



HOW TO SELECT A REASONABLE LAG ORDER FOR TESTING LINEAR GRANGER CAUSALITY?

WANG SHENG

Research Center of Econometrics
College of Economics and Management
South China Agricultural University
Guangzhou 510642, Guangdong, P. R. China
e-mail: swang@scau.edu.cn; wangsheng00@tsinghua.org.cn

Abstract

We derive a new criterion for the optimal and efficient selection of the number of lags in the context of testing linear Granger causality environment in the sense of theory and empirics respectively, which may be better in empirics than those suggested and advocated by Davidson and Mackinnon, Hsiao, and Schwarz. The structural stability of Granger causality can be effectively achieved based on our criterion, but not based on those criteria given by Davidson and Mackinnon, Hsiao, and Schwarz. Some new notations are firstly defined, such as attenuation rate of Granger cause, structural stability of Granger causality, and order of the structural stability of Granger causality.

1. Introduction

The Granger causality defined by Granger [1] is universally applied in the Economic research. The Granger causality describes the relationship between two relevant variables, namely, whether the lagged values of variable X can significantly explain the current values of variable Y in the sense of statistics, or X does not Granger cause Y at

2000 Mathematics Subject Classification: 62P20, 91B82, 91B84.

Keywords and phrases: Granger causality, attenuation rate of Granger cause, structural stability of Granger causality, order of the structural stability of Granger causality.

Received August 4, 2006

some significant level α . Vice versa. But, a problem may arise when the Granger causality is applied, that is the Granger causality between two variables may be changed as the lag of a variable differs. This phenomenon can be caused by the structural un-stability of Granger causality. Otherwise, Granger causality between two variables is not changed as the lag of a variable changes freely in some range. This phenomenon is called the *structural stability of Granger causality*.

So far, there is no best way to avoid the structural un-stability of Granger causality in the practices. R. Davidson and J. G. Mackinnon (Gujarati [2, p.615]) suggest that the lag for testing the Granger causality is selected as large as possible, Hsiao [3] advocates that the best lag is determined by the Akaike Information Criterion (AIC). And the Schwarz Information Criterion (SIC) is suggested by Schwarz to decide the best lag, which is defined as:

$$\min\{m : \{\min : SIC = \ln \hat{\sigma}^2 + m \ln n\}, m > 0\},$$

where $\hat{\sigma}^2$ is the maximum likelihood estimation of σ^2 ($\sigma^2 = \frac{\text{Residual Sum of Squares}}{n}$), m is the lag, n is the observation,

denoted by Gujarati [2, p.627]. But, these methods cannot identify the structural stability or the structural un-stability of Granger causality. We take World Exports as an example, and consider the relationship between the exports of North America (ENA) and Asia (EA), by using the data from 1990 to 2004. The analytical results are shown in Table 1. From Table 1, according to previous Scholars' research, the lag 2 is locked, and the null hypothesis is accepted that at significant level 10%; however, if one takes lag 1, the null hypothesis is rejected that at significant level 10%, which EA does not Granger Cause ENA. The contradiction between the two results demonstrates that Davidson and Mackinnon's suggestion, Hisao's method, and Schwarz's suggestion are not always reasonable in selecting a suitable model for Granger test. To deal with the structural un-stability of Granger causality, a new criterion for Granger test will be investigated in this paper.

The remaining context of this paper is arranged as follows: Section 2 is to establish a criterion for testing linear Granger causality, which is

new in the literature; Section 3 is to compare the selection of empirical models based on four methods mentioned in this paper, Section 4 is to draw the main conclusion of this paper.

1. Criterion for Testing Linear Granger Causality

Suppose that $\{X_t\}$ and $\{Y_t\}$ are two time series, and the forecasts of X_t and Y_t are based on their previous information, which are illustrated by their lagged values. Granger [1] studies the causality between X_t and Y_t . This causality is called *Granger Causality*. Consider the following equations:

$$Y_t = a_1 + \sum_{j=1}^{k_1} b_{1j} X_{t-j} + \sum_{i=1}^{m_1} c_{1i} Y_{t-i} + u_t \quad (1)$$

and

$$X_t = a_2 + \sum_{j=1}^{k_2} b_{2j} X_{t-j} + \sum_{i=1}^{m_2} c_{2i} Y_{t-i} + v_t, \quad (2)$$

where k_1, k_2, m_1, m_2 are all positive integers, u_t, v_t are respectively the random disturbances of models 1 and 2. According to model 1, X does not Granger cause Y at some level α of significance, if the null hypothesis is significantly rejected in the hypothesis test, otherwise, X does Granger cause Y at the level α of significance. Similarly, model 2 can be used to test the Granger causality of Y to X . If a positive integer q exists, and for all k_1, m_1 , there are $k_1 \leq q$, and $m_1 \leq q$, X does not Granger cause Y at some level α of significance; if there is a k_1 or m_1 , when k_1 or m_1 is larger than q , X does Granger cause Y at the same level α of significance, then the model 1 with the lags of q is called *the structural stability of Granger causality*, where q is regarded as the best order. In general, if there are k positive integers q_1, q_2, \dots, q_k , denoted by different subscripts, and they have a relation: $q_1 < q_2 < \dots < q_{k-1} < q_k$, such that

$$k_1, m_1 \in \bigcup_{0 < n \leq \frac{k}{2} + 1} (q_{2n-2}, q_{2n-1}], \quad (3)$$

where $q_0 = 0$, X does not Granger cause Y at some level α of significance; and such that

$$k_1, m_1 \notin \bigcup_{0 < n \leq \frac{k}{2} + 1} (q_{2n-2}, q_{2n-1}] \quad (4)$$

X does Granger cause Y at the same level α of significance, where $n \in \left(0, \frac{k}{2} + 1\right)$, model 1 is called *the structural stability of Granger causality with respect to the order q* , and $q \in (q_{2n-2}, q_{2n-1})$. If there does not exist such a positive q , namely $q = 0$, model 1 is called *the structural un-stability of Granger causality*. For the rest of the paper, we always assume that the structural stability of Granger causality with respect to the order q means the structural stability of Granger causality with respect to the best order q . In other words, *the order q for the structural stability of Granger causality is the best order q* , unless we renew the assumption.

For the sake of convenience, the lag, satisfying $i = j$, is always assumed, while we neglect other cases. The related F-statistic of testing Granger causality is written as: F_i , whose definition is referred in Gujarati [2] or Wang [4], then the *attenuation rate of Granger cause of X with respect to Y* can be defined by γ_i :

$$\gamma_i := \frac{F_i - F_{i-1}}{F_{i-1}}, \quad (5)$$

where $i \in (1, q]$, $q > 1$. If $q = 1$, then we define $\gamma_1 = 0$. As we can see, γ_i may be positive or negative. For example, consider the percentage of domestic loans in the total investment in fixed assets by source (PDI) and the percentage of foreign investment in the total investment in fixed assets by source (PFI). The number of the observations is 23, q is 4 at the level 5% of significance, and γ_2 is positive based on Table 2. But in Table 3, q is 106 at the level 5% of significance, and $\gamma_i < 0$.

Consolidated with Davidson and Mackinnon's suggestion, Hsiao's method and Schwarz's suggestion, the main results are stated as follows:

Theorem (Criterion of the best lag for testing linear Granger causality). *The best lag for testing linear Granger causality is equal to*

$$\max\{n \mid \min_{n \leq q} \{|AIC_n|\}\} \quad \text{or} \quad \max\{n \mid \min_{n \leq q} \{|SIC_n|\}\},$$

where AIC_n and SIC_n respectively denote the AIC and SIC of the corresponding regression model with lag n .

The criterion of the best lag for testing linear Granger causality can ensure the structural stability of Granger causality. This criterion is the main contribution to the theory in this field. *W-criterion* denotes the abbreviation of the criterion of the best lag for testing linear Granger causality.

According to Table 3, if q is sufficiently large, and $n \rightarrow q$, a trend can be detected that $|\gamma_n|$ declines along with the increasing of lags. When $|\gamma_n|$ declines to an extent, based on model 1, the Granger causality of X to Y is becoming weaker for decrease of the corresponding F-statistic in trend, at some level α of significance. And furthermore, if the absolute values of AIC or SIC are smaller, then we can select the model with lag n as the model for testing Granger causality. If n is very big, then it may be inefficient to work out the smallest absolute value of AIC or SIC. So, we empirically suggest to choose the smallest n_0 such that

$$\begin{aligned} |AIC_{n_0}| &\leq \begin{cases} \min\{|AIC_{n_0-1}|, |AIC_{n_0+1}|\}, & n_0 > 1 \\ |AIC_{n_0+1}|, & n_0 = 1 \end{cases}, \\ |SIC_{n_0}| &\leq \begin{cases} \min\{|SIC_{n_0-1}|, |SIC_{n_0+1}|\}, & n_0 > 1 \\ |SIC_{n_0+1}|, & n_0 = 1 \end{cases} \end{aligned} \quad (6)$$

(6) is called *the empirical criterion of the better lag for testing Granger causality*, or *empirical criterion of the better lag* in abbreviation, defined as *W-empirical criterion*. It is worthy observing that there may be more than one n_0 satisfying (6). But, from (6), the smallest n_0 is enough. If there does not exist multiple n_0 satisfying (6), then we only need to choose the unique n_0 as lag such that AIC_n or SIC_n is the smallest.

3. Selection of Empirical Models

Table 1 shows that Davidson and Mackinnon's suggestion, Hisao's method, and Schwarz's suggestion cannot ensure that the selected model is reasonable in the sense of testing Granger causality. The main reasons are that these three methods could neglect the issue of the structural stability of Granger test. Even though the structural stability for Granger test can be accomplished by these three methods, the optimal empirical model may not be efficiently worked out based on them. However, (6) makes up for this disadvantage.

In order to compare the empirical models selected by the four methods respectively, we use the sample data from Shanghai A-stock market in China. The sample contains daily data of 2969 observations, from 20th, Dec. 1990 to 21th, Dec. 2002. The daily data include daily return rate and daily trading volume. The sources are from Chinese Stock Markets Trading Data System, CSMARTRD(2.1).

Let X denote the daily return rate, Y denote the daily trading volume of Shanghai A-stock market. At level 5% of significance, $q = 106$, when the number of lags is less than or equal to 106, X does not Granger cause Y , and when it is bigger than 106, X does significantly Granger cause Y at level 5% of significance. By empirical test, the best lag decided by Theorem coincides with the case suggested by Hsiao, and Schwarz. But it is lack of efficiencies to work out a result by such a model where the best lag is too large. So we take a lag equal to 15 and compare the four methods in Table 3. By Hsiao's method, the lag should be 8. By W -criterion, W -empirical criterion, or Schwarz's suggestion, the lag is 3. And by Davidson and Mackinnon's suggestion, the lag is 15, as large as possible. The regression results by these four methods are shown in Table 4. Obviously, W -empirical criterion is more reasonable and efficient than others in the application, when the lag controlled is not 15, but more than 15.

4. Conclusion

For model 1, X does not Granger cause Y at some level α of significance, if and only if the number of lags is less than the best order of

the structural stability of Granger causality, which is some positive integer.

W-criterion: The best lag for testing linear Granger causality is equal to $\max\{n \mid \min_{n \leq q} \{|AIC_n|\}\}$ or $\max\{n \mid \min_{n \leq q} \{|SIC_n|\}\}$, where AIC_n and SIC_n respectively denote the AIC and SIC of the corresponding regression model with lag n .

In practice, it may be inefficient to work out the best lag based on Theorem. Therefore, an empirical criterion of the better lag is needed. This method is more efficient in empirical test than those suggested or advocated by Davidson and Mackinnon, Hsiao, and Schwarz. This method is called *W-empirical criterion*.

W-empirical criterion: Select the smallest integer n_0 such that

$$\begin{aligned} |AIC_{n_0}| &\leq \begin{cases} \min\{|AIC_{n_0-1}|, |AIC_{n_0+1}|\}, & n_0 > 1, \\ |AIC_{n_0+1}|, & n_0 = 1, \end{cases} \\ |SIC_{n_0}| &\leq \begin{cases} \min\{|SIC_{n_0-1}|, |SIC_{n_0+1}|\}, & n_0 > 1, \\ |SIC_{n_0+1}|, & n_0 = 1. \end{cases} \end{aligned}$$

The structural stability of Granger causality is identified based on W -criterion or W -empirical criterion, but not based on Davidson and Mackinnon's suggestion, Hsiao's method, and Schwarz's suggestion or Schwarz's criterion.

When $q > 0$, W -criterion coincides with Hsiao's method or Schwarz's criterion, but not always Davidson and Mackinnon's suggestion. And furthermore, W -empirical criterion is generally more efficient than those suggested or advocated by Davidson and Mackinnon, Hsiao, and Schwarz in practice under the condition of sufficiently large q .

When $q = 0$, W -criterion does not exist, nor does W -empirical criterion. However, Davidson and Mackinnon's suggestion, Hsiao's method, and Schwarz's suggestion are still reliable, this is the main reason why the models selected based on Davidson and Mackinnon's suggestion, Hsiao's method, and Schwarz's criterion usually can bring contradictory conclusions.

Appendix

Proof of Theorem. Assume

$$\max\{n \mid \min_{n \leq q}\{|AIC_n|\}\} \leq \max\{n \mid \min_{n \leq q}\{|SIC_n|\}\}$$

and p is the best lag satisfying $p \neq \max\{n \mid \min_{n \leq q}\{|AIC_n|\}\}$ by contradiction. Then we have

$$|AIC_p| \leq |AIC_n|, \quad n = \max\{n \mid \min_{n \leq q}\{|AIC_n|\}\}.$$

In the rest of the proof, for the maximum n : $n_{\max} = \max\{n \mid \min_{n \leq q}\{|SIC_n|\}\}$, we only need to discuss two cases: $|AIC_p| = |AIC_{n_{\max}}|$ and $|AIC_p| < |AIC_{n_{\max}}|$.

Case One. $|AIC_p| = |AIC_{n_{\max}}|$. According to $\max\{n \mid \min_{n \leq q}\{|AIC_n|\}\}$, we know p satisfies $p < n_{\max} \leq q$. But the correspondent determinant coefficient R_p^2 is less than $R_{n_{\max}}^2$, namely, the model with lag n_{\max} is more significant than the model with lag p in the sense of the fit efficiency. Therefore, under the condition of $|AIC_p| = |AIC_{n_{\max}}|$, p cannot be the best lag. By the assumption, $|AIC_p| = |AIC_{n_{\max}}|$, cannot occur.

Case Two. $|AIC_p| < |AIC_{n_{\max}}|$. By the definition of the best lag and $\max\{n \mid \min_{n \leq q}\{|AIC_n|\}\}$, we deduce that $p > q$, this implies that for all $q^* \in (q, p]$, q^* is the order of the structural stability of Granger causality. So, we obtain a contradiction to the precondition: q is the best lag of the structural stability of Granger causality. This contradiction clarifies that $|AIC_p| < |AIC_{n_{\max}}|$ cannot occur either.

From Case one and Case two, we demonstrate that p ($p \neq \max\{n \mid \min_{n \leq q}\{|AIC_n|\}\}$) is not the best lag.

If

$$\max\{n \mid \min_{n \leq q}\{|AIC_n|\}\} > \max\{n \mid \min_{n \leq q}\{|SIC_n|\}\},$$

then we can also similarly prove that $\max\{n \mid \min_{n \leq q}\{|SIC_n|\}\}$ must be the best lag. The proof is complete.

Acknowledgement

The author would like to thank Professor Gabriel Talmain and Miss Yajuan Mao for their kind and helpful suggestions and comments on revising this paper. This paper is a part of Guangdong Soft Science Project (No. 2007B070900083).

References

- [1] C. Granger, Investigating causal relation by econometric models and cross-spectral methods, *Econometrica* 37 (1969), 421-438.
- [2] D. N. Gujarati, Basic Econometrics, 3rd ed., Translated by Lin Shaogong, China Renmin University Press, Beijing, 2004 (in Chinese).
- [3] C. Hsiao, Autoregressive modeling and money-income causal detection, *Journal of Monetary Economics* 7 (1981), 85-106.
- [4] Sheng Wang, Introduction to Econometrics, Tsinghua University Press, Beijing, 2006 (in Chinese).

Table 1

In the following table, the relationship between the exports of North America (ENA) and Asia (EA) is complicated in the sense of Granger causality. Limited the observation in data, during 1990 to 2004, the lag for testing Granger causality is limited by 2. If the lag increases, then the freedom degree decreases rapidly, this trend would weak the effect of regression. But, to take 2 as the bigger lag is to be enough to demonstrate the limitation of Davidson and Mackinnon's suggestion, Hsiao's method, and Schwarz's suggestion. According to Davidson and Mackinnon's suggestion, Hsiao's method, or Schwarz's suggestion, the lag 2 is locked, and the null hypothesis: EA does not Granger cause ENA is accepted at significant level 10%. However, if one takes lag 1, then the null hypothesis: EA does not Granger cause ENA is refused at significant level 10%. This contradiction clarifies that the limitation of Davidson and Mackinnon's suggestion, Hsiao's method, and Schwarz's suggestion must be faced.

Observation	Lags	Null Hypothesis	AIC	SIC	Significant level α	Conclusion
14	1	EA does not Granger cause ENA	17.66305	17.79999	0.1	Rejected
13	2	EA does not Granger cause ENA	17.35193	17.56922	0.1	No Rejected

Sources from World Trade Organization Database, see also 2005 International Statistics Year Book.

Table 2

Whether γ is either negative or positive is very difficult to be identified in advance. But the absolute value of γ_i may decline as $i \rightarrow q$ when $q > 1$, see the table below and Table 3. Consider the relationship between the percentage of domestic loans in the total investment in fixed assets by source (PDI) and the percentage of foreign investment in the total investment in fixed assets by source (PFI) the sense of Granger causality, the corresponding γ and q are shown in the following table: $\gamma_2 = 0.704903$, $\gamma_3 = -0.65391$, $q = 4$, at the significant level 5%.

Observation	Lags	Null hypothesis	γ	Conclusion
23	1	PDI does not Granger cause PFI		Rejected
22	2	PDI does not Granger cause PFI	0.704903	Rejected
21	3	PDI does not Granger cause PFI	-0.65391	Rejected

Sources from 2005 China Statistics Year Book.

Table 3

Granger cause and its attenuation rate γ , AIC and SIC, in Shanghai A-Stock Market are shown in the following table. There is only a part of results and conclusion worked out contain here, for q is 106 at the significant level 5%.

Observation	Lags	Null hypothesis	γ	AIC	SIC	Conclusion
2968	1	X does not Granger cause Y		40.71378	40.71984	Rejected
2967	2	X does not Granger cause Y	-0.16281	40.68965	40.69975	Rejected
2966	3	X does not Granger cause Y	-0.34581	40.67623	40.69038	Rejected
2965	4	X does not Granger cause Y	-0.2459	40.67692	40.69512	Rejected
2964	5	X does not Granger cause Y	-0.19147	40.67819	40.70043	Rejected
2963	6	X does not Granger cause Y	-0.11348	40.67639	40.70269	Rejected
2962	7	X does not Granger cause Y	-0.12099	40.67011	40.70046	Rejected
2961	8	X does not Granger cause Y	-0.13523	40.66431	40.69872	Rejected
2960	9	X does not Granger cause Y	-0.0938	40.66459	40.70306	Rejected
2959	10	X does not Granger cause Y	-0.10002	40.66483	40.70736	Rejected
2958	11	X does not Granger cause Y	-0.08339	40.66581	40.71241	Rejected
2957	12	X does not Granger cause Y	-0.08864	40.66661	40.71727	Rejected
2956	13	X does not Granger cause Y	-0.07675	40.66826	40.72298	Rejected
2955	14	X does not Granger cause Y	-0.04449	40.66769	40.72649	Rejected
2954	15	X does not Granger cause Y	-0.07506	40.66705	40.72992	Rejected
:	:	:	:	:	:	:

Sources from CSMARTRD(2.1), Chinese Stock Markets Trading Data System.

Table 4

According to W -criterion, W -empirical criterion, or Schwarz's suggestion, from Table 3, the following model is selected:

$$Y_t = a_{11} + \sum_{j=1}^3 b_{11j} X_{t-j} + \sum_{i=1}^3 c_{11i} Y_{t-i} + u_t. \quad (7)$$

The regression of model 7 is described as follows:

Variable	Coefficient	Std. Error	t-Statistic	Prob.
a_{11}	24323626	4167590.	5.836377	0.0000
X_{t-1}	7.34E+08	81413274	9.011610	0.0000
Y_{t-1}	0.775368	0.018502	41.90792	0.0000
X_{t-2}	-2.51E+08	82046618	-3.055886	0.0023
Y_{t-2}	0.041312	0.023434	1.762872	0.0780
X_{t-3}	-85725261	81418636	-1.052895	0.2925
Y_{t-3}	0.119285	0.018300	6.518315	0.0000
R-squared	0.849576	Mean dependent var		3.88E+08
Adjusted R-squared	0.849271	S. D. dependent var		4.24E+08
S. E. of regression	1.64E+08	Akaike info criterion		40.67623
Sum squared resid	8.00E+19	Schwarz criterion		40.69038
Log likelihood	-60315.85	F-statistic		2785.346
Durbin-Watson stat	2.007623	Prob(F-statistic)		0.000000

Sources from CSMARTRD(2.1), Chinese Stock Markets Trading Data System.

According to Hsiao's method, from Table 3, the following model is selected:

$$Y_t = a_{12} + \sum_{j=1}^8 b_{12j} X_{t-j} + \sum_{i=1}^8 c_{12i} Y_{t-i} + u_t. \quad (8)$$

The regression of model 8 is described as follows:

Variable	Coefficient	Std. Error	t-Statistic	Prob.
α_{12}	18713927	4250792.	4.402457	0.0000
X_{t-1}	7.55E+08	81001963	9.322555	0.0000
Y_{t-1}	0.756909	0.018635	40.61695	0.0000
X_{t-2}	-2.10E+08	82158275	-2.553462	0.0107
Y_{t-2}	0.041561	0.023396	1.776421	0.0758
X_{t-3}	-25801241	82514478	-0.312687	0.7545
Y_{t-3}	0.091076	0.023402	3.891762	0.0001
X_{t-4}	38288650	82510458	0.464046	0.6426
Y_{t-4}	0.012560	0.023470	0.535133	0.5926
X_{t-5}	1707321.	82484823	0.020699	0.9835
Y_{t-5}	-0.025687	0.023477	-1.094136	0.2740
X_{t-6}	-1.16E+08	82424271	-1.402399	0.1609
Y_{t-6}	-0.024616	0.023418	-1.051160	0.2933
X_{t-7}	-1.10E+08	82038542	-1.339269	0.1806
Y_{t-7}	0.016335	0.023372	0.698904	0.4847
X_{t-8}	-75860636	81101766	-0.935376	0.3497
Y_{t-8}	0.083385	0.018391	4.534007	0.0000
R-squared	0.852400	Mean dependent var	3.89E+08	
Adjusted R-squared	0.851598	S.D. dependent var	4.24E+08	
S. E. of regression	1.63E+08	Akaike info criterion	40.66431	
Sum squared resid	7.84E+19	Schwarz criterion	40.69872	
Log likelihood	-60186.51	F-statistic	1062.613	
Durbin-Watson stat	2.005316	Prob(F-statistic)	0.000000	

Sources from CSMARTRD(2.1), Chinese Stock Markets Trading Data System.

According to Davidson and Mackinnon's suggestion, from Table 3, the following model is selected:

$$Y_t = \alpha_{13} + \sum_{j=1}^{15} b_{13j}X_{t-j} + \sum_{i=1}^{15} c_{13i}Y_{t-i} + u_t. \quad (9)$$

The regression of model 9 is described as follows:

Variable	Coefficient	Std. Error	t-Statistic	Prob.
α_{13}	15595150	4350969.	3.584293	0.0003
X_{t-1}	7.61E+08	81069052	9.385704	0.0000
Y_{t-1}	0.749226	0.018759	39.93910	0.0000
X_{t-2}	-1.88E+08	82278363	-2.285754	0.0223
Y_{t-2}	0.037569	0.023444	1.602493	0.1092
X_{t-3}	-17688211	82608727	-0.214120	0.8305
Y_{t-3}	0.087630	0.023441	3.738294	0.0002
X_{t-4}	52170475	82618344	0.631464	0.5278
Y_{t-4}	0.011383	0.023506	0.484259	0.6282
X_{t-5}	26397217	82643423	0.319411	0.7494
Y_{t-5}	-0.025650	0.023515	-1.090818	0.2754
X_{t-6}	-94024374	82624684	-1.137970	0.2552
Y_{t-6}	-0.027829	0.023516	-1.183422	0.2367
X_{t-7}	-71271471	82628817	-0.862550	0.3885
Y_{t-7}	0.006558	0.023521	0.278808	0.7804
X_{t-8}	-23828149	82622608	-0.288397	0.7731
Y_{t-8}	0.063395	0.023492	2.698598	0.0070

X_{t-9}	-72865478	82595171	-0.882200	0.3777
Y_{t-9}	0.002590	0.023524	0.110090	0.9123
X_{t-10}	-56824248	82609024	-0.687870	0.4916
Y_{t-10}	0.018724	0.023519	0.796129	0.4260
X_{t-11}	-45121537	82588475	-0.546342	0.5849
Y_{t-11}	-0.001947	0.023517	-0.082774	0.9340
X_{t-12}	-37588933	82559984	-0.455292	0.6489
Y_{t-12}	0.022583	0.023516	0.960321	0.3370
X_{t-13}	49845069	82519025	0.604043	0.5459
Y_{t-13}	-0.028116	0.023458	-1.198593	0.2308
X_{t-14}	-1.16E+08	82127116	-1.417643	0.1564
Y_{t-14}	0.000824	0.023420	0.035204	0.9719
X_{t-15}	-77328350	81244159	-0.951802	0.3413
Y_{t-15}	0.043811	0.018487	2.369816	0.0179
R-squared	0.853449	Mean dependent var	3.90E+08	
Adjusted R-squared	0.851945	S. D. dependent var	4.24E+08	
S. E. of regression	1.63E+08	Akaike info criterion	40.66705	
Sum squared resid	7.77E+19	Schwarz criterion	40.72992	
Log likelihood	-60034.23	F-statistic	567.4079	
Durbin-Watson stat	1.999252	Prob(F-statistic)	0.000000	

Sources from CSMARTRD(2.1), Chinese Stock Markets Trading Data System.