# AN ANALYSIS OF THE IMPACTS OF MACROECONOMIC FLUCTUATIONS ON CHINA'S STOCK MARKET

### Lin Lingnan

\* Institute of Economics, School of Social Sciences, Tsinghua University, Beijing, China Contact details: Institute of Economics, School of Social Sciences, Tsinghua University, 100084 Beijing, China



How to cite this paper: Lingnan, L. (2019). An analysis of the impacts of macroeconomic fluctuations on China's stock market. Journal of Governance & Regulation, 8(2), 49-60. http://doi.org/10.22495/jgr\_v8\_i2\_p5

Copyright © 2019 The Authors

This work is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0).

 $\frac{https://creativecommons.org/licenses/by/}{4.0/}$ 

ISSN Print: 2220-9352 ISSN Online: 2306-6784

**Received:** 26.03.2019 **Accepted:** 13.06.2019

JEL Classification: E44, G14 DOI: 10.22495/jgr\_v8\_i2\_p5

#### **Abstract**

Research of influence of macroeconomic fluctuations on stock markets suggests different kinds of relationship between them. This paper aims to analyze the relationship between Shanghai Composite Index and China's macroeconomic indexes applying cointegration method and different metrics of money supply: M1 and M2. The time period of data in this paper spans from Quarter 1, 1995 to Quarter 4, 2018. The Vector Error Correction Model (VECM) constituted suggests that: 1) there is a long-run equilibrium between these variables; 2) in the long run, despite of different measures of money supply, real GDP is negatively correlated with SCI, implicating a deviation of a stock market from real economy; 3) in the short run, no matter what measure of money supply we use, real GDP seems to have no significant effect on SCI, which again verifies the deviation of the stock market from real economy. The impulse response analysis suggests the totally opposite direction of effect that money supply and interest rate have on SCI in different specifications, and the forecast-error decomposition analysis indicates that SCI cannot fully reflect macroeconomic fluctuations once again.

**Keywords:** Stock Market, Macroeconomic Fluctuation, Cointegration, VECM

#### 1. INTRODUCTION

The stock market is called an indicator and a barometer of macroeconomy. The maturity of the stock market reflects the economic development in one country. The stock market renders an opportunity for liquidating savings and investing, which is critical to economic growth. Many researchers concern themselves with the dynamic correlations between stock market exchange and macroeconomic indexes. In this paper, we will choose Shanghai Composite Index (SCI) as the representative of China's stock market and several macroeconomic variables to analyze the relationship between them. A cointegration method is applied for this purpose.

The remainder of this paper is organized as follows. Section 2 takes a review of the existing literature that is relevant to our topic. Section 3 introduces our test methodologies and regression models. Section 4 takes a glance of the data set used in this paper and the descriptive statistics. Section 5 describes the econometric results and the final conclusion will be pointed out in Section 6.

#### 2. LITERATURE REVIEW

Factors affecting the stock prices, directly and indirectly, remain in debate for a long time. Al-Tamimi et al. (2011) pointed out external factors, i.e. government regulations, inflation (CPI), market conditions, investor behavior, money supply (MS), competition, uncontrolled natural environmental circumstances which induce the change of stock prices, and developed a regression model to estimate the coefficients of the factors. Auranazeb (2012) found out that foreign investment and exchange rate have a significant positive impact on the stock market in South Asia, while the interest rate and inflation have significant negative effects.

A bunch of literature apply the stock exchange index as the performance of the stock markets and explore the factors causing indexes' fluctuation. Pethe and Karnik (2000) found a weak causality running from the index of industrial production to Sensex /Nifty. Maysami et al. (2004), Ahmed and Imam (2007) investigated the causal effects between the stock market and different macroeconomic variables in Singapore and Bangladesh and found

that Singapore stock market index reflects macroeconomic effects while Bangladesh stock market does not. Erdem et al. (2005) investigated the relationship between Istanbul Stock Exchange (ISE) index and a few macroeconomic factors, and inflation and interest rates were found to affect the change of the ISE index. Alshogeathri (2011) focused on the long run and short-run relationships between Saudi stock market returns and eight variables: M1, M2 as money supply, short-term interest rates, consumer price index, bank credit, world crude oil prices, exchange rate and Standard & Poor's 500 index with monthly data from January 1993 to 2009. Anlas (2012) explored the December relationship between changes in foreign exchange rates and the main composite index at Istanbul Stock Exchange by employing monthly spanning from January 1999 and November 2011. He found that changes in domestic U.S. dollar and Canadian dollar are positively related to changes in ISE 100 while fluctuations in domestic interest rates and Saudi Arabia Riyal have a negative impact on the index.

There is also extant literature concerning the effects of the specific macroeconomic indexes on the stock market. Humpe and Macmillan (2009) investigated the relationship between industrial production index and stock market returns. They found that the industrial production index has a significant positive effect on the stock market returns. Ray (2013) studied the relationship between Indian stock prices and a set of the macroeconomic indexes and reached the conclusion that industrial production index can be used as a representation of overall economic activity including the stock market. The study conducted by Aromolaran et al. (2016) using the data for the period from 1994 to 2012 showed that Index of Industrial Production (IIP) has a positive and significant effect on All-Share Index (ASI) of Nigeria Stock Exchange. Almutair (2015) analyzed the long-run as well as the short-run causality and relationship of money supply and Saudi Stock Price Index (SSPI) using a different measure of money supply: M1 and M2 and different time series: annual data from 1985 to 2012 and monthly data from 2000 to 2013.

Many Chinese researchers discussed correlations between China's stock market and macroeconomic fluctuations. Lanbiao et al. (2001) applied a basic analysis method for the virtual economy and empirical data to find that the link between the stock market and macroeconomy is the idle money produced by deflation. Zhao and Xue (2004) discovered a weak connection between the stock market and macroeconomic fluctuations using the multivariate regression and VAR model. Shaoping (2008) studied the influences of the macroeconomic indexes (among them money supply) on the stock market. He found a long-run and stable relationship between stock prices and money supply with different measures: M0, M1, and M2 in the period from 2005 to 2007. Qi'an et al. (2010) investigated the relationship between China's macroeconomic environment, macroeconomic policies and the stock market with GARCH model, and concluded that China's stock market cannot reflect macroeconomic fluctuation accurately due to the imperfection of the market mechanism.

#### 3. RESEARCH METHODOLOGY

#### 3.1. Augmented Dickey-Fuller (ADF), DF-GLS and **KPSS** test

The cointegration analysis in the empirical study requires all the variables to be integrated for order one, which means all the variables should be nonstationary in level form and stationary in the 1st difference. The unit root tests are usually applied to test whether a variable is stationary. Augmented Dickey-Fuller test is the augmented version of the original test proposed by Dickey and Fuller (1979) with the auto-correlation of error term series being controlled. The ADF test is based on the following regression equation which stems from Vector Autoregression Model (VAR):

$$\begin{array}{l} \Delta y_t = \beta_0 + \delta y_{t-1} + \gamma_1 \Delta \gamma_{t-1} + \gamma_2 \Delta y_{t-2} + \cdots \\ \qquad \qquad + \gamma_{p-1} \Delta y_{t-p+1} + \gamma t + \varepsilon_t \end{array} \tag{1}$$

Where  $y_t$  is the variable tested for unit roots,  $\Delta$ is difference operator,  $\gamma_t$  is the time trend term,  $\beta_0$  is the constant, and p is the lag order selected. The null and alternative hypotheses are:

$$H0: \delta = 0 \quad vs \quad H1: \delta < 0 \tag{2}$$

Using Equation (1) and OLS method, we can get estimator  $\hat{\delta}$  and its t statistic. The ADF test is a leftsided test whereby the reject domain distributes on the left side. When the t statistic of estimator  $\hat{\delta}$  is smaller than (the absolute value is greater) the critical value provided by Mackinnon (1991), the null hypothesis is rejected and the tested variable is stationary. Otherwise, the null hypothesis is accepted and the variable is non-stationary. We need to conduct the test with the 1st difference of the variable. If the 1st difference of the variable is stationary, we can confirm the variable integrated for order one, I(1).

DF-GLS is another more efficient unit root test suggested by Elliot, Rothenberg, and Stock (1996) to reduce the probability of type II error committed by the ADF test. The first step of DF-GLS is to estimate the constant and time trend term  $\beta_0 + \hat{\gamma t}$  of original series  $\{y_t\}$  using a Generalized Least Square (GLS) method and calculate the detrended series  $\{y_t^d \equiv$  $y_t - \beta_0 - \hat{\gamma}t$ . The second step is to test  $\{y_t^d\}$  using the ADF test.

The null hypothesis of the ADF and DF-GLS tests is "H0: unit roots exist". However, for the macroeconomic variables, the probability of type II error the test committed would be large. The KPSS test proposed by Kwiatkowski et al. (1992) changes the null hypothesis to "H0: time series is stationary" and the alternative to "H1: unit roots exist". The KPSS test applies a Lagrange Multiplier method to get the KPSS statistics, which is a right-sided test like  $\chi^2$  test.

#### 3.2. Johansen cointegration test and Vector Error Correction Model (VECM)

After the unit roots test, in order to find out the long-run equilibrium of SCI and the macroeconomic indexes, we will employ widely used Johansen (1988) cointegration test. This test is to identify the number of cointegration relationships between the variables and estimate the parameters of such relationships implementing a Maximum Likelihood Estimation (MLE) method. The Johansen cointegration test is based on the VAR model as follows:

$$y_t = \alpha + \delta t + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \cdots + \Phi_p y_{t-p} + \varepsilon_t \quad (3)$$

Where  $y_t$  is a  $n \times 1$  vector of the variables being tested,  $\alpha$  is a  $n \times 1$  vector of constant terms,  $\delta t$  is a  $n \times 1$  vector of time trend,  $\Phi_t(i=1,2...,p)$  are  $n \times n$  coefficient matrixes of lag terms of  $y_t$ ,  $\varepsilon_t$ , is a  $n \times 1$  vector of error terms. Define the lag polynomial as follows:

$$\Phi(L) = I_n - \Phi_1 L - \Phi_2 L^2 - \dots - \Phi_p L^p \tag{4}$$

Where L is the lag operator. Then the VAR model can be transformed into the following Vector Error Correction Model (VECM):

$$\Delta y_t = \alpha + \Gamma_0 \Delta y_{t-1} + \Gamma_1 \Delta y_{t-1} + \dots + \Gamma_{p-1} \Delta y_{t-p+1} + \varepsilon_t \quad (5)$$

Where  $\Delta$  is the difference operator:

$$\begin{split} &\Gamma_0 = -\Phi(1) = \left(\Phi_1 + \Phi_2 + \dots + \Phi_p\right) - \ \mathrm{I}_n \ , \\ &\Gamma_s = -\left(\Phi_{s+1} + \Phi_{s+2} + \dots + \Phi_p\right), s = 1, 2, \dots, p-1 \end{split}$$

It can be proved that if the cointegration rank  $\{y_t\}$  is h, then  $rank(\Gamma_0) = rank[\Phi(1)] = h$ , and  $\Gamma_0$  can be decomposed as:

$$\Phi(1)_{n \times n} = B_{n \times h}(A')_{h \times n} \tag{6}$$

Where B and A are two  $n \times h$  full column rank matrixes and  $A'y_{t-1}$  is stationary. Hence, h is the number of the cointegration relationships, each column vector of  $A_{n \times h}$  is a cointegration vector.

Johansen (1988) estimated the VECM described by Equation (5) using the MLE method. The Johansen test uses one statistics to identify the number of the cointegration relationships, namely the trace test statistic. The trace test is a likelihood ratio test with the null hypothesis and an alternative as follows:

$$H0: rank(\Gamma_0) = 0$$
 vs  $H1: rank(\Gamma_0) > 0$  (7)

If the null hypothesis is accepted, then the cointegration does not exist. Otherwise, the test:

$$H0: rank(\Gamma_0) = 1$$
 vs  $H1: rank(\Gamma_0) > 1$  (8)

Continue the test in this order until the cointegration rank h is checked out. Thereafter, the long-run (cointegration) and short-run coefficients can be estimated using the conditional MLE.

## 3.3. Impulse response function and forecast-error variance decomposition

Combining Equations (3) and (4) in Section 3, omitting the time trend term, we have:

$$\Phi(L)\mathbf{y}_t = \alpha + \varepsilon_t \tag{9}$$

Define  $\Phi(L)^{-1} \equiv \Psi(L) = \Psi 0 + \Psi 1^L + \Psi 2^{L^2} + \cdots$ ,  $\Phi(L)^{-1}\alpha \equiv \theta$ , Equation (9) can be written in Vector Moving Average (VMA) representation as:

$$y_t = \theta + \Psi 0^{\varepsilon} t + \Psi 1^{\varepsilon} t - 1 + \Psi 2^{\varepsilon} t - 2 + \cdots$$
$$= \theta + \sum_{i=0}^{\infty} \Psi i^{\varepsilon} t - i$$
 (10)

Where  $\Psi 0 \equiv I_n$ . Hence, according to vector derivative rules, we have:

$$\frac{\partial y_{t+s}}{\partial \varepsilon'_t} = \Psi s \tag{11}$$

Equation (11) depicts how the value of the i variable (i=1,2,...,n) in time period t+s represented by  $y_{i,t+s}$  would change if the disturbance term of the j variable (j=1,2,...,n) in time period t represented by  $\varepsilon_{jt}$  increases 1 unit. Equation (11) is the impulse response function (IRF) depending on the time interval s.

One of the most employed functions of the VECM is forecasting. We can predict the value of the i variable (i = 1, 2, ..., n) in time period t + s represented by  $y_{i,t+s}$ , and calculate the Mean Square Error (MSE) as follows:

$$MSE(y_{i,t+s}) \equiv E[(y_{i,t+s} - y_{i,t+s})^2]$$
 (12)

From Equation (12), we can calculate the contribution of the impulse of the j variable to the forecast MSE of  $y_{i,t+s}$ . The sum of the contributions of all variables is equal to 1. That is what we call forecast-error variance decomposition (FEVD).

#### 4. DATA

#### 4.1. Data set

This paper uses the quarterly data for the period from Quarter 1, 1995 to Quarter 4, 2018. The data set incorporates the following data: gross domestic product (GDP); consumer price index (CPI); baseline loan rate; money supply and Shanghai Composite Index (SCI). GDP is a quarterly data. CPI is calculated in the baseline of Jan 1995 using the month-onmonth data. In this study, we will employ two metrics of money supply in terms of M1 and M2 because different measures of money supply will affect the stock market differently. We will check out how the results depend on the different metrics of the money supply. Since these data have different orders of magnitude, we will apply the logarithm of the variables in the following analysis. Our data is obtained from the Chinese Nation Bureau of Statistics and the People's Bank of China through various issues of Annual Reports, Quarterly and Monthly Bulletin.

#### 4.2. Descriptive statistics

Table 1 is the descriptive statistics of original data instead of logarithms. According to the statistics, GDP, M1, and M2 are highly volatile in the chosen time period. For example, a mean value of 204,000.00, 189,000.00 and 595,000.00 is reported

with GDP, M1, and M2, respectively. Their standard deviations are reported as 204,000.00, 160,000.00 and 546,000.00, indicating a highly volatile macroeconomic performance in China. Indeed, the minimum and maximum values of GDP is 12,111.70 billion and 900,309.00 billion respectively, which present us a high-speed growth of China's economy. Meanwhile, M1 and M2 grow from 19,835.70 billion and 47,973.30 billion to 552,000.00 billion and 1,830,000.00 billion, respectively. In contrast, SCI, CPI, and baseline loan rate are more stable than GDP, M1, and M2. The standard deviation of SCI is 978.00, the minimum and maximum values of SCI are 555.29 and 5552.30, indicating that although SCI has significant growth, it is more stable than GDP, M1, and M2. The standard deviation, minimum and maximum values of CPI inform us only mild inflation in China's economy during the time span. Furthermore, the baseline loan rate seems to maintain the most stable of all variables, which may be attributed to the regulation of interest rate in China. From the bottom row of Table 1, we can see that the sign of correlation coefficients with SCI are positive except for the baseline loan rate.

The purpose of this paper is to find out the long-run and the short-run relationship between SCI and the macroeconomic indexes. However, it is noted that there is a long-term equilibrium between money supply, price of goods and real GDP. This equilibrium can be expressed by money demand function as follows:

$$\begin{split} \log m r_t &= \log m_t - \log p_t \\ &= \beta_0 + \beta_1 \log y_t + \beta_2 r_t + \varepsilon_t \end{split} \tag{13}$$

Where  $mr_t$ ,  $m_t$  represents real and nominal money demand respectively,  $p_t$ ,  $y_t$ ,  $r_t$  is the price of goods, real GDP and nominal interest rate. Therefore, in case of interfering with our goal, we discard the variable of  $\log cpi$  and apply the logarithm of real GDP<sup>13</sup> in the following analysis to get rid of the potential extra cointegration of variables.

Before we employ the methodologies in Section 3 to get econometric results, we can check the time trends of variables of interest. Figure 1 plots the time trends of all the variables (in logarithms) analyzed in Section 5. Apparently, real GDP, M1, and M2 have nearly the same time trend, and SCI is consistent with baseline loan rate in the period of time. This reminds us that there is a possibility of long-run equilibrium, i.e. cointegration in these variables which is explored in the next section.

#### 5. ECONOMETRIC RESULTS

#### 5.1. Uniroot test

Table 2 shows the Augmented Dickey-Fuller (ADF) test results for the variables. As we can see, the null hypothesis of unit root cannot be rejected for all the

variables in level since the test statistics is smaller than the 5% critical value. However, the test results for all the variables except for  $\log y$  in the 1st difference exclude the existence of unit roots. Therefore, the 1st differences of variables except for  $\log y$  are stationary, which means that these variables are integrated for order one, I(1).

The ADF test result for  $\log y$  is a little bit abnormal. Since we apply the logarithm of the real GDP, it is expected the unstable factors being removed from the data and  $\log y$  should be at least integrated for order one. Thus, we use the more efficient DF-GLS methodology to repeat the unit root test for  $\log y$ . The results are shown in Table 3. Not surprisingly, the DF-GLS test shows that we should reject the existence of unit root for the 1st difference of  $\log y$  but accept the null hypothesis for the level form of  $\log y$ . Hence, we can conclude that  $\log y$  is also integrated for order one, I(1).

Table 4 displays the KPSS stationary test results for all variables. Once again, they justify the outcome that all variables are integrated for order one I(1) since the null hypothesis of trend stationery can be rejected in the level forms and should be accepted in the 1st difference for all variables.

#### 5.2. Johansen cointegration test

Following the test of existence unit root, we will employ M1 as the caliber for the money supply to check out the cointegration relationship between all variables. From Table 5, Panel A, we can confirm the cointegration relationship exists between all the variables. Both the trace test and the maximum eigenvalue test rejects the null hypothesis of no cointegration (rank=0) against the alternative of at least one cointegration at 5% significant level. The trace test and maximum eigenvalue test also indicate that there is one cointegration expression for both cases.

Panel B of Table 5 shows the cointegration test results whereby we use M2 as the caliber of the money supply. The outcomes are quite similar to that of M1 serving as the measurement of the money supply. Therefore, we can confirm that there is a long run equilibrium between SCI and Chinese macroeconomic indexes.

In order for applying the VECM to explore the long-run relationship between SCI and Chinese macroeconomic indexes, an appropriate lag length should be chosen. This paper proceeds selection of lag order based on the following criteria: Akaike Information Criterion (AIC), Schwarz/Bayesian Information Criterion (SIC/SBIC), Final Prediction Error (FPE), Hannan and Quinn Information Criterion (HQIC). The outputs of the selection process shown in Table 6 suggest that the optimum lag length is four for both M1 and M2 as the caliber of money supply.

#### 5.3. VECM results

As we ascertain the cointegration rank and the lag length which should be chosen, the Vector Error Correction Model (VECM) can be applied to explore

ADF test, as we showed in Section 3, is a left-sided test for unit roots.



<sup>&</sup>lt;sup>13</sup> In fact, the variance of consumer price index (CPI) is reflected in the real GDP which can be written as:  $y_t = \frac{GDP_t}{n_t}$ 

the long-run and the short-run relationship between SCI and Chinese macroeconomic indexes. Table 7 summarizes the VECM results with M1 and M2 as the caliber of money supply, respectively.<sup>15</sup>

The implications of these two specifications are quite different from each other. Panel A of Table 7 indicates a long-run causality running from real GDP, baseline loan rate and M1 to SCI since the sign of the error correction items of SCI is negative and significant. The coefficient of the error correction item implies that one unit short-run deviation from the long-run equilibrium will cause 3 percent of error corrected in the consecutive quarter for SCI. Likewise, Panel B of Table 7 indicates a long-run causality running from real GDP, baseline loan rate and M2 to SCI. Yet, in the context of using M2 as the caliber of money supply, one unit short-run deviation from the long-run equilibrium will cause 7.3 percent of error corrected in the consecutive quarter for SCI.

In the meantime, the VECM results show the multilateral short-run causality between real GDP, baseline loan rate, M1 and SCI. As we can see from Panel A of Table 7, the coefficients  $D(\log m1_{-2})$  of and  $D(\log m1_{-3})$  are positive and significant. This means as money supply increases, part of the money goes to the stock market and makes the stock exchange index boost. This result holds for the specification of using M2 as the caliber of money supply (see Panel B of Table 7). Back to Panel A. the coefficient of  $D(\log lr_{-1})$  indicates a negative and significant effect on the change of SCI. This result is in accordance with the theories proposed by real activity school. The real activity school believes that the rise of interest rate would raise the discount rate, the present value of future earnings decreases, causing the stock prices to go down (Bernanke & Kuttner, 2005).

Most interesting is that the short-run effect of SCI on money supply. The coefficient of  $D(\log sci_{-1})$  in Panel A and coefficient of  $D(\log sci_{-4})$  in Panel B are both significant. However, the signs of these two coefficients are opposite, which indicates a positive effect of SCI on M1 and a negative effect of SCI on M2 in the short run, respectively. This result justifies the theoretical point of post-Keynesians which states that the boom of the stock market stimulates people to liquidate long-term saving deposits. Because of the conventional definition of M1 and M2, the transfer from long-term saving deposits to the demand deposits driven by the liquidation need to participate in the stock market cause M1 to increase and M2 to decrease.

The cointegration equations are shown in Table 8. As we can see, there is a long run cointegration relationship between SCI and the macroeconomic index. SCI can be expressed by M1/M2, real GDP, and baseline loan rate. There is a slight difference in the coefficients. When the long-run cointegration equation expressed with M1 as the caliber of money supply, the coefficients of M1 and real GDP are significant. However, when M2 serves as the caliber of money supply, the coefficients of M2 and real GDP are insignificant, albeit in both case the coefficient of baseline loan rate is significant.

The long-run cointegration equations can be written as:

$$\log sci = -254.83 + 63.20 \log m1 - 84.13 \log y + 11.49 \log lr$$
(14)

$$\log sci = -26.13 + 3.88 \log m2 - 5.85 \log y + 3.38 \log lr$$
 (15)

Equations (1) and (2) indicate that in the long run, the money supply has a positive effect on SCI. This coincides with the real activity theory. However, in the long term, real GDP has a negative effect on SCI which is larger than money supply and baseline loan rate. Therefore, the Chinese stock market has an obvious deviation from macroeconomy, the stock exchange index cannot reflect economic growth. On the other hand, baseline loan rate seems to have a positive effect on SCI. It may be attributed to the regulation of the interest rate in China.

## 5.4. Impulse response and forecast-error variance decomposition

After we get the cointegration equations applying the VECM, we can test the stability of the VECM system. The result is plotted in Figure 2. It is clear that aside from three unit roots the VECM imposes, <sup>16</sup> other roots of the companion matrix of the VECM are located inside the unit circle. Hence, the VECM is stable.

Figure 3 depicts the mutual response of SCI and the macroeconomic indexes to an impulse of one another. The impulse responses are orthogonalized. As we can see, an impulse of one variable will exert persistent influence on another variable, which is quite different from a stationary VAR system. A positive impulse of baseline loan rate will cause M1 decrease persistently but has barely any effect on M2. Nevertheless, a positive increase of baseline loan rate has an enduring and enormous positive effect on SCI in the specification of M1, in comparison with an opposite effect on SCI in the specification of M2. It seems that M2 is more fitted with the theory proposed by Sellin (2001).

When we turn to the impulse of money supply, we can find that the impulse of money supply has hardly any effect on real GDP, which complies with the real activity theory. However, in the two specifications, the impulse of money supply has a totally opposite but significant effect on both baseline loan rate and SCI. Each specification seems to support one of the two opposite points of views proposed by real activity theorists and Sellin. Sellin (2001) argues that a positive money supply shock will cause people to anticipate a contraction of monetary policy. The subsequent sale of bonds will drive up the interest rate, and the stock prices will go down due to the shrink of present values of shares as a result. This is backed up by the graphic response to the impulse of M1. In contrast, real activity theorists believe that increasing money supply reduces the real interest rate, and the stock prices will rise up due to the growth of present

 $<sup>^{16}</sup>$  In this paper, our VECM has four endogenous variables: SCI, money supply, real GDP, baseline loan rate. The cointegration rank of VECM is one. Therefore, when we transform VECM into VAR model, the characteristic equation of VAR has n-rank=4-1=3 unit roots.



An autocorrelation test of residuals is employed after VECM results are procured, the outcome of the test authenticates the existence of autocorrelation, suggesting that a higher lag order should be applied. Therefore, in this paper, a lag length of five is applied in VECM.

values of shares, which is supported by the graphic evidence of impulse of M2.

On the other hand, the stock price shock has barely an effect on money supply and real GDP, which again testifies the deviation of the stock market from macroeconomy in China. However, the stock price shock seems to have a persistent influence on baseline loan rate, the directions of which are opposite in different specifications. Finally, the real GDP shock seems to have positive, significant and persistent effects on the interest rate, money supply, and SCI, which justifies the real business cycle (RBC) theory.

One of the most popular functions of the VECM is prediction ahead of time. Figure 4 plots the variance decomposition of forecast error of different variables 20 quarters forward. We can see that variances of SCI, money supply, and real GDP constitute the largest part of variations of themselves, which means these variables are influenced most by themselves in prediction. Nevertheless, the variances of M1 and SCI account for approximately half of the changes of baseline loan rate, with another half coming from interest rate itself.

#### 6. CONCLUSIONS

This paper employs the cointegration method to analyze the relationship between Shanghai Composite Index and China's macroeconomic indexes using different metrics of money supply: M1 and M2 and the data in the time period from Quarter 1, 1995 to Quarter 4, 2018. Then we apply the VECM to explore the long-run and the short-run relationship between them. The results indicate that: 1) stock exchange index, real GDP, money supply and interest rate are integrated for order one, I(1); 2) despite the caliber we use to measure money

supply, these variables are cointegrated which means a long-run equilibrium between them exists; 3) in the long run, money supply and baseline loan rate (which contradicts the common sense) has a positive effect on SCI, however, real GDP is negatively correlated with SCI, which implicates a deviation of the stock market from the real economy, and the deviation seems to become more serious when M1 serves as the caliber of money supply; 4) in the short run, the effects of money supply and baseline loan rate on SCI is significant and consistent with the common theory. However, no matter what measure of money supply we use, real GDP seems to have no significant effect on SCI, which again verifies the deviation of the stock market from the real economy; 5) the impulse response analysis suggests totally opposite direction of effect that money supply and interest rate have on SCI in different specifications, which supports two opposite kinds of economic theory respectively; the forecast-error decomposition analysis indicates that most of the forecast variance of SCI comes from itself, which again justifies that SCI cannot fully reflect the fluctuations macroeconomy.

From the above analysis, we can conclude that the stock market, serving as the barometer of macroeconomy, does not fully reflect the macroeconomic fluctuation. Due to the ineffective and asymmetric information, there is a deviation of the stock market from macroeconomic fluctuation. On the other hand, compared with developed counties' markets, China's financial market is still in development and immature, and has imperfect regulatory and operational mechanisms. This may be the reason why this empirical study reveals the deviation of China's stock market from macroeconomy.

#### REFERENCES

- 1. Ahmed, M. N., & Imam, M. O. (2007). Macroeconomic factors and Bangladesh stock market: Impact analysis through cointegration approach. *International Review of Business Research Papers, 3(5),* 21-35.
- 2. Almutair, S. (2015). Dynamics of the relationship between bank loans and stock prices in Saudi Arabia. *International Business & Economics Research Journal*, 14(3), 439-453. https://doi.org/10.19030/iber.v14i3.9209
- 3. Alshogeathri, M. A. M. (2011). *Macroeconomic determinants of the stock market movements: Empirical evidence from the Saudi stock market* (Doctoral dissertation). Retrieved from Kansas State University website: http://krex.k-state.edu/dspace/handle/2097/11989
- 4. Al-Tamimi, H. A. H., Alwan, A. A., & Abdel Rahman, A. A. (2011). Factors affecting stock prices in the UAE financial markets. *Journal of Transnational Management*, 16(1), 3-19. https://doi.org/10.1080/15475778.2011.549441
- 5. Anlas, T. (2012). The effects of changes in foreign exchange rates on ISE-100 index. *Journal of Applied Economics and Business Research*, *2*(1), 34-45. Retrieved from https://pdfs.semanticscholar.org/c532/407a72b6c1d7240bf0f0ba384648faca0fa2.pdf
- 6. Aromolaran, A. D., Taiwo, A., Adekoya, A., & Malomo, E. (2016). Index of industrial production an economic index of significant effect on Nigeria stock exchange all share index. *IOSR Journal of Economics and Finance, 7(1),* 31-36. http://doi.org/10.9790/5933-07123136
- 7. Aurangzeb, D. (2012). Factors affecting performance of stock market: Evidence from South Asian countries. *International Journal of Academic Research in Business and Social Sciences, 2(9),* 1-15. Retrieved from http://hrmars.com/admin/pics/1086.pdf
- 8. Bernanke, B. S., & Kuttner, K. N. (2005). What explains the stock market's reaction to Federal Reserve policy? *The Journal of Finance, 60(3),* 1221-1257. https://doi.org/10.1111/j.1540-6261.2005.00760.x
- 9. Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74(366a), 427-431. https://doi.org/10.1080/01621459.1979.10482531
- 10. Elliot, B. E., Rothenberg, T. J., & Stock, J. H. (1996). Efficient tests of the unit root hypothesis. *Econometrica*, 64(8), 13-36. https://doi.org/10.2307/2171846
- 11. Erdem, C., Arslan, C. K., & Sema Erdem, M. (2005). Effects of macroeconomic variables on Istanbul stock exchange indexes. *Applied Financial Economics*, 15(14), 987-994. https://doi.org/10.1080/09603100500120365

- 12. Humpe, A., & Macmillan, P. (2009). Can macroeconomic variables explain long-term stock market movements? A comparison of the US and Japan. *Applied Financial Economics*, 19(2), 111-119. https://doi.org/10.1080/09603100701748956
- 13. Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, 12(2-3), 231-254. https://doi.org/10.1016/0165-1889(88)90041-3
- 14. Kwiatkowski, D., Phillips, P. C., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of Econometrics*, 54(1-3), 159-178. https://doi.org/10.1016/0304-4076(92)90104-Y
- 15. Lanbiao, L., Jingjing, G., & Baowei, L. (2001). On the basic relationship between stock market and economic fluctuations in China. *Nankai Economic Studies*, *3*, 57-62. https://doi.org/10.14116/j.nkes.2001.03.013
- MacKinnon, J. G. (1991). Critical values for cointegration tests (Queen's Economics Department Working Paper No. 1227). Retrieved from http://qed.econ.queensu.ca/working\_papers/papers/qed\_wp\_1227.pdf
- 17. Maysami, R. C., Loo, S. W., & Koh, T. K. (2004). Co-movement among sectoral stock market indices and cointegration among dually listed companies. *Jurnal Pengurusan, 23,* 33-52. http://journalarticle.ukm.my/8063/1/1245-2397-1-SM.pdf
- 18. Pethe, A., & Karnik, A. (2000). Do Indian stock markets matter? Stock market indices and macroeconomic variables. *Economic and Political Weekly*, *35(5)*, 349-356. https://www.jstor.org/stable/4408881
- 19. Qi'an, C., Yuan, Z., & Xing, L. (2010). Macro-economic environment, government regulation policy and stock market fluctuation: Empirical evidence from Chinese stock market. *Economist*, *2*, 90-98. Retrieved from https://doi.org/10.16158/j.cnki.51-1312/f.2010.02.015
- 20. Ray, S. (2013). Causal nexus between gold price movement and stock market: Evidence from Indian stock market. *Sciknow Publications Ltd. Econometrics, Attribution, 3,* 12-19. Retrieved from http://manuscript.sciknow.org/uploads/e/pub/e\_1363955718\_2013\_1\_2\_web.pdf
- 21. Sellin, P. (2001). Monetary policy and the stock market: Theory and empirical evidence. *Journal of Economic Surveys*, 15(4), 491-541. https://doi.org/10.1111/1467-6419.00147
- 22. Shaoping, C. H. (2008). *Positivist analysis on effect of monetary policy on stock price behaviors.* Paper presented at the Conference on Regional Economy and Sustainable Development. Retrieved from http://www.wanfangdata.com.cn/details/detail.do?\_type=conference&id=WFHYXW305104#
- 23. Zhao, Z., & Xue, F. (2004) An empirical study of the relationship between financial development and economic growth. *Journal of Finance*, *8*, 94-99. http://www.cnki.com.cn/Article/CJFDTotal-JRYJ200408011.htm-JRYJ200408011.htm

#### **APPENDIX**

Figure 1. Time trends of variables

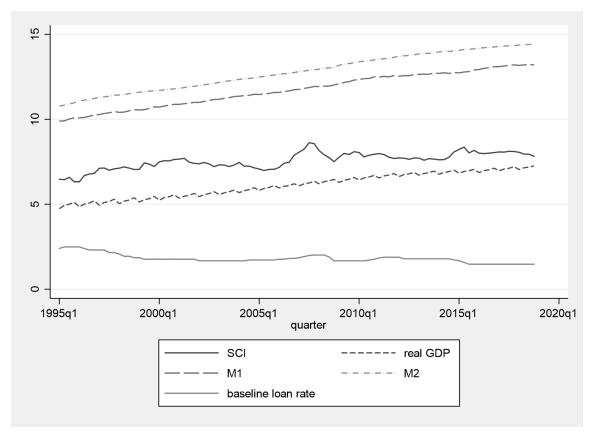
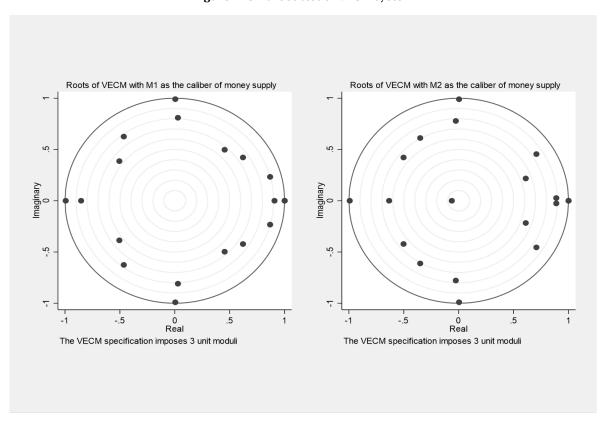


Figure 2. Unit root test of VECM system



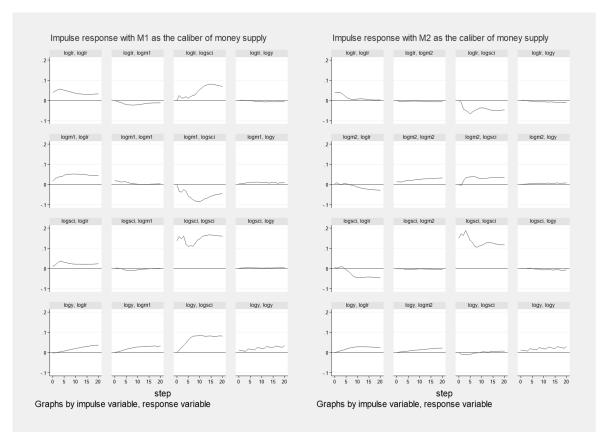
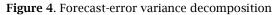


Figure 3. Impulse response of all variables



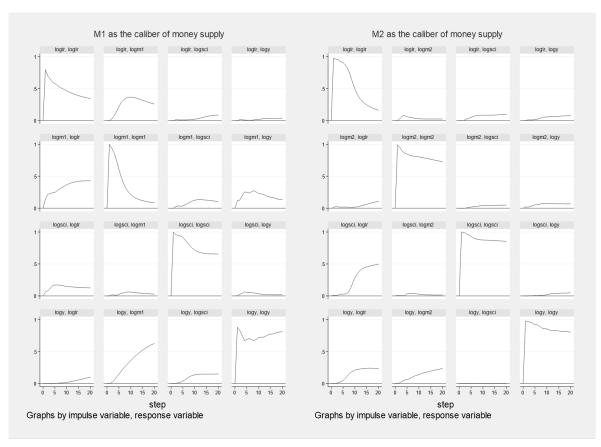


Table 1. Descriptive statistics for data

	SCI	GDP (Billion)	CPI	M1 (Billion)	M2 (Billion)	Loan Rate
N	96	96	96	96	96	96
Mean	2,140.17	204,000.00	135.36	189,000.00	595,000.00	6.30
St.Dev	978.00	204,000.00	22.61	160,000.00	546,000.00	1.88
Median	2,060.91	121,852.00	129.04	127,000.00	355,000.00	5.85
max	5,552.30	900,309.00	176.03	552,000.00	1,830,000.00	12.06
min	555.29	12,111.70	105.23	19,835.70	47,973.30	4.35
Correlation coefficient with SCI	1.00	0.50	0.67	0.63	0.62	-0.48

Table 2. Augmented Dickey-Fuller unit root test

Variable Level with cons		stant and trend	The 1st difference between constant and trend		
variable	Test statistics	5% Critical value	Test statistics	5% Critical value	
logsci	-2.406	-3.465	-4.376	-3.465	
logm1	-0.888	-3.461	-4.364	-3.461	
logm2	-0.007	-3.459	-3.646	-3.459	
logy	-0.537	-3.459	-2.353	-3.459	
loglr	-2.744	-3.456	-7.123	-3.456	

Table 3. DF-GLS unit root test for logy

Vani alda	Level with cons	stant and trend	d The 1st difference between constant and trend		
Variable	Test statistics	5% Critical value	Test statistics	5% Critical value	
logv	-0.602	-2.981	-3.383	-3.006	

**Table 4.** KPSS stationary test (*H0*: variable is stationary)

Variable	Level with constant and trend	The 1st difference between constant and trend
logsci	reject	accept
logm1	reject	accept
logm2	reject	accept
logy	reject	accept
loglr	reject	accept

**Table 5.** Cointegration test between variables

Panel A. Coir	ntegration test with M1 as th	e caliber for money supply				
Rank	Trac	ce test	Maximum eigenvalue test			
Kunk	Test statistics	5% Critical value	Test statistics	5% Critical value		
None	100.7083	54.64	75.8954	30.33		
At most 1	24.8129	34.55	12.9537	23.78		
Panel B. Coin	itegration test with M2 as the	e caliber for money supply				
Rank	Trace test Maximum eigenvalue test					
Kunk	Test statistics	5% Critical value	Test statistics	5% Critical value		
None	115.5562	54.64	85.8612	30.33		
At most 1	29.6950	34.55	18.3480	23.78		

Table 6. Selection of lag order

Panel A	A. Selection of la	ag order with M	1 as the caliber	for money sup	ply			
Lag order	LL	LR	df	р	FPE	AIC	HQIC	SBIC
0	5.83407				.000011	039871	.004382	.069772
1	521.142	1030.6	16	0.000	2.2e-10	-10.8944	-10.6731	-10.3462
2	556.113	69.942	16	0.000	1.4e-10	-11.3068	-10.9085	-10.32
3	590.745	69.263	16	0.000	9.7e-11	-11.7118	-11.1366	-10.2865
4	722.435	263.38*	16	0.000	7.9e-12*	-14.2269*	-13.4746*	-12.3629*
Panel E	<b>B.</b> Selection of la	ig order with M	2 as the caliber	for money sup	ply			
Lag order	LL	LR	df	р	FPE	AIC	HQIC	SBIC
0	-17.1467				.000019	.45971	.503963	.569353
1	554.006	1142.3	16	0.000	1.1e-10	-11.6088	-11.3876	-11.0606
_				0.000	-0.44	44.0004	11 5000	11 0000
2	587.836	67.659	16	0.000	7.3e-11	-11.9964	-11.5982	-11.0096
3	587.836 612.707	67.659 49.741	16 16	0.000	7.3e-11 6.0e-11	-11.9964 -12.1893	-11.5982 -11.614	-11.0096 -10.7639

**Table 7.** VECM result for variables

Panel A. VECM result with M1 as			1	1 .
	(1)	(2)	(3)	(4)
Cointeg	D(logsci) -0.030***	D(logm1) -0.003***	D(logy) 0.001	D(loglr) 0.004*
Conited,	(0.008)	(0.001)	(0.001)	(0.003)
D(logsci ,)	0.106	0.039***	0.010	0.035
	(0.110)	(0.015)	(0.010)	(0.036)
D(logsci )	0.034	-0.018	0.006	0.025
D(Louis)	(0.115)	(0.016)	(0.011)	(0.037)
D(logsci ,)	0.048	0.011 (0.015)	0.004 (0.010)	0.045 (0.036)
D(logsci_)	-0.327***	-0.019	0.002	-0.050
D(logoci <sub>A</sub> )	(0.104)	(0.014)	(0.009)	(0.034)
D(logm1,)	-0.697	0.157	-0.052	0.205
	(0.877)	(0.119)	(0.080)	(0.284)
D(logm1 )	1.545*	0.243**	0.157**	-0.140
D(logm1 <sub>2</sub> )	(0.861) 2.301***	(0.117) -0.013	(0.078) 0.107	(0.279) -0.164
D(logili1 ,)	(0.765)	(0.104)	(0.070)	(0.248)
D(logm1)	0.343	0.422***	0.018	-0.166
	(0.746)	(0.101)	(0.068)	(0.242)
D(logy,)	-1.427	0.006	-0.104	0.472
Date :	(0.908)	(0.123)	(0.083)	(0.294)
D(logy_)	-0.739 (0.799)	0.039 (0.109)	-0.151** (0.073)	0.418 (0.259)
D(logy ,)	-0.599	0.059	-0.172**	0.307
2 (20g) <sub>2</sub> /	(0.740)	(0.101)	(0.067)	(0.240)
D(logy <sub>4</sub> )	-0.254	0.246**	0.800***	0.244
	(0.724)	(0.098)	(0.066)	(0.235)
D(loglr,)	0.963**	-0.073	0.045	0.115
D(L. L.)	(0.424)	(0.058)	(0.039)	(0.137)
D(loglr_)	-0.440 (0.438)	-0.070 (0.059)	-0.041 (0.040)	0.089 (0.142)
D(loglr <sub>2</sub> )	0.105	0.002	-0.007	0.060
B(logii <sub>2</sub> )	(0.436)	(0.059)	(0.040)	(0.141)
D(loglr <sub>4</sub> )	0.339	-0.102**	0.005	-0.118
	(0.380)	(0.052)	(0.035)	(0.123)
Cons	-0.005	-0.004	0.006	-0.038*
	(0.069)	(0.009)	(0.006)	(0.022)
Daniel D. VECM wagult with M2 and	the calibrat for mean and an	arab .		
<b>Panel B.</b> VECM result with M2 as t			(3)	(4)
Panel B. VECM result with M2 as t	(1)	(2)	(3) D(logy)	(4) D(loglr)
Panel B. VECM result with M2 as to			(3) D(logy) -0.008**	(4) D(loglr) -0.050***
Cointeq ,	(1) D(logsci) -0.073* (0.043)	(2) D(logm2) 0.002 (0.004)	D(logy) -0.008** (0.004)	D(loglr) -0.050*** (0.011)
	(1) D(logsci) -0.073* (0.043) 0.228*	(2) D(logm2) 0.002 (0.004) 0.004	D(logy) -0.008** (0.004) 0.005	D(loglr) -0.050*** (0.011) 0.042
Cointeq , D(logsci ,)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117)	(2) D(logm2) 0.002 (0.004) 0.004 (0.011)	D(logy) -0.008** (0.004) 0.005 (0.010)	D(loglr) -0.050*** (0.011) 0.042 (0.030)
Cointeq ,	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005	D(logy) -0.008** (0.004) 0.005 (0.010) 0.008	D(loglr) -0.050*** (0.011) 0.042 (0.030) 0.071**
Cointeq D(logsci ,) D(logsci ,)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026 (0.119)	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005 (0.011)	D(logy) -0.008** (0.004) 0.005 (0.010) 0.008 (0.010)	D(logIr) -0.050*** (0.011) 0.042 (0.030) 0.071** (0.031)
Cointeq , D(logsci ,)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005	D(logy) -0.008** (0.004) 0.005 (0.010) 0.008	D(loglr) -0.050*** (0.011) 0.042 (0.030) 0.071**
Cointeq D(logsci ,) D(logsci ,)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026 (0.119) 0.246**	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005 (0.011) 0.003 (0.011) -0.035***	D(logy) -0.008** (0.004) 0.005 (0.010) 0.008 (0.010) 0.018*	D(logIr) -0.050*** (0.011) 0.042 (0.030) 0.071** (0.031) 0.087***
Cointeq ,  D(logsci ,)  D(logsci ,)  D(logsci ,)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026 (0.119) 0.246** (0.115) -0.112 (0.123)	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005 (0.011) 0.003 (0.011) -0.035*** (0.011)	D(logy) -0.008** (0.004) 0.005 (0.010) 0.008 (0.010) 0.018* (0.010) 0.016 (0.010)	D(loglr) -0.050*** (0.011) 0.042 (0.030) 0.071** (0.031) 0.087*** (0.030) -0.001 (0.032)
Cointeq ,  D(logsci ,)  D(logsci ,)  D(logsci ,)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026 (0.119) 0.246** (0.115) -0.112 (0.123) 0.101	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005 (0.011) 0.003 (0.011) -0.035*** (0.011) -0.054	D(logy) -0.008** (0.004) 0.005 (0.010) 0.008 (0.010) 0.018* (0.010) 0.016 (0.010) -0.009	D(loglr) -0.050*** (0.011) 0.042 (0.030) 0.071** (0.031) 0.087*** (0.030) -0.001 (0.032) 0.551*
Cointeq ,  D(logsci ,)  D(logsci ,)  D(logsci ,)  D(logsci ,)  D(logsci ,)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026 (0.119) 0.246** (0.115) -0.112 (0.123) 0.101 (1.109)	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005 (0.011) 0.003 (0.011) -0.035*** (0.011) -0.054 (0.104)	D(logy) -0.008** (0.004) 0.005 (0.010) 0.008 (0.010) 0.018* (0.010) 0.016 (0.010) -0.009 (0.093)	D(logIr) -0.050*** (0.011) 0.042 (0.030) 0.071** (0.031) 0.087*** (0.030) -0.001 (0.032) 0.551* (0.286)
Cointeq D(logsci )  D(logsci )  D(logsci )  D(logsci )	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026 (0.119) 0.246** (0.115) -0.112 (0.123) 0.101 (1.109) 2.184**	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005 (0.011) 0.003 (0.011) -0.035*** (0.011) -0.054	D(logy) -0.008** (0.004) 0.005 (0.010) 0.008 (0.010) 0.018* (0.010) 0.016 (0.010) -0.009 (0.093) 0.111	D(loglr) -0.050*** (0.011) 0.042 (0.030) 0.071** (0.031) 0.087*** (0.030) -0.001 (0.032) 0.551*
Cointeq ,  D(logsci ,)  D(logsci ,)  D(logsci ,)  D(logsci ,)  D(logsci ,)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026 (0.119) 0.246** (0.115) -0.112 (0.123) 0.101 (1.109)	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005 (0.011) 0.003 (0.011) -0.035*** (0.011) -0.054 (0.104) -0.020	D(logy) -0.008** (0.004) 0.005 (0.010) 0.008 (0.010) 0.018* (0.010) 0.016 (0.010) -0.009 (0.093)	D(loglr) -0.050*** (0.011) 0.042 (0.030) 0.071** (0.031) 0.087*** (0.030) -0.001 (0.032) 0.551* (0.286)
Cointeq.  D(logsci.)  D(logsci.)  D(logsci.)  D(logsci.)  D(logm2.)  D(logm2.)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026 (0.119) 0.246** (0.115) -0.112 (0.123) 0.101 (1.109) 2.184** (1.074) 1.450 (1.070)	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005 (0.011) 0.003 (0.011) -0.035*** (0.011) -0.054 (0.104) -0.020 (0.100) 0.141 (0.100)	D(logy) -0.008** (0.004) 0.005 (0.010) 0.008 (0.010) 0.018* (0.010) 0.016 (0.010) -0.009 (0.093) 0.111 (0.091) 0.145 (0.090)	D(loglr) -0.050*** (0.011) 0.042 (0.030) 0.071** (0.031) 0.087*** (0.030) -0.001 (0.032) 0.551* (0.286) -0.360 (0.277) 0.055 (0.276)
Cointeq D(logsci ,)  D(logsci ,)  D(logsci ,)  D(logsci ,)  D(logm2 ,)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026 (0.119) 0.246** (0.115) -0.112 (0.123) 0.101 (1.109) 2.184** (1.074) 1.450 (1.070) 0.160	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005 (0.011) 0.003 (0.011) -0.035*** (0.011) -0.054 (0.104) -0.020 (0.100) 0.141 (0.100) 0.209**	D(logy) -0.008** (0.004) 0.005 (0.010) 0.008 (0.010) 0.018* (0.010) 0.016 (0.010) -0.009 (0.093) 0.111 (0.091) 0.145 (0.090) 0.149*	D(logIr) -0.050*** (0.011) 0.042 (0.030) 0.071** (0.031) 0.087*** (0.030) -0.001 (0.032) 0.551* (0.286) -0.360 (0.277) 0.055 (0.276) 0.507*
Cointeq,  D(logsci,)  D(logsci,)  D(logsci,)  D(logsci,)  D(logm2,)  D(logm2,)  D(logm2,)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026 (0.119) 0.246** (0.115) -0.112 (0.123) 0.101 (1.109) 2.184** (1.074) 1.450 (1.070) 0.160 (1.029)	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005 (0.011) 0.003 (0.011) -0.035*** (0.011) -0.054 (0.104) -0.020 (0.100) 0.141 (0.100) 0.209** (0.096)	D(logy) -0.008** (0.004) 0.005 (0.010) 0.008 (0.010) 0.018* (0.010) 0.016 (0.010) -0.009 (0.093) 0.111 (0.091) 0.145 (0.090) 0.149* (0.087)	D(loglr) -0.050*** (0.011) 0.042 (0.030) 0.071** (0.031) 0.087*** (0.030) -0.001 (0.032) 0.551* (0.286) -0.360 (0.277) 0.055 (0.276) 0.507* (0.266)
Cointeq.  D(logsci.)  D(logsci.)  D(logsci.)  D(logsci.)  D(logm2.)  D(logm2.)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026 (0.119) 0.246** (0.115) -0.112 (0.123) 0.101 (1.109) 2.184** (1.074) 1.450 (1.070) 0.160 (1.029) -1.031	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005 (0.011) 0.003 (0.011) -0.035*** (0.011) -0.054 (0.104) -0.020 (0.100) 0.141 (0.100) 0.209** (0.096) 0.189**	D(logy) -0.008** (0.004) 0.005 (0.010) 0.008 (0.010) 0.018* (0.010) 0.016 (0.010) -0.009 (0.093) 0.111 (0.091) 0.145 (0.090) 0.149* (0.087) -0.207***	D(loglr) -0.050*** (0.011) 0.042 (0.030) 0.071** (0.031) 0.087*** (0.030) -0.001 (0.032) 0.551* (0.286) -0.360 (0.277) 0.055 (0.276) 0.507* (0.266) -0.032
Cointeq D(logsci ,)  D(logsci ,)  D(logsci ,)  D(logsci ,)  D(logm2 ,)  D(logm2 ,)  D(logm2 ,)  D(logm2 ,)  D(logm2 ,)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026 (0.119) 0.246** (0.115) -0.112 (0.123) 0.101 (1.109) 2.184** (1.074) 1.450 (1.070) 0.160 (1.029) -1.031 (0.858)	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005 (0.011) 0.003 (0.011) -0.035*** (0.011) -0.054 (0.104) -0.020 (0.100) 0.141 (0.100) 0.209** (0.096) 0.189** (0.080)	D(logy) -0.008** (0.004) 0.005 (0.010) 0.008 (0.010) 0.018* (0.010) 0.016 (0.010) -0.009 (0.093) 0.111 (0.091) 0.145 (0.090) 0.149* (0.087) -0.207*** (0.072)	D(loglr) -0.050*** (0.011) 0.042 (0.030) 0.071** (0.031) 0.087*** (0.030) -0.001 (0.032) 0.551* (0.286) -0.360 (0.277) 0.055 (0.276) 0.507* (0.266) -0.032 (0.222)
Cointeq,  D(logsci,)  D(logsci,)  D(logsci,)  D(logsci,)  D(logm2,)  D(logm2,)  D(logm2,)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026 (0.119) 0.246** (0.115) -0.112 (0.123) 0.101 (1.109) 2.184** (1.074) 1.450 (1.070) 0.160 (1.029) -1.031	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005 (0.011) 0.003 (0.011) -0.035*** (0.011) -0.054 (0.104) -0.020 (0.100) 0.141 (0.100) 0.209** (0.096) 0.189**	D(logy) -0.008** (0.004) 0.005 (0.010) 0.008 (0.010) 0.018* (0.010) 0.016 (0.010) -0.009 (0.093) 0.111 (0.091) 0.145 (0.090) 0.149* (0.087) -0.207***	D(loglr) -0.050*** (0.011) 0.042 (0.030) 0.071** (0.031) 0.087*** (0.030) -0.001 (0.032) 0.551* (0.286) -0.360 (0.277) 0.055 (0.276) 0.507* (0.266) -0.032
Cointeq.  D(logsci_,)  D(logsci_,)  D(logsci_,)  D(logsci_,)  D(logm2_,)  D(logm2_,)  D(logm2_,)  D(logm2_,)  D(logm2_,)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026 (0.119) 0.246** (0.115) -0.112 (0.123) 0.101 (1.109) 2.184** (1.074) 1.450 (1.070) 0.160 (1.029) -1.031 (0.858) -0.493 (0.822) -0.520	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005 (0.011) -0.035*** (0.011) -0.054 (0.104) -0.020 (0.100) 0.141 (0.100) 0.209** (0.096) 0.189** (0.080) 0.227***	D(logy) -0.008** (0.004) 0.005 (0.010) 0.008 (0.010) 0.018* (0.010) 0.016 (0.010) -0.009 (0.093) 0.111 (0.091) 0.145 (0.090) 0.149* (0.087) -0.207*** (0.072) -0.196*** (0.069) -0.179***	D(logIr) -0.050*** (0.011) 0.042 (0.030) 0.071** (0.031) 0.087*** (0.030) -0.001 (0.032) 0.551* (0.286) -0.360 (0.277) 0.055 (0.276) 0.507* (0.266) -0.032 (0.222) -0.006 (0.212) 0.080
Cointeq,  D(logsci,)  D(logsci,)  D(logsci,)  D(logm2,)  D(logm2,)  D(logm2,)  D(logm2,)  D(logm2,)  D(logm2,)  D(logm2,)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026 (0.119) 0.246** (0.115) -0.112 (0.123) 0.101 (1.109) 2.184** (1.074) 1.450 (1.070) 0.160 (1.029) -1.031 (0.858) -0.493 (0.822) -0.520 (0.798)	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005 (0.011) 0.003 (0.011) -0.035*** (0.011) -0.054 (0.104) -0.020 (0.100) 0.141 (0.100) 0.209** (0.096) 0.189** (0.080) 0.227*** (0.077) 0.206*** (0.075)	D(logy) -0.008** (0.004) 0.005 (0.010) 0.008 (0.010) 0.018* (0.010) 0.016 (0.010) -0.009 (0.093) 0.111 (0.091) 0.145 (0.090) 0.149* (0.087) -0.207*** (0.072) -0.196*** (0.069) -0.179*** (0.067)	D(logIr) -0.050*** (0.011) 0.042 (0.030) 0.071** (0.031) 0.087*** (0.030) -0.001 (0.032) 0.551* (0.286) -0.360 (0.277) 0.055 (0.276) 0.507* (0.266) -0.032 (0.222) -0.006 (0.212) 0.080 (0.206)
Cointeq,  D(logsci,)  D(logsci,)  D(logsci,)  D(logsci,)  D(logm2,)  D(logm2,)  D(logm2,)  D(logm2,)  D(logm2,)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026 (0.119) 0.246** (0.115) -0.112 (0.123) 0.101 (1.109) 2.184** (1.074) 1.450 (1.070) 0.160 (1.029) -1.031 (0.858) -0.493 (0.822) -0.520 (0.798)	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005 (0.011) 0.003 (0.011) -0.035*** (0.011) -0.054 (0.104) -0.020 (0.100) 0.141 (0.100) 0.209** (0.096) 0.189** (0.080) 0.227*** (0.077) 0.206*** (0.075) 0.167**	D(logy) -0.008** (0.004) -0.005 (0.010) -0.008 (0.010) -0.018* (0.010) -0.016 (0.010) -0.009 (0.093) -0.111 (0.091) -0.145 (0.090) -0.149* (0.087) -0.207*** (0.072) -0.196*** (0.067) -0.803***	D(logIr) -0.050*** (0.011) 0.042 (0.030) 0.071** (0.031) 0.087*** (0.030) -0.001 (0.032) 0.551* (0.286) -0.360 (0.277) 0.055 (0.276) 0.507* (0.266) -0.032 (0.222) -0.006 (0.212) 0.080 (0.206) 0.161
Cointeq.  D(logsci_,)  D(logsci_,)  D(logsci_,)  D(logm2_,)  D(logm2_,)  D(logm2_,)  D(logm2_,)  D(logm2_,)  D(logy_,)  D(logy_,)  D(logy_,)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026 (0.119) 0.246** (0.115) -0.112 (0.123) 0.101 (1.109) 2.184** (1.074) 1.450 (1.070) 0.160 (1.029) -1.031 (0.858) -0.493 (0.822) -0.520 (0.798) -0.713 (0.789)	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005 (0.011) -0.035*** (0.011) -0.054 (0.104) -0.020 (0.100) 0.141 (0.100) 0.209** (0.096) 0.189** (0.080) 0.227*** (0.077) 0.206*** (0.075) 0.167** (0.074)	D(logy) -0.008** (0.004) 0.005 (0.010) 0.008 (0.010) 0.018* (0.010) 0.016 (0.010) -0.009 (0.093) 0.111 (0.091) 0.145 (0.090) 0.149* (0.087) -0.207*** (0.072) -0.196*** (0.069) -0.179*** (0.067) 0.803*** (0.066)	D(loglr) -0.050*** (0.011) 0.042 (0.030) 0.071** (0.031) 0.087*** (0.030) -0.001 (0.032) 0.551* (0.286) -0.360 (0.277) 0.055 (0.276) 0.507* (0.266) -0.032 (0.222) -0.006 (0.212) 0.080 (0.204)
Cointeq,  D(logsci,)  D(logsci,)  D(logsci,)  D(logm2,)  D(logm2,)  D(logm2,)  D(logm2,)  D(logm2,)  D(logm2,)  D(logm2,)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026 (0.119) 0.246** (0.115) -0.112 (0.123) 0.101 (1.109) 2.184** (1.074) 1.450 (1.070) 0.160 (1.029) -1.031 (0.858) -0.493 (0.822) -0.520 (0.798) -0.713 (0.789) 0.014	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005 (0.011) -0.035*** (0.011) -0.054 (0.104) -0.020 (0.100) 0.141 (0.100) 0.209** (0.09%) (0.189** (0.077) 0.206*** (0.077) 0.206*** (0.074) -0.099***	D(logy) -0.008** (0.004) 0.005 (0.010) 0.008 (0.010) 0.018* (0.010) 0.016 (0.010) -0.009 (0.093) 0.111 (0.091) 0.145 (0.090) 0.149* (0.087) -0.207*** (0.069) -0.179*** (0.067) 0.803*** (0.066) 0.073**	D(loglr) -0.050*** (0.011) 0.042 (0.030) 0.071** (0.031) 0.087*** (0.030) -0.001 (0.032) 0.551* (0.286) -0.360 (0.277) 0.055 (0.276) 0.507* (0.266) -0.032 (0.222) -0.006 (0.212) 0.080 (0.206) 0.161 (0.204) 0.191*
Cointeq,  D(logsci,)  D(logsci,)  D(logsci,)  D(logsci,)  D(logm2,)  D(logm2,)  D(logm2,)  D(logm2,)  D(logm2,)  D(logy,)  D(logy,)  D(logy,)  D(logy,)  D(logy,)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026 (0.119) 0.246** (0.115) -0.112 (0.123) 0.101 (1.109) 2.184** (1.074) 1.450 (1.070) 0.160 (1.029) -1.031 (0.858) -0.493 (0.822) -0.520 (0.798) -0.713 (0.789)	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005 (0.011) -0.035*** (0.011) -0.054 (0.104) -0.020 (0.100) 0.141 (0.100) 0.209** (0.096) 0.189** (0.080) 0.227*** (0.077) 0.206*** (0.075) 0.167** (0.074)	D(logy) -0.008** (0.004) 0.005 (0.010) 0.008 (0.010) 0.018* (0.010) 0.016 (0.010) -0.009 (0.093) 0.111 (0.091) 0.145 (0.090) 0.149* (0.087) -0.207*** (0.072) -0.196*** (0.069) -0.179*** (0.067) 0.803*** (0.066)	D(loglr) -0.050*** (0.011) 0.042 (0.030) 0.071** (0.031) 0.087*** (0.030) -0.001 (0.032) 0.551* (0.286) -0.360 (0.277) 0.055 (0.276) 0.507* (0.266) -0.032 (0.222) -0.006 (0.212) 0.080 (0.204)
Cointeq.  D(logsci_,)  D(logsci_,)  D(logsci_,)  D(logm2_,)  D(logm2_,)  D(logm2_,)  D(logm2_,)  D(logm2_,)  D(logy_,)  D(logy_,)  D(logy_,)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026 (0.119) 0.246** (0.115) -0.112 (0.123) 0.101 (1.109) 2.184** (1.074) 1.450 (1.070) 0.160 (1.029) -1.031 (0.858) -0.493 (0.822) -0.520 (0.798) -0.713 (0.789) 0.014 (0.401)	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005 (0.011) -0.003 (0.011) -0.035*** (0.011) -0.054 (0.104) -0.020 (0.100) 0.141 (0.100) 0.209** (0.096) 0.189** (0.098) 0.227*** (0.077) 0.206*** (0.075) 0.167** (0.074) -0.099**	D(logy) -0.008** (0.004) 0.005 (0.010) 0.008 (0.010) 0.018* (0.010) 0.016 (0.010) -0.009 (0.093) 0.111 (0.091) 0.145 (0.090) 0.149* (0.087) -0.207*** (0.072) -0.196*** (0.069) -0.179*** (0.067) 0.803*** (0.066) 0.073** (0.034)	D(loglr) -0.050*** (0.011) 0.042 (0.030) 0.071** (0.031) 0.087*** (0.030) -0.001 (0.032) 0.551* (0.286) -0.360 (0.277) 0.055 (0.276) 0.507* (0.266) -0.032 (0.222) -0.006 (0.212) 0.080 (0.206) 0.161 (0.204) 0.191* (0.104)
Cointeq,  D(logsci,)  D(logsci,)  D(logsci,)  D(logsci,)  D(logm2,)  D(logm2,)  D(logm2,)  D(logm2,)  D(logm2,)  D(logy,)  D(logy,)  D(logy,)  D(logy,)  D(logy,)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026 (0.119) 0.246** (0.115) -0.112 (0.123) 0.101 (1.109) 2.184** (1.074) 1.450 (1.070) 0.160 (1.029) -1.031 (0.858) -0.493 (0.822) -0.520 (0.798) -0.713 (0.789) 0.014 (0.401) -0.549 (0.440) 0.369	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005 (0.011) 0.003 (0.011) -0.035*** (0.011) -0.054 (0.104) -0.020 (0.100) 0.141 (0.100) 0.209** (0.096) 0.189** (0.080) 0.227*** (0.077) 0.206*** (0.075) 0.167** (0.074) -0.099** (0.038) -0.074 -0.099** (0.038) -0.064 (0.041) -0.003	D(logy) -0.008** (0.004) -0.005 (0.010) -0.008 (0.010) -0.016 (0.010) -0.009 (0.093) -0.111 (0.091) -0.145 (0.090) -0.149* (0.087) -0.207*** (0.072) -0.196*** (0.069) -0.179*** (0.067) -0.803*** (0.066) -0.073** (0.037) -0.000 (0.037) -0.015	D(loglr) -0.050*** (0.011) 0.042 (0.030) 0.071** (0.031) 0.087*** (0.030) -0.001 (0.032) 0.551* (0.286) -0.360 (0.277) 0.055 (0.276) 0.507* (0.266) -0.032 (0.222) -0.006 (0.212) 0.080 (0.206) 0.161 (0.204) 0.191* (0.104) 0.217* (0.114)
Cointeq,  D(logsci_,)  D(logsci_,)  D(logsci_,)  D(logm2_,)  D(logm2_,)  D(logm2_,)  D(logm2_,)  D(logm2_,)  D(logy_,)  D(logy_,)  D(logy_,)  D(logy_,)  D(loglr_,)  D(loglr_,)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026 (0.119) 0.246** (0.115) -0.112 (0.123) 0.101 (1.109) 2.184** (1.074) 1.450 (1.070) 0.160 (1.029) -1.031 (0.858) -0.493 (0.822) -0.520 (0.798) -0.713 (0.789) 0.014 (0.401) -0.549 (0.440) 0.369 (0.436)	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005 (0.011) -0.035*** (0.011) -0.054 (0.104) -0.020 (0.100) 0.141 (0.100) 0.209** (0.096) 0.189** (0.080) 0.227*** (0.077) 0.206*** (0.075) 0.167** (0.074) -0.099** (0.038) -0.064 (0.041) -0.003	D(logy) -0.008** (0.004) 0.005 (0.010) 0.008 (0.010) 0.018* (0.010) -0.009 (0.093) 0.111 (0.091) 0.145 (0.090) 0.149* (0.087) -0.207*** (0.072) -0.196*** (0.069) -0.179*** (0.067) 0.803*** (0.066) 0.073** (0.037) -0.000 (0.037) -0.015	D(logIr) -0.050*** (0.011) 0.042 (0.030) 0.071** (0.031) 0.087*** (0.030) -0.001 (0.032) 0.551* (0.286) -0.360 (0.277) 0.055 (0.276) 0.507* (0.266) -0.032 (0.222) -0.006 (0.212) 0.080 (0.206) 0.161 (0.204) 0.191* (0.104) 0.217* (0.114) 0.017
Cointeq,  D(logsci,)  D(logsci,)  D(logsci,)  D(logm2,)  D(logm2,)  D(logm2,)  D(logm2,)  D(logm2,)  D(logy,)  D(logy,)  D(logy,)  D(logy,)  D(logy,)  D(logy,)  D(logy,)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026 (0.119) 0.246** (0.115) -0.112 (0.123) 0.101 (1.109) 2.184** (1.074) 1.450 (1.070) 0.160 (1.029) -1.031 (0.858) -0.493 (0.822) -0.520 (0.798) -0.713 (0.789) 0.014 (0.401) -0.549 (0.440) 0.369 (0.436) 0.244	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005 (0.011) -0.035*** (0.011) -0.054 (0.104) -0.020 (0.100) 0.141 (0.100) 0.209** (0.096) 0.189** (0.080) 0.227*** (0.077) 0.206*** (0.075) 0.167** (0.074) -0.099** (0.038) -0.064 (0.041) -0.003	D(logy) -0.008** (0.004) 0.005 (0.010) 0.008 (0.010) 0.018* (0.010) 0.016 (0.010) -0.009 (0.093) 0.111 (0.091) 0.145 (0.090) 0.149* (0.087) -0.207*** (0.072) -0.196*** (0.069) -0.179*** (0.067) 0.803*** (0.066) 0.073** (0.034) 0.000 (0.037) -0.015 (0.037) -0.015	D(logIr) -0.050*** (0.011) 0.042 (0.030) 0.071** (0.031) 0.087*** (0.030) -0.001 (0.032) 0.551* (0.286) -0.360 (0.277) 0.055 (0.276) 0.507* (0.266) -0.032 (0.222) -0.006 (0.212) 0.088 (0.206) 0.161 (0.204) 0.191* (0.104) 0.217* (0.114) 0.017 (0.113) -0.082
Cointeq.  D(logsci.)  D(logsci.)  D(logsci.)  D(logsci.)  D(logm2.)  D(logm2.)  D(logm2.)  D(logm2.)  D(logm2.)  D(logy.)  D(logy.)  D(logy.)  D(logy.)  D(logy.)  D(logy.)  D(loglr.)  D(loglr.)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026 (0.119) 0.246** (0.115) -0.112 (0.123) 0.101 (1.109) 2.184** (1.074) 1.450 (1.070) 0.160 (1.029) -1.031 (0.858) -0.493 (0.822) -0.520 (0.798) -0.713 (0.789) 0.014 (0.401) -0.549 (0.440) 0.369 (0.436) 0.244 (0.399)	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005 (0.011) -0.035*** (0.011) -0.054 (0.104) -0.020 (0.100) 0.141 (0.100) 0.209** (0.096) 0.189** (0.096) 0.189** (0.077) 0.206*** (0.077) 0.206*** (0.075) 0.167** (0.075) 0.167** (0.074) -0.099** (0.099) 0.189** (0.097)	D(logy) -0.008** (0.004) 0.005 (0.010) 0.008 (0.010) 0.018* (0.010) 0.016 (0.010) -0.009 (0.093) 0.111 (0.091) 0.145 (0.090) 0.149* (0.087) -0.207*** (0.069) -0.179*** (0.069) -0.179*** (0.067) 0.803*** (0.066) 0.073** (0.034) 0.000 (0.037) -0.015 (0.037) -0.011	D(loglr) -0.050*** (0.011) 0.042 (0.030) 0.071** (0.031) 0.087*** (0.030) -0.001 (0.032) 0.551* (0.286) -0.360 (0.277) 0.055 (0.276) 0.507* (0.266) -0.032 (0.222) -0.006 (0.212) 0.088 (0.206) 0.161 (0.204) 0.191* (0.104) 0.217* (0.114) 0.017 (0.113) -0.082 (0.050)
Cointeq,  D(logsci_,)  D(logsci_,)  D(logsci_,)  D(logm2_,)  D(logm2_,)  D(logm2_,)  D(logm2_,)  D(logm2_,)  D(logy_,)  D(logy_,)  D(logy_,)  D(logy_,)  D(loglr_,)  D(loglr_,)	(1) D(logsci) -0.073* (0.043) 0.228* (0.117) 0.026 (0.119) 0.246** (0.115) -0.112 (0.123) 0.101 (1.109) 2.184** (1.074) 1.450 (1.070) 0.160 (1.029) -1.031 (0.858) -0.493 (0.822) -0.520 (0.798) -0.713 (0.789) 0.014 (0.401) -0.549 (0.440) 0.369 (0.436) 0.244	(2) D(logm2) 0.002 (0.004) 0.004 (0.011) -0.005 (0.011) -0.035*** (0.011) -0.054 (0.104) -0.020 (0.100) 0.141 (0.100) 0.209** (0.096) 0.189** (0.080) 0.227*** (0.077) 0.206*** (0.075) 0.167** (0.074) -0.099** (0.038) -0.064 (0.041) -0.003	D(logy) -0.008** (0.004) 0.005 (0.010) 0.008 (0.010) 0.018* (0.010) 0.016 (0.010) -0.009 (0.093) 0.111 (0.091) 0.145 (0.090) 0.149* (0.087) -0.207*** (0.072) -0.196*** (0.069) -0.179*** (0.067) 0.803*** (0.066) 0.073** (0.034) 0.000 (0.037) -0.015 (0.037) -0.015	D(logIr) -0.050*** (0.011) 0.042 (0.030) 0.071** (0.031) 0.087*** (0.030) -0.001 (0.032) 0.551* (0.286) -0.360 (0.277) 0.055 (0.276) 0.507* (0.266) -0.032 (0.222) -0.006 (0.212) 0.088 (0.206) 0.161 (0.204) 0.191* (0.104) 0.217* (0.114) 0.017 (0.113) -0.082

**Table 8.** Cointegrating equations

Panel A. Cointeg	rating equations wit	h M1 as the caliber fo	or money supply				
beta	Coef.	Std. Err.	z	<i>P&gt; z </i>	[95% Conf. Interval]		
logsci	1						
logm1	63.20234	10.57087	5.98	0.000	42.48381	83.92087	
logy	-84.1272	13.96625	-6.02	0.000	-111.5005	-56.75386	
loglr	11.49021	3.059969	3.76	0.000	5.492785	17.48764	
_cons	-254.8253	÷		·		•	
Wald test		$\chi^2 = 39.39247$			p=0.0000		
Panel B. Cointeg	rating equations wit	h M2 as the caliber fo	or money supply				
beta	Coef.	Std. Err.	z	<b>P</b> >/ <b>z</b> /	[95% Con	f. Interval]	
logsci	1						
logm2	3.847801	2.635177	1.46	0.144	-1.31705	9.012652	
logy	-5.85292	3.809129	-1.54	0.124	-13.31868	1.612835	
loglr	3.381274	.7348876	4.60	0.000	1.940921	4.821628	
_cons	-26.1321						
Wald test		$\chi^2 = 53.09907$		p=0.0000			