Accepted Manuscript

Econometric testing on linear and nonlinear dynamic relation between stock prices and macroeconomy in China

Sumuya Borjigin, Yating Yang, Xiaoguang Yang, Leilei Sun

PII: S0378-4371(17)31043-9
DOI: https://doi.org/10.1016/j.physa.2017.10.033
Reference: PHYSA 18747

To appear in: *Physica A*

Received date : 26 January 2017
Revised date : 9 August 2017

Please cite this article as: S. Borjigin, Y. Yang, X. Yang, L. Sun, Econometric testing on linear and nonlinear dynamic relation between stock prices and macroeconomy in China, *Physica A* (2017), https://doi.org/10.1016/j.physa.2017.10.033

1. The nonlinear dynamic Granger causality between China's stock prices and macroeconomy is stronger than linear dynamic Granger causality between them.
2. The nonlinear dynamic Granger causality from macroeconomy to stock prices is stronger than the nonlinear dynamic Granger causality from stock prices to macroeconomy.
3. The nonlinear dynamic Granger causality from stock prices to GDP is stronger than the nonlinear dynamic Granger causality from GDP to stock prices.
4. The nonlinear Granger causality test results on static data can not reflect the causality from stock prices to macroeconomy is greater than the causality from macroeconomy to the stock prices.

Econometric Testing on Linear and Nonlinear Dynamic Relation Between Stock Prices and Macroeconomy in China

Borjigin Sumuya[1,2], Yating Yang[1], Xiaoguang Yang[2], Leilei Sun[3]
(1.School of Economics and Management, Inner Mongolia University, Hohhot 010021;
2. Academy of Mathematics and Systems Science, Chinese Academy of Sciences, Beijing 100190;
3. School of Economics and Management, Tsinghua University, Beijing 100084)

Abstract: Many researchers have realized that there is a strong correlation between stock prices and macroeconomy. In order to make this relationship clear, a lot of studies have been done. However, the casual relationship between stock prices and macroeconomy has still not been well explained. A key point is that, most of the existing research adopts linear and stable models to investigate the correlation of stock prices and macroeconomy, while the real causality of that may be nonlinear and dynamic. To fill this research gap, we investigate the nonilnear and dynamic causal relationships between stock prices and macroeconomy. Based on the case of China's stock prices and macroeconomy measures from January 1992 to March 2017, we compare the linear Granger causality test models with nonlinear ones. Results demonstrate that the nonlinear dynamic Granger causality is much stronger than linear Granger causality. From the perspective of nonlinear dynamic Granger causality, China's stock prices can be viewed as "national economic barometer". On the one hand, this study will encourage researchers to take nonlinearity and dynamics into account when they investigate the correlation of stock prices and macroeconomy; on the other hand, our research can guide regulators and investors to make better decisions.

Keywords: stock prices; macroeconomy; relation

1 Introduction

The relationship between stock prices and macroeconomy has been studied for many years, which provides a great deal of views and insights for government officers and managers. In previous literature, the research of relationship between stock prices and macroeconomy can be divided into two types: "stable correlation theory" and "divergence theory".

"Stable correlation theory" holds that the real economic activity is the basis of stock prices, so the stock prices should lead the real economy activity. In financial theory, Gorden's formula holds that the stock prices are determined by the discounted value of future dividends. In securities investment, the well-known Graham’s method also stands on the values of securities. The "stable correlation theory" has a wide and profound impact on the researchers in finance society and securities investment society. The conclusion "stock prices are leading indicators for macroeconomy" was derived from the "stable correlation theory". Many empirical analysis results support the "stable correlation theory", among which the most representative ones are the empirical results of Fama [1] and Schwert [2]. Fama's statistical analysis of stock returns in the United States between 1953 and 1987 shows that stock returns have significant explanations for future real economic activity, and there is a higher correlation between monthly, quarterly, annual returns and future production growth rates. Schwert also achieved a similar result. Following them, many scholars have drawn similar conclusions by using different econometric models at different frequencies, different time spans, or different macroeconomic indexes of different countries or regions. From the perspective of time frequency, there are daily data (see e.g. [3,4]), weekly data (see e.g. [5]), monthly data (see e.g. [6,7]), quarterly data (see e.g. [8-11]) and annual data (see e.g. [12-14]). In addition, some researches take into account different time frequencies simultaneously (see e.g. [15-17]). Time span varies from several years(see e.g. [3,17,18]) to several decades(see e.g. [5,7,12,19,20]). Focusing on a single country, many articles consider the relationship between US stocks and macroeconomic metrics (see e.g. [7-9,21-23]). On contrary, there are also articles study the relationship between the stock prices and mocroeconomy in G7 (see e.g. [26]), G20 (see e.g. [12]), India (see e.g. [6,19]), China (see e.g. [3,13]), Canada (see e.g. [27]), Austria (see e.g. [15]), Belgium (see e.g. [28]), South Africa (see e.g. [14]) and Malaysia (see e.g. [18,29]). As to the selected macroeconomic indicators, the studied metrics include GDP (see e.g. [14,17,27]), CPI (see e.g. [8]), M1 (see e.g. [8]), and also some other macroeconomic indexes (see e.g. [9]). Among these researches, the most popularly used testing model is linear Granger causality. Signal decomposition techniques (see e.g. [21]), dynamic factor model (see e.g. [22]), MRW method and GMM method (see e.g. [11]) model have been adopted in few researches, but not widely used. It is noteworthy that only a few of researches take both linear and nonlinear Granger causality test models into account. Specifically, Choudhry, Papadimitriou and Shabi [23] used monthly data from January 1990 to December 2011 to investigate the relationship between stock price volatility and the business cycle in the US, Canada, Japan and the UK via both linear and nonlinear bivariate causality tests. Results suggest that there is a bidirectional causal relationship between stock price volatility and the business cycle within each country. Literature [3,29] adopt the linear and nonlinear Granger causality model simultaneously to test the correlation of stock prices with the futures market, and that with the bond market.

"Deviation theory" holds such a view that the change of asset prices is usually deviate from development of the real economy. This view has also arose a lot of attentions, and widely studied by scholars. Among this researches, famous conclusions include: Shiller (see e.g. [30]), Stiglitz (see e.g. [31]) and Kindleberger (see e.g. [32]) presented an explanation of this view by using "bubble theory", Tobin (see e.g. [33]) provided an interpretation of this phenomenon from the perspective of "capital separation", Minsky’s (see e.g. [34]) analysis was based on expected instability. Till to now, it is still one of the most important issues in modern financial theory, the deviation phenomenon of asset prices and real economy has not been well explained yet.

In fact, only a few of scholars' empirical results support the "deviation theory". For instance, Pradhan, Arvin and Bahmani (see e.g. [35]) studied 34 OECD countries over the time period of 1960-2012 utilizing three measures of stock prices development with a panel VAR model. Result demonstrates that the development of stock prices in developed countries has no significant impact on economic growth. Empirical results of Bekiros, Gupta, and Kyei (see e.g. [36]) with monthly data from December 1899 to February 2014 shows that the U.S. macroeconomic indexes can not predict the return of the stock prices by nonlinear Granger causality, which is contrary to the results of the linear Granger causality test. It is noteworthy that, considering the instability of parameters, authors recommended nonlinear Granger causality test model to analyze the relationship between variables.

In summary, the empirical studies of the relationship between stock prices and macroeconomy have been implemented in different countries, on different kinds of data sets, with different theoretical models, and also draw different conclusions. As there has not been a unifying view achieved so far, the remaining problems include: 1) considering the relationship between stock prices and macroeconomy as a dynamic process rather than a static one previously used; 2) replacing linear Granger causality model with nonlinear Granger causality testing model. Though linear Granger causality has been widely used in previous literature, due to the nonlinear characteristics of financial time series, the classical linear VAR model is not suitable for testing the nonlinear Granger causality between economic variables (see e.g. [37]). For instance, Bekiros, Gupta, and Kyei [36] recommend nonlinear Granger causality model to analyze the relationship between stock prices and macroeconomy indicators. However, only a few empirical studies have used the nonlinear Granger causality method to analyze the relation between the variables (see e.g. [3, 23,29, 36]); 3) the nonlinear dynamic Granger causality between China's stock prices and macroeconomy has been rarely studied, the comparison of nonlinear dynamic model with linear ones or static ones on China's case has not been studied yet. To fill this research gaps, we examine both linear and nonlinear dynamic Granger causality of stock prices and macroeconomy on China's case.

The remaining sections of this paper is organized as follows: In the second Section, both linear and nonlinear Granger causality test models are introduced. Section 3 tests the linear and nonlinear dynamic Granger causality between China's stock prices and macroeconomy, also the linear and nonlinear static Granger causality of that. Section 4 presents the discussions of our research and concludes the results in Section 5.

2 Methodology

This section introduces the linear and nonlinear Granger causality test methods, which were developed by economist Clive Granger (see e.g. [38]) to test whether a historical or current information of a time series has a predictive effect on current or future values of another time series. Based on the classical Granger causality, many variants have been invented. In this paper, we focus on the classical Granger causality model, and called Granger causality for short. The Granger causality can be tested by both linear and nonlinear approaches.

2.1 Linear Granger Causality Test Method

The linear Granger causality test method can be performed under the framework of Vector AutoRegression (VAR) model. A VAR model consists of two stochastic endogenous variables, which can be expressed as

$$X_t^K = \alpha_1 + \sum_{i=1}^{m} \beta_{1,i} X_{t-i}^K + \sum_{i=1}^{n} \gamma_{1,i} Y_{t-i}^K + \varepsilon_{1,t}^K \tag{1}$$

$$Y_t^K = \alpha_2 + \sum_{i=1}^{p} \beta_{2,i} X_{t-i}^K + \sum_{i=1}^{q} \gamma_{2,i} Y_{t-i}^K + \varepsilon_{2,t}^K \tag{2}$$

where $X_t^K = (x_t, x_{t+1}, \cdots, x_{t+K-1})$ and $Y_t^K = (y_t, y_{t+1}, \cdots, y_{t+K-1})$ represent two stationary time series with length *K*, α_i, β_i, γ_i, i = 1,2,…, *K*, are the parameters to be estimated, $\{\varepsilon_{i,t}\}$, *i* = 1,2,…, *K*, are residuals and $\{\varepsilon_{i,t}\} \sim i.i.N(0,1)$, m, n, p and q are the maximum lag orders of the autoregressive term. In the framework of VAR model, the linear Granger causality between variables is tested by the joint significance of autoregressive coefficients. If the joint significance null hypothesis $\gamma_{i,t} = 0$, $i = 1,2,\cdots,n$, in the equation (1) is rejected, it means that Y_t^K Granger causes X_t^K. Similarly, if the null hypothesis of equation (2) is rejected, then it means that X_t^K Granger causes Y_t^K. If both of the two null hypothesis are rejected at the same time, there is a bidirectional Granger causality between X_t^K and Y_t^K.

2.2 Nonlinear Granger Causality Test Method

A linear Granger causality test can be performed under the VAR model framework as we introduced previously. Due to the nonlinear characteristics of financial time series, nonlinear Granger causality test is also required in this paper. As the classical VAR model cannot be directly used in nonlinear causality test, Baek and Brock (see e.g. [39]) proposed a nonlinear statistical Granger causality test based on nonparametric statistics. However, Baek and Brock's method is still not suitable for the problem studied in this paper, because their model is based on such a hypothesis that the tested time series are independent of each other and obey independent indentity distribution, which is too strict in practical cases. Hiemstra and Jones [37] modified this hypothesis, and derive a weak correlation testing method.

The nonlinear Granger causality test method modified by Hiemstra and Jones are as follows: consider two strictly stationary and weakly dependent time series X_t^K and Y_t^K, $t = 1,2,\cdots$, denote the *L*-length lead vectors of X_t^K by X_t^L, and the *Lx*-length and *Ly*-length lag vectors of X_t^K and Y_t^K by $X_{t-L_x}^{L_x}$ and $Y_{t-L_y}^{L_y}$ respectively. That is,

$$X_t^L = (x_t, x_{t+1}, \cdots, x_{t+L-1}), L = 1,2,\cdots, t = 1,2,\cdots \tag{3}$$

$$X_{t\text{-}L_x}^{L_x} = (x_{t\text{-}L_x}, x_{t\text{-}L_x+1}, \cdots, x_{t-1}), L_x = 1,2,\cdots, t = L_x+1, L_x+2,\cdots \tag{4}$$

$$Y_{t\text{-}L_y}^{L_y} = (y_{t\text{-}L_y}, y_{t\text{-}L_y+1}, \cdots, y_{t-1}), L_y = 1,2,\cdots, t = L_y+1, L_y+2,\cdots \tag{5}$$

For given values of L, L_x, L_y and $e > 0$, Y does not strictly cause X if:

$$\begin{aligned} &\Pr(\|X_t^L - X_s^L\| < e \,\|X_{t-L_x}^{L_x} - X_{s-L_x}^{L_x}\| < e, \|Y_{t-L_y}^{L_y} - Y_{s-L_y}^{L_y}\| < e) \\ &= \Pr(\|X_t^L - X_s^L\| < e \,\|X_{t-L_x}^{L_x} - X_{s-L_x}^{L_x}\| < e) \end{aligned} \tag{6}$$

Where $\Pr(\cdot)$ denotes probability and $\|\cdot\|$ denotes the maximum norm.

Let $\dfrac{C1(L+L_x, L_y, e)}{C2(L_x, L_y, 2)}$ and $\dfrac{C3(L+L_x, e)}{C4(L_x, 2)}$ denote the ratios of joint probabilities corresponding to the LHS and RHS of equation (7). These joint probabilities are defined as,

$$C1(L+L_x, L_y, e) = \Pr(\|X_{t-L_x}^{L+L_x} - X_{s-L_x}^{L+L_x}\| < e, \|Y_{t-L_y}^{L_y} - Y_{s-L_y}^{L_y}\| < e) \tag{7}$$

$$C2(L_x, L_y, e) = \Pr(\|X_{t-L_x}^{L_x} - X_{s-L_x}^{L_x}\| < e, \|Y_{t-L_y}^{L_y} - Y_{s-L_y}^{L_y}\| < e) \tag{8}$$

$$C3(L+L_x, e) = \Pr(\|X_{t-L_x}^{L+L_x} - X_{s-L_x}^{L+L_x}\| < e) \tag{9}$$

$$C4(L_x, e) = \Pr(\|X_{t-L_x}^{L_x} - X_{s-L_x}^{L_x}\| < e) \tag{10}$$

The strict Granger noncausality condition in equation (6) can then be expressed as

$$\frac{C1(L+L_x, L_y, e)}{C2(L_x, L_y, 2)} = \frac{C3(L+L_x, e)}{C4(L_x, 2)}, \tag{11}$$

Correlation integral estimators of the joint probabilities can be written as

$$C1(L+\hat{L}_x, L_y, e) = \frac{2}{n(n-1)} \sum_{1\le t<s}\sum I(\|X_{t-L_x}^{L+L_x} - X_{s-L_x}^{L+L_x}\| < e) I(\|Y_{t-L_y}^{L_y} - Y_{s-L_y}^{L_y}\| < e) \tag{12}$$

$$C2(\hat{L}_x, L_y, e) = \frac{2}{n(n-1)} \sum_{1\le t<s}\sum I(\|X_{t-L_x}^{L_x} - X_{s-L_x}^{L_x}\| < e) I(\|Y_{t-L_y}^{L_y} - Y_{s-L_y}^{L_y}\| < e) \tag{13}$$

$$C3(L+\hat{L}_x, e) = \frac{2}{n(n-1)} \sum_{1\le t<s}\sum I(\|X_{t-L_x}^{L+L_x} - X_{s-L_x}^{L+L_x}\| < e) \tag{14}$$

$$C4(\hat{L}_x, e) = \frac{2}{n(n-1)} \sum_{1\le t<s}\sum I(\|X_{t-L_x}^{L_x} - X_{s-L_x}^{L_x}\| < e) \tag{15}$$

Where $\max(L_x, L_y) + 1 \le t < s \le T - L + 1, n = T - L + 1 - \max(L_x, L_y)$, T is the total sample size. For given values of L, L_x, L_y and $e > 0$, under the assumption that X_t^K and Y_t^K strictly stationary, weakly dependent, if Y_t^K does not strictly Granger cause X_t^K, then,

$$\sqrt{n}\left(\frac{C1(L+L_x, L_y, e)}{C2(L_x, L_y, 2)} - \frac{C3(L+L_x, e)}{C4(L_x, 2)}\right) \overset{a}{\sim} N(0, \sigma^2(L, L_x, L_y, e)) \tag{16}$$

In summary, the nonlinear Granger causality test between stationary time series X_t^K and Y_t^K includes the following steps: (1) Test the linear Granger causality between stationary time series X_t^K and Y_t^K; (2) If there is a linear Granger causality, the VAR model is established, the residuals are taken and then normalized; (3) If there is no linear Granger causality, the original sequence is normalized; (4) The nonlinear Granger causality test is performed in the normalized data (see e.g. [37]).

2.3 Linear and Nonlinear Dynamic Granger Causality Test Method

A sliding time window with fixed time interval is used to examine the dynamic Granger causality between China's stock prices and the macroeconomic indicators. Following the existing research, we first set the length of time window as 24 months and the step size of that as 2 months. In order to get an overall and comprehensive testing result, we also set the length of time window as 30 months, and set the step size of that as 3 months (see results in Appendix), the lag orders of the linear Granger causality test and the nonlinear Granger causality test vary from 1 to 8.

3 Numerical Analysis

This section consists of three parts: first, we introduce the relevant indexes and parameters; then, we summary the testing results of linear and nonlinear dynamic Granger causality; last, results of linear and nonlinear static Granger causality test method are discussed.

3.1 Data Selection and Parameters Setting

According to the existing literature, this paper selected 14 indexes, which are shown in Table 1.

Table 1：Stock market and macroeconomic indexes

Serial number	index	type	frequency	begin & end time
1	Shanghai Composite Index	stock market	monthly	1992/01~2017/03
2	Shenzhen Component Index	stock market	monthly	1992/01~2017/03
3	CSI 300	stock market	monthly	2002/01~2017/03
4	GDP	macroeconomic	quarterly	1992/01~2017/03
5	CPI	macroeconomic	monthly	1992/01~2017/03
6	macroeconomic climate index	macroeconomic	monthly	1992/01~2017/03

7	above-scale industrial added value	macroeconomic	monthly	1992/01~2017/03
8	import and export trade	macroeconomic	monthly	1995/01~2017/03
9	balance of trade	macroeconomic	monthly	1995/01~2017/03
10	fixed assets investment	macroeconomic	monthly	1992/02~2017/03
11	M1	macroeconomic	monthly	1996/01~2017/03
12	M2	macroeconomic	monthly	1996/01~2017/03
13	financial institutions RMB deposit	macroeconomic	monthly	1992/01~2017/03
14	Li Keqiang Index	macroeconomic	monthly	2009/07~2017/03

The first three items in Table 1 are indicators of China's stock prices, while the rest are major macroeconomic indicators, where only GDP is a quarterly indicator, the others are all monthly indicators. As most of the scholars choose monthly indicators for analysis, we convert GDP to a monthly indicator. In this paper, quarterly GDP indicator are converted into monthly GDP indicator by four frequency conversion methods: constant-match average, constant-match sum, quadratic-match average and quadratic-match sum. Since the sum of the constant-match average and the quadratic-match average exceeds the sum of the quarterly GDP indicator, so the quadratic match sum and constant-match sum are selected for further analysis. Quadratic match sum converts quarterly data to monthly data by quadratic difference method, constant-match average converts quarterly data to monthly data by equal division method. Taking into account the robustness of the results (for more details, please refer to the Discussions and Appendix 1~4), this paper chooses quadratic match sum for further analysis.

The confidence parameters of the ADF test, the linear Granger causality test, and the nonlinear Granger causality test method mentioned above are all set as 0.05. Since Granger causality test is based on the hypothesis that the time series considered to be stable, and therefore all the data below are logarithmic rate of return. For ease of discussion, all the macroeconomic indicators are represented by the corresponding serial numbers in the following discussions.

Table 2~9 present the experimental results of our analysis. In the dynamic Granger causality method, the maximum ratio stands for the most possible dynamic Granger causality between the variables. So, the dynamic Granger causalities between China's stock prices and macroeconomy are shown in Table 2~5. Similarly, the minimum P-value stands for the most possible static Granger causality between the variables. So, the static Granger causalities between China's stock prices and macroeconomy are shown in Table 6~9.

3.2 Analysis of Experimental Results

Table 2 and Table 4 show the dynamic Granger causality from China's stock prices to macroeconomy. The first line is the serial numbers of the corresponding indexes in Table 1, the first column is the three stock indexes and the corresponding lag orders. Table 2 and Table 4 show the maximum ratio values of the linear and nonlinear dynamic Granger causality from stock prices to macroeconomy and the corresponding lag orders, respectively. On contrary, Table 3 and Table 5, show the dynamic Granger causality from China's macroeconomy to stock prices. For ease of interpretation, the horizontal arrows in Tables 2 and 4 show the row-to-column causal relationship, and the vertical arrows in Tables 3 and 5 represent the column-to-row causal relationship.

Table 2: Maximum Ratio of Linear Dynamic Granger Causality from Stock Prices to Macroeconomy (→)

	4	5	6	7	8	9	10	11	12	13	14
ratio-Shanghai	0.04	0.13	0.11	0.17	0.06	0.09	0.06	0.12	0.07	0.07	0.12
lag-Shanghai	1	3	2	3	1	2	6	1	2	7	3
ratio-Shenzhen	0.06	0.17	0.12	0.18	0.09	0.09	0.06	0.15	0.07	0.09	0.17
lag-Shenzhen	3	2	1	3	2	2	2	1	2	1	1
ratio-CSI 300	0.05	0.11	0.06	0.17	0.08	0.08	0.06	0.17	0.09	0.08	0.15
lag-CSI 300	5	2	1	1	2	2	1	1	2	1	1

The ratio in Table 2 ranges from 0.0400 to 0.1800, with an average of 0.1027, where 14 of them are larger than 0.10, none of them is larger than 0.50.

Table 3: Maximum Ratio of Linear Dynamic Granger Causality from Macroeconomy to Stock Prices (↓)

	4	5	6	7	8	9	10	11	12	13	14
ratio-Shanghai	0.10	0.14	0.11	0.08	0.09	0.12	0.09	0.08	0.09	0.06	0.06
lag-Shanghai	2	2	6	7	4	3	1	7	4	1	1
ratio-Shenzhen	0.09	0.15	0.14	0.09	0.11	0.1	0.1	0.13	0.06	0.06	0.06
lag-Shenzhen	2	2	5	7	4	6	2	7	4	2	4
ratio-CSI 300	0.11	0.17	0.09	0.16	0.12	0.12	0.14	0.1	0.1	0.1	0.08
lag-CSI 300	2	2	3	2	4	5	2	4	4	2	2

The ratio in Table 3 ranges from 0.0600 to 0.1700, with an average of 0.1030, where 19 of them are larger than 0.10, none of them is larger than 0.50.

Table 4: Maximum Ratio of Nonlinear Dynamic Granger Causality from Stock Prices to Macroeconomy (→)

	4	5	6	7	8	9	10	11	12	13	14
ratio-Shanghai	0.99	0.65	0.81	0.27	0.45	0.41	0.35	0.62	0.57	0.35	0.42
lag-Shanghai	7	3	8	6	4	3	4	8	8	4	8
ratio-Shenzhen	0.99	0.69	0.81	0.27	0.46	0.4	0.39	0.62	0.57	0.37	0.49
lag-Shenzhen	7	3	8	6	4	4	5	8	8	3	3
ratio-CSI 300	0.99	0.7	0.81	0.24	0.45	0.34	0.32	0.63	0.57	0.32	0.42
lag-CSI 300	7	8	8	6	4	4	5	8	8	8	8

The ratio in Table 4 ranges from 0.2400 to 0.9900, with an average of 0.5376, where 33 of them are larger than 0.10, 15 of them are larger than 0.50.

Table 5: Maximum Ratio of Nonlinear Dynamic Granger Causality from Macroeconomy to Stock Prices (↓)

	4	5	6	7	8	9	10	11	12	13	14
ratio-Shanghai	0.66	0.61	0.71	0.61	0.56	0.58	0.56	0.66	0.68	0.58	0.58
lag-Shanghai	3	3	3	8	8	8	8	3	3	3	8
ratio-Shenzhen	0.68	0.7	0.68	0.72	0.71	0.71	0.66	0.68	0.71	0.66	0.73
lag-Shenzhen	3	3	3	8	8	8	8	3	3	8	8

ratio-CSI 300	0.52	0.58	0.58	0.59	0.51	0.51	0.48	0.53	0.53	0.49	0.53
lag-CSI 300	3	3	3	8	8	8	8	3	3	3	8

The ratio in Table 5 ranges from 0.4800 to 0.7300, with an average of 0.6145, where 33 of them are larger than 0.10, 31 of them are larger than 0.50.

3.3 Results of Linear and Nonlinear Static Granger Causality Test Method

This section shows the results obtained in the previous section with the linear and nonlinear causal relationships in the static case. Table 6~9 show the minimum P-values and the corresponding lag order which is from 1 to 8.

Table 6: Minimum P-Value of Static Linear Granger Causality from Stock Prices to Macroeconomy (→)

	4	5	6	7	8	9	10	11	12	13	14
P-value-Shanghai	0.053	0.245	0.455	**0.016**	**0.031**	0.464	0.117	0.094	0.096	0.311	**0.034**
lag-Shanghai	5	3	3	6	5	2	3	1	4	8	5
P-value-Shenzhen	0.083	0.175	0.413	**0.016**	**0.037**	0.268	0.154	**0.050**	0.145	0.141	**0.040**
lag-Shenzhen	5	3	1	6	7	8	7	5	4	1	4
P-value-CSI 300	**0.022**	0.215	0.137	0.081	0.157	0.275	**0.042**	0.124	0.216	0.182	**0.035**
lag-CSI 300	5	3	3	6	2	2	7	5	1	8	4

At the 0.05 confidence level, the Shanghai Composite index Granger causes 7, 8 and 14, Shenzhen Component Index Granger causes 7, 8, 11 and 14, CSI 300 index Granger causes 4, 10 and 14.

Table 7: Minimum P-Value of Static Linear Granger Causality from Macroeconomy to Stock Prices (↓)

	4	5	6	7	8	9	10	11	12	13	14
P-value-Shanghai	0.135	**0.048**	0.057	**0.036**	0.071	0.697	0.279	**0.015**	0.172	**0.045**	0.070
lag-Shanghai	6	6	2	8	1	1	8	1	6	5	1
P-value-Shenzhen	0.085	0.363	0.101	0.087	0.051	0.456	0.188	**0.009**	0.166	**0.015**	0.146
lag-Shenzhen	6	4	8	8	8	1	8	3	7	2	1
P-value-CSI 300	0.194	**0.014**	**0.004**	**0.026**	0.319	0.780	0.309	**0.005**	0.116	**0.001**	**0.044**
lag-CSI 300	8	2	5	3	8	2	8	1	5	5	1

At the 0.05 confidence level, 5,7,11 and 14 Granger cause the Shanghai Composite, 11 and 13 Granger cause the Shenzhen Component Index, 5,6,7,11,13 and 14 Granger cause the CSI 300 index.

Table 8: Minimum P-Value of Static Nonlinear Granger Causality from Stock Prices to Macroeconomy (→)

	4	5	6	7	8	9	10	11	12	13	14
P-value-Shanghai	**0.000**	**0.000**	**0.000**	**0.031**	**0.000**	**0.002**	**0.000**	**0.000**	**0.000**	**0.000**	**0.017**
lag-Shanghai	6	6	5	8	7	8	8	5	6	5	3
P-value-Shenzhen	**0.003**	**0.000**	**0.000**	0.075	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.009**
lag-Shenzhen	6	6	5	8	7	8	8	5	6	6	5
P-value-CSI 300	**0.014**	**0.000**	**0.000**	**0.014**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.014**
lag-CSI 300	6	6	5	8	7	8	7	5	6	5	5

At the 0.05 confidence level, Shenzhen Component Index does not Granger cause 7, in other cases, the

Shanghai Composite Index, the Shenzhen Component Index and the CSI 300 index Granger cause all the macroeconomic indices.

Table 9: Minimum P-Value of Static Nonlinear Granger Causality from Macroeconomy to Stock Prices (↓)

	4	5	6	7	8	9	10	11	12	13	14
P-value-Shanghai	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	0.055
lag-Shanghai	5	4	6	8	7	8	8	6	6	6	8
P-value-Shenzhen	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.040**
lag-Shenzhen	5	4	5	7	7	8	7	5	6	5	5
P-value-CSI 300	**0.000**	**0.000**	**0.000**	**0.004**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	0.064
lag-CSI 300	6	7	5	3	7	8	8	6	5	5	7

At the 0.05 confidence level, 14 does not Granger cause the Shanghai Composite Index, the Shenzhen Component Index and the CSI 300 index, in other cases, the macroeconomic indices Granger cause the Shanghai Composite Index, the Shenzhen Component Index and the CSI 300 index.

4 Discussions

In this paper, we use the linear Granger causality test model and the nonlinear Granger causality test model to examine the dynamic correlation between China's stock prices and macroeconomy in monthly data sets from January 1992 to March 2017. The dynamic correlation of 139 sliding windows is tested for each lagging parameter with a range of 1 to 8, a length of 24 months and a step size of 2 months.

Based on the above experiments, we get the following results:

(1) The nonlinear dynamic Granger causality between China's stock prices and macroeconomy is stronger than linear dynamic Granger causality between them.

From Table 2 we can see that, the maximum ratio of linear dynamic Granger causality from stock prices to macroeconomy is 0.1800, the minimum ratio is 0.0400, the average ratio is 0.1027, the total number of not less than 0.10 values and 0.50 values is 14 and 0 respectively.

In Table 4, the maximum ratio of nonlinear dynamic Granger causality from stock prices to macroeconomy is 0.9900, the minimum ratio is 0.2400, the average ratio is 0.5376, the total number of not less than 0.10 values and 0.50 values is 33 and 15 respectively.

By comparing Table 2 and 4, it can be concluded that nonlinear dynamic Granger causality from stock prices to macroeconomy is stronger than linear dynamic Granger causality from stock prices to macroeconomy.

Similarly, by comparing Table 3 and 5, it can be known that nonlinear dynamic Granger causality from macroeconomy to stock prices is stronger than linear dynamic Granger causality from macroeconomy to stock prices.

In summary, the nonlinear dynamic Granger causality between China's stock prices and macroeconomy is stronger than linear dynamic Granger causality between them.

This conclusion is in contrast to the conclusion of Bekiros, Gupta and Kyei [36] in the America's stock prices and macroeconomy, and different from the results concluded by Choudhry, Papadimitriou and Shabi [23]. On China's case, we find that linear correlation between stock prices and macroeconomy is weak.

(2) The nonlinear dynamic Granger causality from macroeconomy to stock prices is stronger than the nonlinear dynamic Granger causality from stock prices to macroeconomy.

The average ratio of Table 4 is 0.5376, the total number of not less than 0.10 values and 0.50 values is 33 and 15 respectively. The average ratio of Table 5 is 0.6145, the total number of not less than 0.10 values and 0.50 values is 33 and 31 respectively.

So, it can be concluded that, the nonlinear dynamic Granger causality from macroeconomy to stock prices is stronger than the nonlinear dynamic Granger causality from stock prices to macroeconomy, which means that the rapid and steady growth of China's economy has great impact on the stock prices, while the increase of stock prices has also contributed to China's sustained economic growth in turn.

(3) The nonlinear dynamic Granger causality from stock prices to GDP is stronger than the nonlinear dynamic Granger causality from GDP to stock prices.

From the third column of Table 4 we can see that the maximum ratio of nonlinear dynamic Granger causality from the Shanghai Composite Index, Shenzhen Component Index and CSI300 to GDP is all equal to 0.99. From the third column of Table 5 we can see that the maximum ratio of nonlinear dynamic Granger causality from GDP to the Shanghai Composite Index, Shenzhen Component Index and CSI300 is 0.66, 0.68 and 0.52 respectively.

So, it can be known that, the nonlinear dynamic Granger causality from stock prices to GDP is stronger than the nonlinear dynamic Granger causality from GDP to stock prices.

From the column 3 of Table 4 in Appendix 1~3, we can find that the lag orders are all equal to 7. Similarly, from the column 3 of Table 4 in Appendix 4, we can find that the lag orders range from 4~6.

To sum up, we conclude that, from the perspective of nonlinear dynamic Granger causality, China's stock prices has the function of "national economy barometer", and China's stock prices lead GDP nearly half year.

(4) The static nonlinear Granger causality between China's stock prices and macroeconomy is stronger than static linear Granger causality between them.

From Table 6 we can see that, at the 0.05 confidence level, the Shanghai Composite index Granger causes 7, 8 and 14, Shenzhen Component Index Granger causes 7, 8, 11 and 14, CSI 300 index Granger causes 4, 10 and 14.

From Table 8 we can see that, at the 0.05 confidence level, Shenzhen Component Index does not cause 7, in other cases, the Shanghai Composite Index, the Shenzhen Component Index and the CSI 300 index Granger cause all the macroeconomic indices.

By comparing Table 6 and 8 it can be concluded that static nonlinear Granger causality from stock prices to macroeconomy is stronger than static linear Granger causality from stock prices to macroeconomy.

Similarly, by comparing Table 7 and Table 9, it can be known that static nonlinear Granger causality from macroeconomy to stock prices is stronger than static linear Granger causality from macroeconomy to stock prices.

In summary, the static nonlinear Granger causality between China's stock prices and macroeconomy is stronger than static linear Granger causality between them.

(5) The nonlinear Granger causality test results on static data can not reflect the causality from stock prices to macroeconomy is greater than the causality from macroeconomy to the stock prices.

By comparing the minimum P-values in Table 8 and Table 9, we can easily conclude that nonlinear Granger causality test results on static data can not reflect the causality from stock prices to macroeconomy is greater than the causality from macroeconomy to the stock prices.

(6) As a whole, the results on different parameters show that the empirical results in this paper are robust.

The parameters considered in this paper are in order of the confidence parameter of ADF test, the confidence parameter of linear Granger causality test, the confidence parameter of nonlinear Granger causality test, the length parameter of sliding window and the interval parameter of adjacent window. In the empirical analysis, the confidence parameter is usually chosen as 0.01, 0.05 and 0.10 respectively. For the selected length parameter of sliding window and the interval parameter of adjacent window, we test the linear and nonlinear dynamic Granger causality between stock prices and macroeconomy in different confidence parameters, each confidence parameter is chosen as 0.01, 0.05 and 0.10 respectively. The results are shown in Appendix 1~Appendix3. We also test the impact of the length parameter of sliding window and the interval parameter of adjacent window, the results are shown in the Appendix 4.

By comparing the results in Appendix 1~Appendix4, it is not difficult to find that the influence of different parameters on the results is not great. Therefore, the empirical results in this paper are robust.

(7) It is more reasonable to convert the quarterly GDP data to monthly GDP via quadratic-match sum method.

By comparing the results in the second column and and the third column in Table 2~Table 5 of the Appendix 1~Appendix3 we can find that the results of the constant-match sum (C for short in the tables) and the quadratic-match sum (Q for short in the tables) are similar. However, the results in the column 2 in Table 4 and Table 5 of the Appendix 4 are not consist with the results in the third column in Table 4 and Table 5 of the Appendix 4 and the results in the second column and and the third column in Table 4~Table 5 of the Appendix 1~Appendix3.

So, according to the robustness of the results, it is more reasonable to convert the quarterly GDP data to monthly GDP via quadratic-match sum method.

5 Conclusions

This paper explores the linear and nonlinear dynamic correlation between China's stock prices and macroeconomy. The results show that the nonlinear Granger causality between China's stock prices and macroeconomy is stronger than the linear Granger causality between them. Compared the static nonlinear Granger causality test method with the dynamic nonlinear Granger causality test method, it can be known that stock prices have the functions of “national economic barometer”. The results of the study can provide decision support to regulators and investors.

The widely used linear Granger causality test method describes whether the historical value of one variable is linearly related to the present or future value of another one. Though it has an advantage that the results are intuitive and can be well explained by economic theories, it is difficult for us judge the size or the sign (positive or negative) of the coefficients. Compared with the linear Granger causality test method, the nonlinear Granger causality test method can extract the complex nonlinear relationship between variables more comprehensively and accurately, but economic meaning of the nonlinear Granger causality is not as intuitive as before (see e.g. [37]). Therefore, our research is suitable for find economic clues, while the explanation of our discoveries by economic theories needs to be improved in a further step. The following are some promising future work:

(1) To improve the existing nonlinear Granger causality test method, so that it has a more clear economic implications.

(2) The conclusion that China's stock prices are barometer of national economy is only established in the sense of Nonlinear Dynamic Granger Causality test, and its specific mechanism needs to be studied.

(3) To study the actual performances and consequences of the conclusion that nonlinear Granger causality between China's stock prices and macroeconomy is stronger than the linear Granger causality between them.

Acknowledgment

This work was partly supported by National Natural Science Foundation of China (Grant No. 61463039), China Postdoctoral Science Foundation (Grant No. 2015M581192) and Natural Science Foundation of Inner Mongolia (Grant No. 2014BS0706).

References

[1] E. Fama, Stock Returns, Expected returns, and real activity, J. Financ., 45(1990)1089-1108.

[2] W. Schwert, Stock returns and real activity: A century of evidence, J. Financ., 45(1990)1237-1257.

[3] X. Xu, Intraday price information flows between the CSI300 and futures market: an application of wavelet analysis, Empir. Econ., (2017)1-29.

[4] Y.T. Chen, K.Vincent, Money and economic growth, J. Forecast., 35(2016)504-527.

[5] E. Kole, D.V. Dijk, How to identify and forecast bull and bear markets ? J. Appl. Econom., 32(2017)120-139.

[6] A. Tiwari, M. Mutascu, C. Albulescu, P. Kyophilavong, Frequency domain causality analysis of stock market and economic activity in India, Int. Rev. Econ. Financ., 39(2015)224-238.

[7] S.Chen, Predicting the bear stock market: Macroeconomic variables as leading indicators, J. Bank Financ., 33(2009)211-223.

[8] K. Mun, The joint response of stock and foreign exchange markets to macroeconomic surprises: Using

US and Japanese data, J. Bank Financ., 36(2012)383-394.

[9] S. Jank, Mutual fund flows, expected returns, and the real economy, J. Bank Financ., 36(2012)3060-3070.

[10] C. Croux, P. Reusens, Do stock prices contain predictive power for the future economic activity ? A Granger causality analysis in the frequency domain, J. Macroecon., 35(2013)93-103.

[11] A. Cooray, Do stock markets lead to economic growth ? J. Policy Model., 32(2010)448-460.

[12] R. Pradhan, M. Arvin, A. Ghoshray, The dynamics of economic growth, oil prices, stock market depth, and other macroeconomic variables: Evidence from the G-20 countries, Int. Rev. Financ. Anal., 39(2015)84-95.

[13] J. Westerlund, P. Narayan, Testing for predictability in panels of any time series dimension, Int. J. Forecast., 32(2016)1162-1177.

[14] A. Polat, M. Shahbaz, I.U.Rehman, S.L. Satti, Revisiting linkages between financial development, trade openness and economic growth in South Africa: fresh evidence from combined cointegration test, Qual. Quant., 49(2015)785-803.

[15] K. Smimo, W. Khallouli, Does the Euro affect the dynamic relation between stock market liquidity and the business cycle ? Emerg. Mark. Rev., 25(2015)125-153.

[16] N.T. Vu, Stock market volatility and international business cycle dynamics: Evidence from OECD economies, J. Int. Money Finan., 50(2015)1-15.

[17] F. Abid, S. Bahloul, M. Mroua, Financial development and economic growth in MENA countries, J. Policy Model., 38(2016)1099-1117.

[18] W. Mahmood, N. Dinniah, Stock returns and macroeconomic influences: evidence from the six Asian-Pacific countries, Int. J. Financ. Econ., 30(2009)154-164.

[19] G. Girish, S. Vijayalakshmi, Is stock prices and economic activity in India co-integrated ? Theor. Econ. Lett., 6(2016)269-275.

[20] H. Nyberg, Predicting bear and bull stock markets with dynamic binary time series models, J. Bank Financ., 37(2013)3351-3363.

[21] M. Gallegati, Wavelet analysis of stock returns and aggregate economic activity, Comput. Stat. Data Anal., 52(2008)3061-3074.

[22] M. Chauvet, Z. Senyuz, E. Yoldas, What does financial volatility tell us about macroeconomic fluctuations ? J. Econ. Dyn. Control, 52(2015)340-360.

[23] T. Choudhry, F. Papadimitriou, S. Shabi, Stock market volatility and business cycle: Evidence from linear and nonlinear causality tests, J. Bank Financ., 66(2016)89-101.

[24] H. Nyberg, H. Ponka, International sign predictability of stock returns: The role of the United States, Econ. Model., 58(2016)323-338.

[25] S. Zeng, F. Bec, Do stock returns rebound after bear markets? An empirical analysis from five OECD countries, J. Empir. Financ., 30(2015)50-61.

[26] E.M. Diaz, J.C. Molero, F.P.D. Graci, Oil price volatility and stock returns in the G7 economies, Energy

Econ., 54(2016)417-430.

[27] K. Smimo, Consumer attitudes, stock market liquidity, and the macro economy: A Canadian perspective, Int. Rev. Financ. Anal., 33(2014)186-209.

[28] S.J. Wu, W.M. Lee, Predicting severe simultaneous bear stock markets using macroeconomic variables as leading indicators, Financ. Res. Lett., 13(2015)196-204.

[29] S.L. Ong, C.M. Ho, Testing for linear and nonlinear granger non-causality hypothesis between stock and bond: the cases of malaysia and singapore, Singap. Econ. Rev., 59(2014)1450045.

[30] R. Shiller, Fashions, Fads and Bubbles in Financial Markets, Oxford University Press, Oxford, 2003.

[31] J. Stiglitz, Symposium on bubbles, J. Econ. Perspect., 4(1990)13-18.

[32] C. Kindleberger, Manias, Panics and Crashes: A History of Financial Crises, John Wiley & Sons, New York, 2000.

[33] J. Tobin, Money and economic growth, Econometrica, 33(1965)671-684.

[34] H. Minsky, Stabilizing an unstable economy, Yale University Press, New Haven, 1986.

[35] R. Pradhan, M. Arvin, S. Bahmani, Causal nexus between economic growth, inflation, and stock market development: The case of OECD countries, Glob. Financ. J., 27(2015)98-111.

[36] S. Bekiros, R. Gupta, C. Kyei, On economic uncertainty, stock market predictability and nonlinear spillover effects, N. Am. Econ. Financ., 36(2016)184-191.

[37] C. Hiemstra, J. Jones, Testing for linear and nonlinear Granger causality in the stock price-volume relation, J. Financ., 49(1994)1639-1664.

[38] C. Granger, Investigating Causal relations by econometric models and cross-spectral methods, Econometrica, 37(1969)424-438.

[39] E. Baek, W. Brock, A nonparametric test for independence of a multivariate time series, Stat. Sin., 2(1992)137-156.

Caption for appendix

In this paper, quarterly GDP indicator are converted into monthly GDP indicator by the following two frequency conversion methods: constant-match average, constant-match sum. Quadratic match sum converts quarterly data to monthly data by quadratic difference method, constant-match average converts quarterly data to monthly data by equal division method. The experimental results corresponding to different methods and parameters are shown in Appendix 1~4.