $\boldsymbol{\varepsilon}_t$ is the reduced-form residuals, which is called as innovations vector. Equation (1) can be written as,

$$\boldsymbol{A}(L)\boldsymbol{y}_t = \boldsymbol{\varepsilon}_t, \qquad \boldsymbol{A}(L) = \boldsymbol{I}_k - \boldsymbol{A}_1 L - \boldsymbol{A}_2 L^2 - \cdots - \boldsymbol{A}_p L^p \tag{2}$$

The above VAR models can be changed into moving average (MV) form as follow,

$$\boldsymbol{y}_t = \boldsymbol{C}(L)\boldsymbol{\varepsilon}_t \tag{3}$$

Where $\boldsymbol{C}(L)$ is a $(k \times k)$ convergent matrix polynominal in the lag operator L,

$$\boldsymbol{C}(L) = \boldsymbol{A}(L)^{-1}, \qquad \boldsymbol{C}(L) = \boldsymbol{C}_0 + \boldsymbol{C}_1 L + \boldsymbol{C}_2 L^2 + \cdots, \qquad \boldsymbol{C}_0 = \boldsymbol{I}_k \tag{4}$$

The weakness of unrestricted VAR models is that the simultaneity relationships among variables are not identifiable. In this case, structural vector autoregressive (SVAR) models are introduced. For a bivariate SVAR, the models with one lag are as following,

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[1] The summary of coefficients is attached in appendix A.

$$x_t = b_{10} + b_{12}z_t + \gamma_{11}x_{t-1} + \gamma_{12}z_{t-1} + u_{xt}$$

$$z_t = b_{20} + b_{22}x_t + \gamma_{21}x_{t-1} + \gamma_{22}z_{t-1} + u_{zt}$$

$$(5)$$

Where b_{12} measures the contemporaneous effect of z_t on x_t while b_{22} represents the simultaneous effect of x_t on z_t.

The models can be converted into matrix notation as,

$$\boldsymbol{B}_0\boldsymbol{y}_t = \boldsymbol{\Gamma}_0 + \boldsymbol{\Gamma}_1\boldsymbol{y}_{t-1} + \boldsymbol{u}_t \qquad (6)$$

Where

$$\boldsymbol{B}_0 = \begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix}, \quad \boldsymbol{y}_t = \begin{bmatrix} x_t \\ z_t \end{bmatrix}, \quad \boldsymbol{\Gamma}_0 = \begin{bmatrix} b_{10} \\ b_{20} \end{bmatrix},$$

$$\boldsymbol{\Gamma}_1 = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix}, \quad \boldsymbol{y}_{t-1} = \begin{bmatrix} x_{t-1} \\ z_{t-1} \end{bmatrix}, \quad \boldsymbol{u}_t = \begin{bmatrix} u_{xt} \\ u_{zt} \end{bmatrix}$$

$$(7)$$

The matrix form of the SVAR models included k variables with p lags is as following

$$\boldsymbol{B}_0\boldsymbol{y}_t = \boldsymbol{\Gamma}_1\boldsymbol{y}_{t-1} + \cdots + \boldsymbol{\Gamma}_p\boldsymbol{y}_{p-1} + \boldsymbol{u}_t \qquad (8)$$

Since the lag operator form of the SVAR models can be written as $\boldsymbol{B}(L)\boldsymbol{y}_t = \boldsymbol{u}_t$, where $\boldsymbol{B}(L)$ is a $(k \times k)$ parameter matrix of the lag operator L. The models can be inverted in terms of its moving average (MA) representation,

$$\boldsymbol{y}_t = \boldsymbol{D}(L)\boldsymbol{u}_t \qquad (9)$$

Where $\boldsymbol{u}_t$ is the structural disturbance term, which is an innovations vector that assumed to be identically and independently distributed. $\boldsymbol{D}(L)$ is a $(k \times k)$ convergent matrix polynominal in the lag operator L,

$$\boldsymbol{D}(L) = \boldsymbol{B}(L)^{-1}, \qquad \boldsymbol{D}(L) = \boldsymbol{D}_0 + \boldsymbol{D}_1 L + \boldsymbol{D}_2 L^2 + \cdots, \qquad \boldsymbol{D}_0 = \boldsymbol{B}_0^{-1} \qquad (10)$$

However, the SVAR models are not identifiable without restrictions. To identify expression 9, short-run or long-run restrictions should be imposed based on economics theory. In general, short-run constraints are set on $\boldsymbol{D}_0$ directly while the long-run restrictions can be imposed on $\boldsymbol{D}_q$ $(q = 1,2,\dots)$ to identify $\boldsymbol{D}_0$. According to the MV representations of unrestricted VAR

models (equation 3) and structural VAR models (equation 9), the following equation is obtained,

$$\boldsymbol{y}_t = \boldsymbol{C}(L)\boldsymbol{\varepsilon}_t = \boldsymbol{D}(L)\boldsymbol{u}_t \tag{11}$$

Due to $\boldsymbol{C}_0 = \boldsymbol{I}_k$, it can be concluded that, $\boldsymbol{\varepsilon}_t = \boldsymbol{D}_0\boldsymbol{u}_t$. That is, the simplified distributions can be written as linear combination of the structural distribution. It can also be retrieved that

$$\boldsymbol{D}(L)\boldsymbol{u}_t = \boldsymbol{C}(L)\boldsymbol{D}_0\boldsymbol{u}_t, \qquad \boldsymbol{D}(L) = \boldsymbol{C}(L)\boldsymbol{D}_0 \tag{12}$$

Moreover, according to equation 4 and equation 10, we can obtain that,

$$\boldsymbol{D}_q = \boldsymbol{C}_q\boldsymbol{D}_0, \qquad q = 0,1,2,\dots \tag{13}$$

Since $\boldsymbol{C}_q$ can be estimated from the unrestricted VAR models (equation 3), the matrix $\boldsymbol{D}_0$ is identifiable if setting long-run restrictions on coefficient matrix $\boldsymbol{D}_q$ ($q = 1,2,3,\dots$). To have a deeper understanding, the long-run restrictions can be illustrated through the impulse responses functions (IRF). The coefficient matrix of the bivariate SVAR models can be written as $\boldsymbol{D}_q = \left(d_{ij}^{(q)}\right), q = 0,1,2,\dots, i,j = 1,2$, while the models can be presented as,

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} d_{11}^{(0)} & d_{12}^{(0)} \\ d_{21}^{(0)} & d_{22}^{(0)} \end{pmatrix}\begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix} + \begin{pmatrix} d_{11}^{(1)} & d_{12}^{(1)} \\ d_{21}^{(1)} & d_{22}^{(1)} \end{pmatrix}\begin{pmatrix} u_{1t-1} \\ u_{2t-1} \end{pmatrix} + \begin{pmatrix} d_{11}^{(2)} & d_{12}^{(2)} \\ d_{21}^{(2)} & d_{22}^{(2)} \end{pmatrix}\begin{pmatrix} u_{1t-2} \\ u_{2t-2} \end{pmatrix} + \cdots \tag{14}$$

Based on the impulse responses functions, assuming $\sum_{q=0}^{\infty} d_{ij}^{(q)}$ equals zero can be viewed as no accumulated long-run responses of variable j to variable i.[2] Thus the SVAR models can be identified owing to the constraint set on the accumulated long-run responses.

In this paper, the variables in SVAR models include stock returns (s_t) and interest rates (r_t). Hence, we have a (2×1) vector of variables, ordered as

$$\mathbf{y}_t = [s_t, r_t]' \tag{15}$$

The uncorrelated structural disturbance term $\boldsymbol{u}_t$ is a (2×1) matrix and $\boldsymbol{C}(L)$ is a (2×2) convergent matrix. The structural distribution is defined as $\boldsymbol{u}_t = [u_t^s, u_t^r]'$. To be specific,

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[2] The impulse response function (IRF) of y_i caused by y_j is $d_{ij}^{(q)} = \frac{\partial y_{i,t+q}}{\partial u_{it}}$. In general, by imposing one unit impulse to y_j at t=0, the accumulate IRF of y_i is $\sum_{q=0}^{\infty} d_{ij}^{(q)}$. See details in appendix C.

u_t^s, u_t^r are defined as stock returns shock and interest rates shock respectively. Following the method of Bjornland and Leitemo (2009), we assume that interest rates and stock returns have simultaneous impacts to each other. Under this assumption, the models can be written as follow,

$$\begin{bmatrix} s_t \\ r_t \end{bmatrix} = \boldsymbol{C}(L) \begin{bmatrix} d_{11}^{(0)} & d_{12}^{(0)} \\ d_{21}^{(0)} & d_{22}^{(0)} \end{bmatrix} \begin{bmatrix} u_t^s \\ u_t^t \end{bmatrix} \tag{16}$$

It is obvious that interest rates and stock returns can respond contemporaneously to each other since $d_{12}^{(0)}$ is not assumed to be zero in the model. This is different from general researches that based on unrestricted VAR models, which assume stock returns respond with a lag to interest rates or in turn. To identify the structural models, we add the long-run restriction according to Bjornland and Leitemo (2009). That is, we should impose the constraint that shocks to interest rates do not affect the level of real stock prices in the long run. Hence, we set $\sum_{q=0}^{\infty} d_{12}^{(q)}$ equal to zero, in other words, the accumulate impulse response of stock returns to the shock of interest rates is zero in long term. Denote $\boldsymbol{D}(1) = \sum_{q=0}^{\infty} \boldsymbol{D}^q$ as the (2×2) long-run matrix of $\boldsymbol{D}(L)$, the long-run restriction can be rewritten as

$$D_{12}(1) = \sum_{q=0}^{\infty} d_{12}^{(q)} = 0 \tag{17}$$

The equation $\mathbf{D}(1) = \boldsymbol{C}(1)\boldsymbol{D}_0$ can be retrieved according to equation 12). Thus, we have

$$C_{11}(1)d_{12}^{(0)} + C_{12}(1)d_{22}^{(0)} = 0 \tag{18}$$

The SVAR models are just identifiable now.

3.2   Unit root test

The time-series of variables should be stationary to build SVAR models. In this paper, the Augmented Dickey-Fuller (ADF) unit root test is carried out to test the stability of time series variables. The test function is as follow,

$$\Delta y_t = \gamma y_{t-1} + a + \delta t + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + u_t, \qquad t = 1,2,\dots,T \qquad (19)$$

Where a is a constant, δ is the coefficient of a time trend and i is the lag order of the autoregressive (AR) process.

The unit root test is under the null hypothesis of $\gamma = 0$ against the alternative hypothesis of $\gamma < 0$. The null hypothesis of $\gamma = 0$ represents that time series contains a unit root. Hence, if the test statistic is less than the critical value, the null hypothesis is rejected and the time series is stationary.

3.3   Lag Length Selection

The determination of lag length for VAR models should be careful in case of inefficient estimators. Small lag length may lead to autocorrelation of error terms, while greater lag length requires a large number of parameters and thus decreases the degrees of freedom. The likelihood ratio (LR) test which are used to compare the goodness of fit of two models is applied to select the lag length of the SVAR models in this paper. The model that contains zero coefficients of the last q lags is defined as the restricted model and the other one is called as unrestricted model. Denote $|\hat{\Sigma}_r|$ and $|\hat{\Sigma}_u|$ as the determinant of the error variance-covariance matrix of the restricted model and the unrestricted model respectively. Assuming the sample size to be T, the joint null hypothesis that the last q lags have zero coefficients is given by,

$$\text{LR} = \text{T}\big[log|\hat{\Sigma}_r| - log|\hat{\Sigma}_u|\big] \qquad (20)$$

For the models contain g equations and q lags restricted, the LR test is distributed as χ^2 with $g^2 q$ degrees of freedom. If $|\hat{\Sigma}_r|$ and $|\hat{\Sigma}_u|$ are close enough, the null hypothesis cannot be rejected and thus the restricted model should be used.

3.4 Methods of interpretation

To interpret the interaction relationship between interest rates and stock returns, impulse response functions (IRF) and variance decompositions will be applied to analyze the structural VAR models. Impulse response functions measure how the shocks to each independent variable affect dependent variables in SVAR models. If imposing a unit shock to the error of each function, we will obtain the influences on the whole models over time. The impulse would gradually disappear if the model is stable. The basic thought of impulse responses function for VAR models and SVAR models can be seen in appendix C. By employing impulse responses, we can get the sign of the relationship and how long these effects require to take place. Therefore, the interaction between interest rates and stock returns can be obtained.

Variance decompositions reveal the contributions to the movements in each dependent variable given by shocks to itself and other variables in the autoregressions. In other words, it shows the proportion of error variance of each variable that explained by shocks to itself and other variables. Variance decompositions can be employed as supplement to the analysis of impulse responses when discussing the interdependence between interest rates and stock returns.

3.5 Choice of variables and data

3.5.1 Choice of variables

The variables in our SVAR models contain interest rates and stock returns. The following are detailed explanations for the variables we use in both Chinese and American markets.

Interest rates: For US, we choose to use the 4-week Treasury bill rate as the proxy variable of interest rates. For China, the 7-day Shanghai interbank offered rate (SHIBOR) is employed as the interest rates we use. China established the SHIBOR system in January 2007 and the rate is calculated as an arithmetic average of renminbi offered rates by participating banks (currently 18), just being set in a similar way to LIBOR. In current Chinese market, SHIBOR

can reflect the currency market supply and demand better than other interest rates and thus is selected as the proxy variable of the interest rates in this topic. Many literatures have chosen SHIBOR as the proxy variable of monetary policy (see e.g. Zhang et al, 2013).

Stock returns: We use S&P 500 stock price index to represent the stock prices in US. Mainland China has two stock markets, Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE). SSE was established on November 26, 1990 and started its operations on December 19 of the same year while SZSE was founded on December 1, 1990 and started operating on July 3, 1991. Currently, SSE is much larger than SZSE in terms of market size. By the end of 2014, the total market capitalization of SSE is RMB 24397.4 billion[3] and the total market capitalization of SZSE is RMB 12857.2 billion[4]. Considering the great dependence between the two stock markets and their market size, we choose to focus on the stock market of SSE. Shanghai exchange stock composite index, which is a stock market index of all stocks that are traded at the SSE, is selected to be the proxy variable of stock prices in our model. Stock returns are calculated based on the stock prices.

3.5.2   Choice of data

The sample period we choose starts from January 2010 and ends with December 2014, monthly data are used. The reason for the choice of the sample period is that the relationship between interest rates and stock returns can be time-varying. The rapid pace of institutional and structural change in China and the global financial crisis happened between 2007 and 2008 may have great impact on the relation we study. Our purpose for this paper is to study the current situations and therefore the data of recent five years is selected.

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[3] Source:
http://www.sse.com.cn/market/dealingdata/overview/stock/abshare/absharedealmonth_index.shtml?YEAR=2014&prodType=9&sytle=1

[4] Source: http://www.szse.cn/main/marketdata/tjsj/jyjg/ .

4 Analysis and Discussion

The period of data sample we choose starts from January 2010 and ends with December 2014 (60 observations). Both interest rates and stock prices are observed daily, but averaged monthly. Stock returns are employed in the SVAR models instead of stock price index since the latter are not stationary in most cases. The stock price index are deflated by consumer price index to be measured in real terms, and then transformed to stock returns by taking the logarithm of stock price index and differenced, that is,

$$S_t = \ln(\frac{P_t}{P_{t-1}}) \tag{21}$$

Where S_t is the market return at period t, P_t is the price index at period t and P_{t-1} is the price index at period t-1. The summary statistics of data are shown in Table 4.1. The volatility of interest rates in China is much higher than that in US during the sample period, one of the reasons is that Federal Reserve reduced the federal funds rate target gradually from 5.25 percent to a range of 0 to 0.25 percent in December 2008 and the target has been remained for the following years. Meanwhile, the variation of stock returns in US is less than that in China.

Table 4.1 Summary statistics for each of the time series

	Mean	Std. Dev.	Min	Max
China				
Stock return	-0.003685	0.049195	-0.134046	0.180555
SHIBOR	0.034660	0.010416	0.014689	0.067978
US				
Stock return	0.008850	0.029163	-0.114443	0.059431
Treasury bill rate	0.000596	0.000443	0.000001	0.001567

Stationarity of time series is necessary since it ensures that the moving average form of VAR model converges. All of the time series processes in this paper are stationary according to

Augmented Dickey-Fuller unit root tests, and the results are available in Table 1 in appendix B. Moreover, to ensure the results, another unit root test (Phillips-Perron test) and a stationarity test (Kwiatkowski-Phillips-Schmidt-Shin test) are done, both implying stationary for all of the time series processes. The choice of lag length is critical to establish VAR models. The LR tests results (available in Table 2 in appendix B) suggest that one lag should be used for both China and US. The VAR models with one lag meet stability condition due to all inverse roots of characteristic polynomial lie inside the unit circle (AR roots graphs are attached in Figure 1 in appendix B). Furthermore, the basic residuals tests show no evidence of autocorrelation or heteroscedasticity for all variables (Table 3 and Table 4 in appendix B). The SVAR models are estimated after adding a long-term restriction to the obtained unrestricted VAR models. The estimation is available in Table 5 in appendix B. [5]

4.1   Empirical Results

4.1.1   Impulse Response Functions

Impulse response functions measure how the shocks to each independent variable affect dependent variables in SVAR models. The information about the sign of the relationship and how long these effects require to take place are supplied. Thus the interaction relationship between interest rates and stock returns can be obtained from the IRF. As shown from Figure 4.1 to Figure 4.4, it is obvious that interest rates and stock returns have simultaneous impacts on each other based on the SVAR models with a long-run restriction.

The impulse response of stock returns to interest rates shocks are given in Figure 4.1 (China) and Figure 4.2 (US). Apparently, interest rates shock has a strong impact on stock returns in China, where a 79 basis points increase in SHIBOR caused by interest rate shock lead to an immediate decrease in stock returns of around 33 basis points and then an increase of 8.7 basis points in the third month. The small positive impact dies out eventually in the long run. The trend pattern is consistent with the findings of Bjornland and Leitemo (2009) about US while the magnitude is much smaller in China than that in US. According to Bjornland and

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[5] EViews supplies the result of long-run pattern matrix for SVAR model instead of the estimate coefficient for each dependent variable.

Leitemo (2009), in US, an increase of 100 base points in interest rate leads stock returns to fall by seven to nine percent immediately and revert to the average level as the long-run restriction bites. However, what we find about US over the period from 2010 to 2014 is differentiated from the previous research. An interest rates shock that raises Treasury bill rate by 3 basis points results in an immediate increase rather than a decrease in the stock by around 16 basis points. The positive impact is temporary and in the second month, the impact turns into negative with a magnitude of 4 basis points.
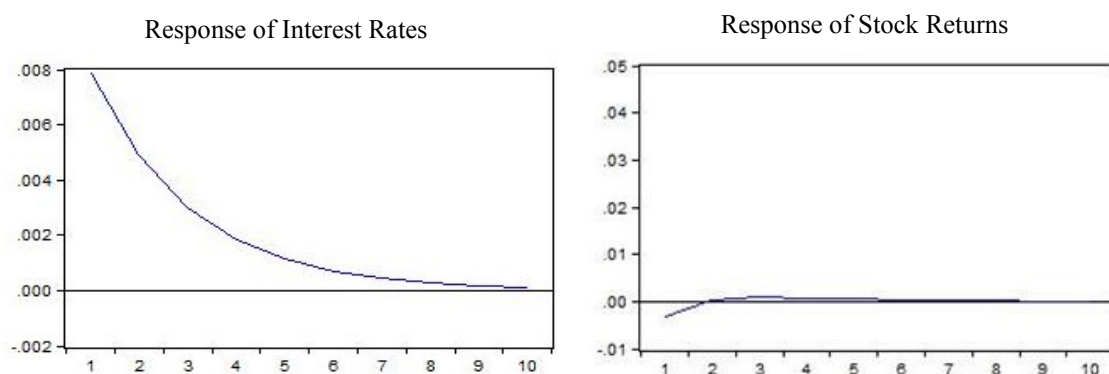

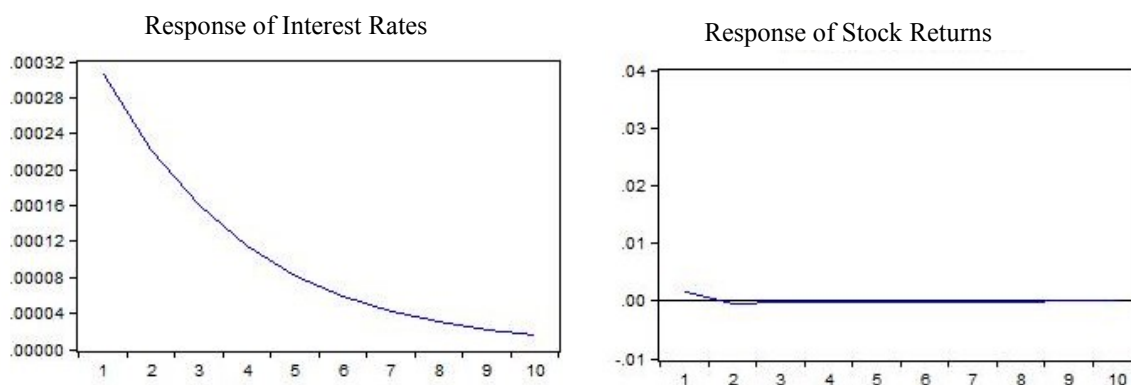*Figure 4.1 Impulse Responses to Interest Rates Shock (China)*

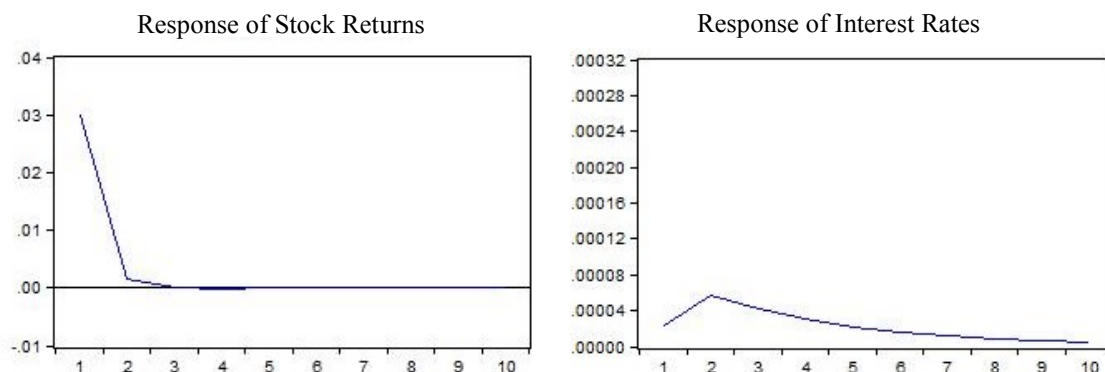*Figure 4.2 Impulse Responses to Interest Rates Shock (US)*

Response of Stock Returns   Response of Interest Rates

Figure 4.3 Impulse Responses to Stock Return Shock (US)

Response of Stock Returns   Response of Interest Rates
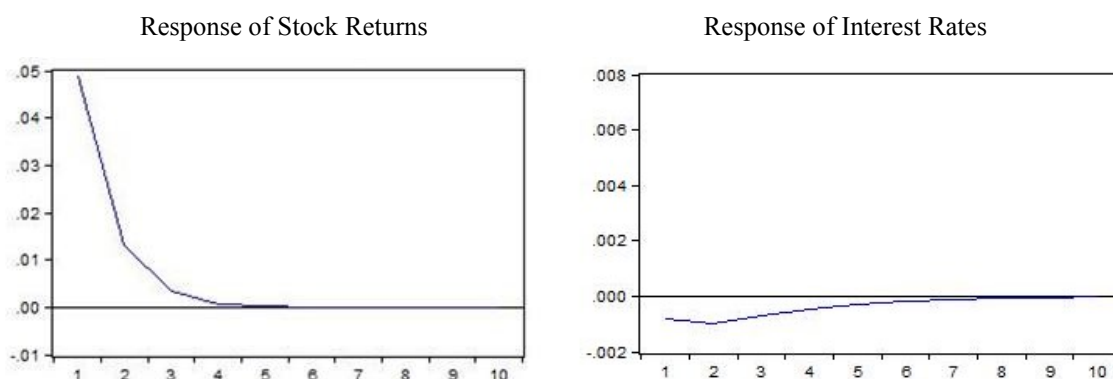
Figure 4.4 Impulse Responses to Stock Returns Shock (China)

As shown in Figure 4.3 (US) and Figure 4.4 (China), stock returns shocks are important indicators for interest rates setting. The 3 percent increase of stock returns in US caused by stock returns shock raises Treasury bill rate around 0.2 basis points initially and arrives at 0.6 basis points in the second month. The impact dies out gradually. This result is similar to what Bjornland and Leitemo (2009) obtain from US except that the magnitude is smaller now. However, the impact of stock return shock on interest rates is different in China, the stock returns shock that increases stock returns by 4.9 percent leads to the an immediate fall on SHIBOR around 8 basis points. The decline reaches 10 basis points in the second month and the effect eventually disappears within eight months.

In general, there are interactions between interest rates and stock returns though the interaction is not symmetric in both countries. The effect of stock returns on interest rates is weaker than the impact of interest rates on stock prices, but sustains longer.

4.1.2   Variance Decompositions

Variance decompositions reveal the contributions to the movements in each dependent variable given by shocks to itself and other variables in the model. The variance decompositions of stock returns and interest rates are given in Table 4.2 and Table 4.3 respectively.[6] Since only two variables are used in our model to show the direct interaction, the results of the variance decompositions should be seen in a comparative way.

Table 4.2 The Variance Decompositions of Stock Returns

China

Period	Stock returns	SHIBOR
1	99.5552	0.4448
2	99.5797	0.4203
3	99.5521	0.4479
4	99.5325	0.4675
5	99.5234	0.4766
10	99.5172	0.4828
15	99.5171	0.4829

US

Period	Stock returns	Treasury bill rate
1	99.7264	0.2736
2	99.7127	0.2873
3	99.7001	0.2999
4	99.6934	0.3066
5	99.6899	0.3101
10	99.6864	0.3136
15	99.6863	0.3137

The contributions of SHIBOR shocks to the fluctuations of stock returns in China is about 44 basis points at the initial period and keeps at 48 basis points after five periods, while the contributions of Treasury bill rate shocks to the fluctuations in stock returns in US is smaller. The proportion is 27 basis points initially and reaches 31 basis points after four periods. Stock returns shock in China accounts for about 1 percent of the variance in SHIBOR at the first

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[6] The full table is attached in Table 6 in appendix B.

period and the proportion increases to 2.4 percent after four periods. In US, stock returns shock contributes only about 0.6 percent to Treasury bill rate fluctuations initially and the contributions reach 3.7 percent after six periods. From the above analysis, the interaction relationship between interest rates and stock returns is confirmed in both China and US.

Table 4.3 The Variance Decompositions of Interest Rates

China		
Period	Stock returns	SHIBOR
1	1.0824	98.9176
2	1.8510	98.1490
3	2.2062	97.7938
4	2.3536	97.6464
5	2.4119	97.5881
10	2.4481	97.5519
15	2.4484	97.5516
US		
Period	Stock returns	Treasury bill rate
1	0.5908	99.4092
2	2.5800	97.4200
3	3.2327	96.7673
4	3.4979	96.5021
5	3.6194	96.3806
10	3.7341	96.2659
15	3.7380	96.2620

4.2   Discussion

From Figure 4.2, it can be observed from the impulse responses functions that the relationship between interest rates shocks and stock returns in US is not negative. This is different from the results obtained from previous researches, where the usual results show the negative relationship (see e.g. Bjornland and Leitemo, 2009). The negative relationship is supported by modern financial theory which posits that stock price equals the present value of expected future cash flow discounted by an appropriate interest rate, and thus the increase in interest rate could lower the stock price directly or through lowering future dividends. Furthermore,

proved by Bernanke and Kuttner (2003), a tightening monetary policy can lead investors to view stocks as riskier investments and thus demand a higher expected return, leading to a lower stock price. Compared to previous researches, the sample period we used is different and therefore the differences in results are most likely caused by the different monetary policies implemented before and after the financial crisis. Beginning from September 2007, the Federal Reserve reduced the federal funds rate target gradually from 5.25 percent to a range of 0 to 0.25 percent in December 2008 and the target has been remained for the following years. After the zero lower bound for nominal interest rates being set, the conventional monetary policy may turn to ineffectiveness. Kontonikas et.al (2013) also shows that a structural shift occurred in late 2007, altering the response of the stock returns to federal funds rate shocks. To counteract the financial crisis, unconventional monetary policies in US were put forward, mainly consisted of the forward guidance about the future path of federal funds rate and large scale asset purchases of private and public longer-term securities. The effectiveness of forward guidance actually is based on the theory of negative relationship between interest rates and stock returns. Thus, the theoretical basis for a negative relationship remains.

Due to the out-of-the-ordinary relation appeared in US market, the conclusions of Bjornland and Leitemo (2009) will instead be used for comparison. From the impulse response functions, it can be concluded that the impact of interest rates on stock returns is negative which is consistent with the previous research while the magnitude is much smaller in China than that in US. The response of the market interest rates to the shock of stock returns in China is not strong as well. The above results indicate that though interaction between interest rates and stock returns do exist in China, the effectiveness of interest rates as a monetary policy tool is still low. Such differences between the two countries may result from different degrees of market efficiency. The information processing technology in developed markets like US market is usually more advanced than that in the emerging markets such as Chinese market. Furthermore, the low liberalization of financial systems in China may account for a lot. First, administrative tools such as the so-called window guidance policy are still employed by Chinese authorities. The window guidance policy contains quantitative restrictions on bank lending and hence reduces the banks' price sensitivity. Second, state-owned enterprises (SOEs), local governments and their investment vehicles are remain the big borrowers in Chinese market and they are not so sensitive and responsive to the market

interest rates. Third, restructuring of the banking sector has not been completed yet and there are still some banks with high level of non-performing loans and little capital. Still, though interest rate deregulations have been carried out in recent years, the interest rate liberalization has not been fully completed. Since the usefulness of money supply as an intermediate monetary target has declined due to the financial innovation ad reforms (see e.g. Liao and Tapsoba, 2014), to improve the efficiency of the monetary policy, interest rate transmission channel should play a more important role in the monetary policy transmission. Further reforms for the liberalization of the financial systems are needed for this purpose.

5   Conclusion

Stock market is playing an increasing important role in Chinese economy market and many literatures have showed the importance of China's monetary policy to move toward a more price-based target such as interest rate. The purpose of our study is to find the interaction relationship between interest rates and stock returns in China and explain it. The pace of institutional and structural change is rapid in China, thus we focus on the recent period. Monthly data from January 2010 to December 2014 are selected to be used. The interdependence between interest rates and stock returns in US is also analyzed as a comparison.

Following Bjornland and Leitemo (2009), the structural vector autoregressive (SVAR) models with a long-run restriction are adopted for studying this issue. The data is updated and the methodologies are applied to research the Chinese market for the first time to our best understanding. Through analyzing the impulse responses and variance decompositions generated from the SVAR models, we find that the interdependence do exist between interest rates and stock returns in China. That is, the 79 basis points increase in SHIBOR caused by interest rates shock leads stock returns to drop around 33 basis points immediately while the stock returns shock that increases stock returns by 4.9 percent leads to an immediate fall on SHIBOR around 8 basis points. Nonetheless, compared to that in US, the magnitude of interaction in China is much smaller, showing that the effectiveness of interest rates as a monetary policy tool is still low. Profound liberalization of the financial system is needed to make the interest rate policy transmission channel more effective.

In our research, only direct relationship between interest rates and stock returns is considered while the indirect impact is not included. This is the limitation of this paper. Future research should introduce more macroeconomic variables to build models that can fully present both the direct and indirect impacts. Then the results can be more conform to the reality.

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Appendix A

Table 1: Summary for coefficients in VAR and SVAR models

$A(L)$	A $(k \times k)$ convergent matrix polynominal in the lag operator L	VAR
$C(L)$	$C(L) = A(L)^{-1}$, $C(L) = C_0 + C_1 L + C_2 L^2 + \cdots$	VAR
ε_t	Reduced-form residuals	VAR
$B(L)$	A $(k \times k)$ convergent matrix polynominal in the lag operator L	SVAR
$D(L)$	$D(L) = B(L)^{-1}$, $D(L) = D_0 + D_1 L + D_2 L^2 + \cdots$	SVAR
D_q	For a bivariate SVAR, $D_q = \left(d_{ij}^{(q)} \right), q = 0,1,2,\dots, i,j = 1,2$	SVAR
$\sum_{q=0}^{\infty} d_{ij}^{(q)} = 0$	No accumulated long-run responses of variable j to variable i	SVAR
$D(1)$	Denote as $\sum_{q=0}^{\infty} D^q$, the (2×2) long-run restriction matrix	SVAR
u_t	Structural disturbance residuals	SVAR
u_t^s	Stock returns shock	SVAR
u_t^r	Interest rates shock	SVAR

Appendix B

Table 1: Augmented Dickey-Fuller Unit Root Tests

Null Hypothesis: the time series has a unit root				
Augmented Dickey-Fuller test statistic	SHIBOR	Stock return (China)	Treasury	Stock return (US)
t-statistic	-3.7984	-4.9871	-3.0102	-7.1862
Prob.*	0.0049	0.0001	0.0397	0.0000

*MacKinnon (1996) one-sided p-values.

The table shows that t-statistics are all smaller than the critical value with 5% significant level, and these Augmented Dickey-Full unit root tests indicate all data series are stationary.

Table 2: The lag length selection according to the LR test

China									
Lag	0	1	2	3	4	5	6	7	8
LogL	260.64	269.44	270.14	271.31	273.80	278.21	278.95	280.58	284.17
LR	NA	16.58*	1.27	2.03	4.13	6.95	1.11	2.31	4.84
US									
Lag	0	1	2	3	4	5	6	7	8
LogL	446.94	466.74	467.37	469.46	471.79	472.14	472.99	479.25	481.18
LR	NA	37.32*	1.14	3.61	3.84	0.55	1.25	8.94	2.60

*indicates lag order selected by the criterion
LR: sequential modified LR test statistic (at 5% level)

The table shows that one lag should be used for both China and US.

Table 3: Residual Serial Correlation LM Tests

Lags	LM-Stat	Prob
Null Hypothesis: no serial correlation at lag		
China		
1	4.3575	0.3598
2	2.6702	0.6144
3	3.3220	0.5055
4	2.6525	0.6176
5	3.2540	0.5163
6	4.2405	0.3744
7	5.8271	0.2124
8	1.0413	0.9035
9	3.1879	0.5269
10	3.4575	0.4844
11	2.0365	0.7290
12	1.0154	0.9075
US		
1	2.9082	0.5733
2	2.9062	0.5736
3	2.8846	0.5773
4	3.3251	0.5050
5	2.2483	0.6902
6	4.2581	0.3722
7	4.0010	0.4059
8	2.2986	0.6810
9	1.7574	0.7803
10	5.9442	0.2034
11	3.6902	0.4496
12	0.6751	0.9544

Probs from chi-square with 4 df.

The table shows that p-values are all greater than the critical value with 5% significant level, thus the null hypothesis should be accepted, that is, there is no serial correlation at lags.

Table 4: Residual Heteroscedasticity Tests

China

Joint test:

Chi-sq	df	Prob.
18.0524	12	0.1141

Individual components:

Dependent	R-squared	$F_{(4,54)}$	Prob.	Chi-sq(4)	Prob.
res1*res1	0.0687	0.9959	0.4178	4.0533	0.3988
res2*res2	0.0055	0.0742	0.9897	0.3225	0.9883
res2*res1	0.0683	0.9893	0.4213	4.0284	0.4022

US

Joint test:

Chi-sq	df	Prob.
12.2138	12	0.5538

Individual components:

Dependent	R-squared	$F_{(4,54)}$	Prob.	Chi-sq(4)	Prob.
res1*res1	0.0056	0.0763	0.9892	0.3314	0.9877
res2*res2	0.1185	1.8141	0.1395	6.9890	0.1365
res2*res1	0.0327	0.4568	0.7670	1.9309	0.7485

The table shows that p-values are all greater than the critical value with 5% significant level, thus the null hypothesis there is no heteroscedasticity should be accepted, that is, there is no heteroscedasticity in residuals.

Table 5: Structural VAR Estimates

Model: Ae = Bu where E[uu']=I
Restriction Type: long-run pattern matrix
Long-run response pattern:

$D_{11}(1)$	$D_{12}(1)$
$D_{21}(1)$	$D_{22}(1)$

China

Order: Stock returns, SHIBOR

	Coefficient	Prob.
$D_{11}(1)$	0.0662 *** (0.0061)	0.0000
$D_{21}(1)$	-0.0038 (0.0027)	0.1611
$D_{22}(1)$	0.0206 *** (0.0019)	0.0000

US

Order: Stock returns, Treasury bill rate

	Coefficient	Prob.
$D_{11}(1)$	0.0311*** (0.0029)	0.0000
$D_{21}(1)$	0.0002 (0.0001)	0.1059
$D_{22}(1)$	0.0011*** (0.0001)	0.0000

*** denotes that the coefficient is statistically significant with 1% level
** denotes that the coefficient is statistically significant with 5% level
* denotes that the coefficient is statistically significant with 10% level

The structural VAR models are just-identified with the long-run restriction. Each model includes 59 observations after adjustments. The standard errors for each variable are included in ( ). The estimated coefficient for each variable is not given by EViews directly, but the estimators in long-run response matrix $D(1)$ are available from the above table. $D_{11}(1)$ measures how stock returns shocks influence stock returns in long term. $D_{21}(1)$ estimates the long-run impact of stock returns shocks on interest rates while $D_{22}(1)$ measures the long-run effect of interest rates shocks on the interest rates. And $D_{12}(1)=0$ is our long-run restriction.

Table 6: The Variance Decompositions

Variance Decomposition of Stock Return:

China

Period	S.E.	Stock return	SHIBOR
1	0.0491	99.5552*	0.4448*
2	0.0508	99.5797*	0.4203*
3	0.0509	99.5521*	0.4479*
4	0.0509	99.5325*	0.4675*
5	0.0509	99.5234*	0.4766*
6	0.0509	99.5196*	0.4804*
7	0.0509	99.5181*	0.4819*
8	0.0509	99.5175*	0.4825*
9	0.0509	99.5173*	0.4827*
10	0.0509	99.5172*	0.4828*
15	0.0509	99.5171*	0.4829*

US

Period	S.E.	Stock return	Treasury bill rate
1	0.0299	99.7264*	0.2736*
2	0.0299	99.7127*	0.2873*
3	0.0299	99.7001*	0.2999*
4	0.0299	99.6934*	0.3066*
5	0.0299	99.6899*	0.3101*
6	0.0299	99.6881*	0.3119*
7	0.0299	99.6872*	0.3128*
8	0.0299	99.6868*	0.3132*
9	0.0299	99.6865*	0.3135*
10	0.0299	99.6864*	0.3136*
15	0.0299	99.6863*	0.3137*

* denotes that the estimate is statistically significant. Two standard deviations bands are implied, the estimator is considered to be significant if it is at least twice the standard error.

The Variance Decompositions (Cont.)

Variance Decomposition of Interest Rate:

**China**

Period	S.E.	Stock return	SHIBOR
1	0.0079	1.0824*	98.9176*
2	0.0093	1.8510*	98.1490*
3	0.0098	2.2062*	97.7938*
4	0.0100	2.3536*	97.6464*
5	0.0101	2.4119*	97.5881*
6	0.0101	2.4345*	97.5655*
7	0.0101	2.4431*	97.5569*
8	0.0101	2.4464*	97.5536*
9	0.0101	2.4477*	97.5523*
10	0.0101	2.4481*	97.5519*
15	0.0101	2.4484*	97.5516*

US

Period	S.E.	Stock return	Treasury bill rate
1	0.0003	0.5908*	99.4092*
2	0.0004	2.5800*	97.4200*
3	0.0004	3.2327*	96.7673*
4	0.0004	3.4979*	96.5021*
5	0.0004	3.6194*	96.3806*
6	0.0004	3.6783*	96.3217*
7	0.0004	3.7077*	96.2923*
8	0.0005	3.7226*	96.2774*
9	0.0005	3.7302*	96.2698*
10	0.0005	3.7341*	96.2659*
15	0.0005	3.7380*	96.2620*

* denotes that the estimate is statistically significant. All estimators are statistically significant in above tables.

Figure 1: Inverse Roots of AR Characteristic Polynomial

China
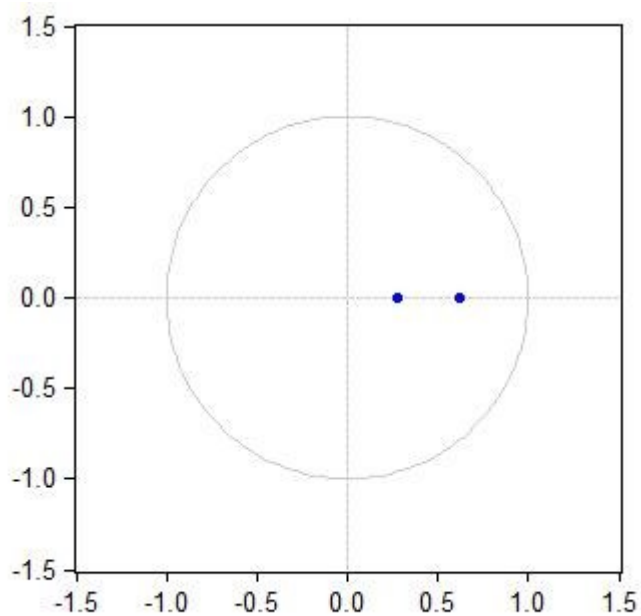
US
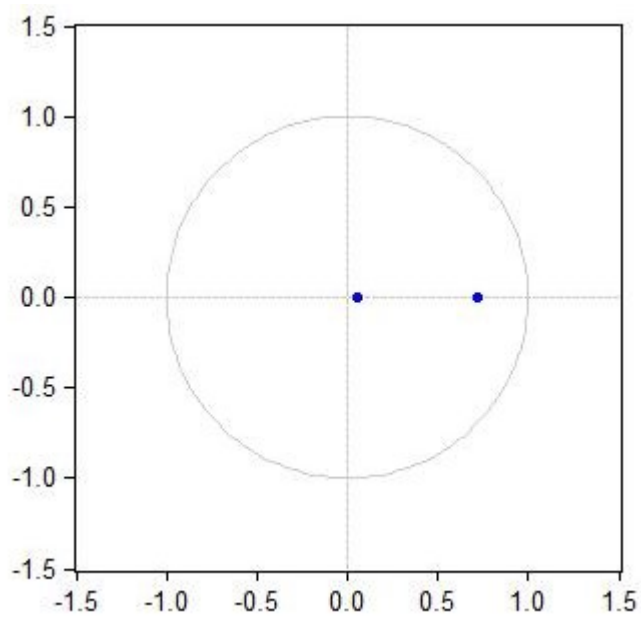
The graphs show that all inverse roots of characteristic polynomial lie inside the unit, thus the VAR models with one lag meet stability condition.

Appendix C

The Impulse Response Functions

The basic thought of impulse response functions for VAR models are as follow. Based on equation 1 and equation 4, the following functions can be retrieved,

$$\boldsymbol{y}_t = (\boldsymbol{I}_k + \boldsymbol{C}_1 L + \boldsymbol{C}_2 L^2 + \cdots)\boldsymbol{\varepsilon}_t \quad t = 1,2,\dots,T \tag{22}$$

$$\boldsymbol{y}_{it} = \sum_{j=1}^{k} \left(c_{ij}^{(0)} \varepsilon_{jt} + c_{ij}^{(1)} \varepsilon_{jt-1} + c_{ij}^{(2)} \varepsilon_{jt-2} + \cdots \right), \quad t = 1,2,\dots,T \tag{23}$$

For a bivariate model, $\boldsymbol{C}_q = \left(c_{ij}^{(q)} \right), q = 0,1,2,3,\dots, i,j = 1,2$

$$\binom{y_{1t}}{y_{2t}} = \begin{pmatrix} c_{11}^{(0)} & c_{12}^{(0)} \\ c_{21}^{(0)} & c_{22}^{(0)} \end{pmatrix} \binom{\varepsilon_{1t}}{\varepsilon_{2t}} + \begin{pmatrix} c_{11}^{(1)} & c_{12}^{(1)} \\ c_{21}^{(1)} & c_{22}^{(1)} \end{pmatrix} \binom{\varepsilon_{1t-1}}{\varepsilon_{2t-1}} + \begin{pmatrix} c_{11}^{(2)} & c_{12}^{(2)} \\ c_{21}^{(2)} & c_{22}^{(2)} \end{pmatrix} \binom{\varepsilon_{1t-2}}{\varepsilon_{2t-2}} + \cdots \tag{24}$$

Keeping ε_{2t} $(t = 0,1,2,\dots)$ equals zero and impose one unit impulse to y_1 at t=0,

$$\varepsilon_{1t} = \begin{cases} 1, & t = 0 \\ 0, otherwise \end{cases} \tag{25}$$

The IRF of y_2 to the impulse can be calculated as,

$$t = 0, \quad y_{20} = c_{21}^{(0)}$$

$$t = 1, \quad y_{21} = c_{21}^{(1)} \tag{26}$$

$$t = 2, \quad y_{22} = c_{21}^{(2)}$$

Therefore, the IRF of y_i to the impulse of y_j can be calculated as,

$$c_{ij}^{(0)}, c_{ij}^{(1)}, c_{ij}^{(2)}, c_{ij}^{(3)} \dots \tag{27}$$

The accumulate IRF of y_i caused by y_j is $\sum_{q=0}^{\infty} c_{ij}^{(q)}$.

Generally speaking, the IRF of the element in row i and column j of matrix $\boldsymbol{C}_q$ can be written as

$$c_{ij}^{(q)} = \frac{\partial y_{i,t+q}}{\partial \varepsilon_{jt}}, \qquad t = 1,2,\dots,T \tag{28}$$

The matrix form can be written as $\boldsymbol{C}_q = \frac{\partial \boldsymbol{y}_{t+q}}{\partial \boldsymbol{\varepsilon}_t{}'}$.

Thus, it is possible to retrieve IRF for the SVAR models, which is

$$\boldsymbol{y}_t = \boldsymbol{D}(L)\boldsymbol{u}_t = \boldsymbol{C}(L)\boldsymbol{D}_0\boldsymbol{u}_t = (\boldsymbol{I}_k + \boldsymbol{C}_1 L + \boldsymbol{C}_2 L^2 + \cdots)\,\boldsymbol{D}_0\boldsymbol{u}_t \tag{29}$$

The IRF of SVAR models can be obtained according to equation 28, that is,

$$d_{ij}^{(q)} = \frac{\partial y_{i,t+q}}{\partial u_{jt}}, \qquad t = 1,2,\dots,T \tag{30}$$

The accumulated long-run responses can be written as $\sum_{q=0}^{\infty} d_{ij}^{(q)}$.

The matrix form is as follow,

$$\boldsymbol{D}_q = \frac{\partial \boldsymbol{y}_{t+q}}{\partial \boldsymbol{u}_t{}'}, \qquad t = 1,2,\dots,T \tag{31}$$