Review of Economics & Finance

Submitted on 20/09/2018

Article ID: 1923-7529-2019-03-35-16

Xiao-Lin Li, Yi-Na Li, and Lu Bai

Stock Market Cycle and Business Cycle in China: Evidence from a Bootstrap Rolling Window Approach[1]

Prof. Dr. ***Xiao-Lin Li***
Department of Finance, Ocean University of China, Qingdao, Shandong, CHINA
Tel. +86-18562583085 E-mail: smileman2004@126.com

Yi-Na Li
Department of Finance, Ocean University of China, Qingdao, Shandong, CHINA
Tel. +86-15806586728 E-mail: Liyina1799352937@163.com

Lu Bai (Correspondence author)
Department of Finance, Ocean University of China, Qingdao, Shandong, CHINA
Tel. +86-17865321720 E-mail: 1652660579@qq.com

Abstract: This paper investigates the causality between the stock market cycle and business cycle in China using the bootstrap full-sample causality test and sub-sample rolling-window causality test. The full-sample causality test suggests a unidirectional causality from the stock market cycle to the business cycle in China. However, we find the parameters in the VAR models consisting of the full-sample data are unstable by conducting a parameter stability test. This implies that the results from the full-sample causality test cannot be relied upon. Consequently, we turn to employ a bootstrap rolling window approach which can identify the time-varying feature in the causality. Using a 24-quarter window size, we do find that the bi-directional causality between the stock market cycle and business cycle in China does exhibit substantial time variations. Moreover, the causal effect of the stock market cycle on the business cycle is much weaker than that of the business cycle on the stock market cycle. In other words, stock market volatility is not the main factor that affects the business cycle formation and development in China. These findings have important implications for policy makers and investors.

Keywords: Stock market cycle; Business cycle; Time variations; Bootstrap; Rolling window

JEL Classification: C22, E32, G10

1. Introduction

Scores of people think that stock prices follows a random walk and is a gambler's game. However, just the opposite is likely to occur. In terms of something such as a "typical business cycle", our stock portfolio often goes through stages of expansions (bull market) and contractions (bear market), and this is the so-called stock market cycle (Kim and Zumwalt, 1979; Cochran and DeFina, 1995; Lunde and Timmermenn, 2004; Pagan and Sossounov, 2003; Wu, *et al*., 2007;

[1] The study is funded by the national social science foundation of China (Grant number: 16CJY069), and by the social science foundation of Qingdao (Grant number: QDSKL1801008).

Harman and Zuehlke, 2007; Chen, 2009; Choudhry, *et al*., 2016). For instance, Cochran and DeFina (1995) observe that the U.S. stock market undergoes cycles of expansion and contraction during the period from January 1885 to July 1992. Extending the work of Cochran and DeFina (1995), Harman and Zuehlke (2007) also provide the estimates for the U.S. stock market expansions and contractions during the period from February 1948 to September 2002. Wu, *et al*. (2007) identify bull and bear market cycles for China using B-B algorithm, and find that the Chinese stock market cycles are extremely pronounced but have moderated as the market matures.

Can the stock market cycle affect the business cycle formation and development? Conversely, can the business cycle determine the stock market cycle to a certain extent? Understanding these problems is a matter of utmost significance for policy and investment decision makers. Substantial studies have arrived at a strong consensus on the significance of the stock market in economic growth. For example, Harris (1997) examines the relationship between the stock market and economic growth for both developing and developed countries. He finds that the effect of stock market development on economic growth is much weaker in developing countries than in developed countries. Paul and Franck (2006) find that stock market cycle can explain about 50 percent of business cycle fluctuations. Næs, *et al*. (2011) suggest that the stock market is considered a strong leading predictor of the business cycle. Bloom (2009) and Bloom, *et al*. (2012) argue that stock market shock plays an important role in the business cycle, and stock returns have a negative correlation with economic growth. Carlston (2018) studies the relationship between stock market and real economy, and finds stock market development can predict the real economy.

There have also been significant literature that suggests the business cycle can determine the stock returns. For instance, Binswanger (2000) revisits the causal relationship between stock price and the business cycle, and finds that macroeconomic recession leads to the volatility of the stock market price because the stock price is the current discounted value of the future stock dividend. Odhiambo (2009) also finds that the real economic development is the Granger cause of the stock market development in South Africa over the period 1971 to 2007 by employing the ARDL model. By conducting a multivariate regression analysis, DeStefano (2004) presents evidence that fundamental determinants exert a larger impact on stock returns during recessions than during expansions in the U.S. Miao, *et al.* (2015) also pay special interest in the dynamic relationship of stock market bubbles and business cycles. They find that the great recession can explain the U.S. stock market fluctuations. By employing European leading economic indicator, Zhu and Zhu (2014) find this prime business cycle indicator can strongly predict European stock returns. Prabheesh and Vidya (2018) investigate the relationship among technology shocks, business cycles and stock returns by estimating the SVAR model. Their empirical results show that global business cycles have played a significant role in determining the stock returns of India.

Limited studies have been undertaken to examine the causal relationship between the business cycle and stock market cycle. Choudhry, *et al.* (2016) conduct linear and nonlinear bivariate causality tests and find that there is a bidirectional causal linkage between the stock market volatility and business cycle in the U.S., the UK, Canada and Japan. Emilios and Evangelos (2015) also provide evidence that there is a two-way causal nexus between stock market liquidity and macroeconomic variables in all G7 countries except the U.S.

As seen, the existing studies have yielded many enlightening results. However, most of them adopts traditional linear methods and ignores the possible time variations in the causal relationships between the stock market cycle and business cycle. As we know, China has experienced substantial reforms or transforms in the real economy and stock market over the past few decades. The stock market has made great contributions to the real economy, and began to serve as an economic barometer. At the same time, China also suffered significant economic turmoil and stock market volatility from the Asian financial crisis in 1997 and the global financial crisis in 2008. Particularly, in recent years, China's economy has maintained a good momentum of growth, but the stock market has hit bottom. These probably led to remarkable fluctuation characteristics or structural breaks in China's stock market and real economy. The previous literature that ignores structural shifts or instability, and then adopts the linear full-sample Granger causality test may lead to misleading conclusions with respect to the linkage mechanisms between the stock market development and real economy.

This study is motivated by a desire to provide some new insights into the causal relationship between the stock market cycle and business cycle in China. First, while most related studies have focused on the relationship between stock market volatility and economic growth, our paper examines the relationship between the stock market and real economy from the perspective of cyclical fluctuations. For this purpose, we employ an H-P filtering technique to decompose the stock price and output series of China into cyclical and structural components, and then, we use the cyclical components as the proxy for the stock market cycle and business cycle, respectively. Second, this paper considers the time-varying nature that may exist in the causal links between the stock market cycle and business cycle in China. A proper approach to modeling such time variations is the bootstrap rolling-window causality test. Rather than simply testing for causality on the full sample data, the method detects the causal relationship in the sub-samples with a fixed size window, which allows us to capture structural changes in the model and the evolution of causality between sub-periods. To our knowledge, this is the first paper to study the time-varying relationship between the stock market cycle and business cycle in China using this method.

The rest of the paper is structured as follows. Section 2 describes a brief theoretical model. Section 3 presents the methodology employed. Section 4 describes the data applied. Section 5 presents and discusses the empirical results. The final section concludes.

2. Theoretical Model

Williams (1938) proposed the well-known dividend discount model (DDM) which suggests that the intrinsic value of a stock is the present value of expected dividends over time. The model can be expressed as:

$$p_0 = \sum_{t=1}^{\infty} \frac{D_t}{(1+r)^t}, \tag{1}$$

where p_0 represents the current stock price; D_t is the expected cash dividends per share at the end of period t; and r is the expected rate of return for equity investors, which is theoretically equal to the risk-free rate of interest plus the rate of risk compensation.

Based on the assumption that stable companies generally pay substantial dividends and hence the dividends will grow at constant rate, Gordon (1963) proposed another widely used version of DDM, which can be defined as:

$$p_0 = \sum_{t=1}^{\infty} \frac{D_0(1+g)^t}{(1+r)^t}, \tag{2}$$

where D_0 represents the cash dividend for the current period; g denotes the constant growth rate in perpetuity expected for the future dividends. The two models express the similar idea that the current price of a stock is the sum of its discounted future dividends. However, future cash flows in equation (1) are completely unpredictable whereas they are predictable in equation (2).

Based on the analysis above, we consider a two-period case in which the stock price of a company in period t, p_t, is the present value of the expected dividend in period $t+1$. Moreover, the expected dividend is defined as a proportion of the expected income of the company. As such, the DDM can be rewritten as:

$$p_t = \frac{\lambda\left(C + E_{t+1}\right)}{1+r_t^*}, \tag{3}$$

where C is a constant which represents the income of the company in period t; E_{t+1} represents the company's expected income growth in period $t+1$; λ is the dividend payout ratio; and r_t^* is the interest rate in period t. From equation (3), we find that the stock price is positively correlated with the expected future income and negatively correlated with the interest rate.

Next, we analyze the relationship between stock price and economic variables. Calculating the first derivative of equation (3) with respect to time t, we can obtain the following equation:

$$\frac{1}{p}\frac{dp}{dt} = \frac{1}{E+C}\frac{dE}{dt} - \frac{1}{(1+r^*)}\frac{dr}{dt}. \tag{4}$$

Equation (4) reveals that stock price movements are closely associated with the business cycle fluctuations. First, when the interest rate in current period declines and the income in next period is expected to rise, i.e., $dr/dt < 0$ and $dE/dt > 0$, the stock price will rise. This situation usually occurs at the bottom of the business cycle, when the stock market has already passed the bottom of its cycle and starts to pick up. It means that the stock market downturn would lead the economic downturn. Second, when the interest rate rises and the expected income declines, i.e. $dr/dt > o$ and $dE/dt < 0$, the stock price will decline. It implies that when the real economy is approaching its peak, the stock market has already peaked and is entering into a new downturn. That is, the stock market boom would lead the economic boom. Third, when both the interest rate and the expected income increase, i.e. $dr/dt > 0$ and $dE/dt > 0$, stock price movements depend on the signs of $(dE/dt)/(E+C) - (dr/dt)/(1+r)$. If $(dE/dt)/(E+C) - (dr/dt)/(1+r) > 0$, that is, the positive effect of the rising expected income is greater than the negative effect of the rising interest rate, then the stock price would increase. Otherwise, the stock price would decline. This situation often occurs in expansion phase of the business cycle. Fourth, when both the interest rate and the expected income decrease, i.e. $dr/dt < 0$ and $dE/dt < 0$, stock price movements also rely on the signs of $(dE/dt)/(E+C) - (dr/dt)/(1+r)$. If $(dE/dt)/(E+C) - (dr/dt)/(1+r) < 0$, then the stock price would increase. Otherwise, the stock price would decrease. This situation often occurs in recession phase of the business cycle. Finally, if $(dE/dt)/(E+C) = (dr/dt)/(1+r)$, then the stock market either reaches its peak when the stock price has been rising, or the stock market reaches the bottom when the stock price has been declining.

Our theoretical model suggests that there exists a bi-directional causal relationship between the business cycle and stock market cycle, and the stock market cycle has a positive effect on the business cycle. The model also highlights the role of monetary policy (variations in interest rate) in stock market fluctuations and business cycle dynamics, which has been supported by a number of empirical studies, such as Andrés, *et al.* (2009), Canova and Menz (2011), Marfatia (2014), Babajide, *et al.* (2016), Hong, *et al.* (2018) and Arias, *et al.* (2019). Despite this, the focus of the present study is to investigate the causality between the business cycle and stock market cycle in China. Of course, such a theoretical analysis is not sufficient to convince the real nature of the causality. Moreover, the causality might be subject to considerable variations due to such changes in economic structure as those in macroeconomic policy and in the regimes involved in economic development of China. In light of this, a rigorous econometric analysis allowing us to consider possible time- variations in the causal relationship needs to be conducted.

3. Methodology

3.1 Bootstrap full-sample causality test

We employ the residual-based bootstrap *(RB)* modified-*LR* Granger causality test based on the bivariate VAR framework to examine the causal relationship between the stock market cycle and business cycle in China. The bivariate VAR (p) framework is represented as follows:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} \phi_{10} \\ \phi_{20} \end{bmatrix} + \begin{bmatrix} \phi_{11}(L) & \phi_{12}(L) \\ \phi_{21}(L) & \phi_{22}(L) \end{bmatrix} \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}. \tag{5}$$

where $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})$ is a zero-mean independent white noise process with nonsingular covariance matrix $\sum$. The Schwarz Information Criteria (SIC) is used to determine the optimal lag length p, where y_{1t} and y_{2t} indicate the cyclical fluctuation components of the stock market and GDP of China, respectively, and where $\phi_{ij}(L) = \sum_{k=1}^{p+1} \phi_{ij} L^k$, ($i, j$ = 1, 2, ..., p) and L is the lag operator defined as $L^k x_t = x_{t-k}$. The null hypothesis that the stock market cycle does not Granger cause the business cycle is tested by imposing the restriction, $\phi_{12,k} = 0$ for k = 1, 2, ..., p. Analogously, the null hypothesis that the business cycle does not Granger cause the stock market cycle is tested by imposing the restriction, $\phi_{21,k} = 0$ for k = 1, 2, ..., p.

3.2 Parameter stability test

The full-sample causality test usually assumes that parameters are constant over time. However, in the presence of structural changes, the assumption may be violated. Hence, the results obtained from the full-sample causality test will accordingly be invalid. Granger (1996) stresses that the most challenging issue faced by many empirical studies is parameter non-constancy.

To check for the stability of parameters in the VAR model, this paper conducts the *Sup-F, Mean-F* and *Exp-F* tests developed by Andrews (1993) and by Andrews and Ploberger (1994). Specifically, the *Sup-F* test is under the null hypothesis of parameter constancy against a one-time break in the parameters, while the *Mean-F* and *Exp-F* tests are under the null hypothesis that the parameters follow a martingale process against the possibility that the parameters might evolve gradually. All these tests are calculated from the sequence of *LR* statistics. In particular, considering that they do not follow standard asymptotic distributions, Andrews (1993) and Andrews and Ploberger (1994) report critical values and p-values using the parametric bootstrap procedure.

3.3 Sub-sample rolling-window causality test

We use the sub-sample rolling-window causality test to overcome the parameter non-constancy and avoid pre-test bias. Note that when conducting the rolling-window technique, a rolling window including *l* observations should be given in advance. In doing so, the full-sample is converted to a sequence of *T-l* sub-samples rolling sequentially from the beginning to the end of the full sample, that is, τ-l+1, τ-l, ..., T for $\tau = l$, l+1, ..., T. We then apply the *RB*-based modified-*LR* causality test to each sub-sample. By calculating the bootstrap *p*-values of observed *LR* statistics rolling through *T- l* sub-samples, possible structural changes in the causal links are intuitively observed. The impact of the business cycle on the stock market cycle is defined as the average of the entire bootstrap estimates derived from $N_b^{-1}\sum_{k-1}^{p}\hat{\phi}_{21,k}^{*}$, with N_b representing the number of bootstrap repetitions; in a similar manner, the impact of the stock market cycle on the business cycle is calculated from $N_b^{-1}\sum_{k-1}^{p}\hat{\phi}_{12,k}^{*}$. Both $\hat{\phi}_{21,k}^{*}$ and $\hat{\phi}_{12,k}^{*}$ are bootstrap estimates from the VAR models. Following Balcilar, *et al*. (2010), the 90% confidence intervals are also computed, where the lower and upper limits equal the 5th and 95th quantiles of $\hat{\phi}_{21,k}^{*}$ and $\hat{\phi}_{12,k}^{*}$, respectively.

The increment interval of each regression and the window size *l* are the key parameters to determine the accuracy and performance of rolling window estimation. Pesaran and Timmerman (2005) suggest that if there are frequent breaks in underlying series, then the window size can be as low as twenty. Although there has been no inconsistent criterion to choose the optimal window size, two conflicting demands may help us. A large window size will improve the precision of estimates but may reduce the representativeness of parameters, particularly in the presence of heterogeneity. The small window size is just the opposite. Consequently, considering the trade-off between accuracy and representativeness, we choose a relatively small window size of 24 quarters and use the bootstrap technique in the rolling estimation for better precision.

4. Data

We first obtain the quarterly data of the stock price and GDP. The Shanghai stock exchange composite index is the proxy of the stock price of China, which is obtained from the *Wind* database of China. GDP measures the output and is obtained from the National Bureau of Statistics of China. Second, all the original data are transformed into natural logarithms so as to correct for potential heteroscedasticity and dimensional difference between series and have also been seasonally adjusted. Third, we obtain cyclical components of stock price and GDP by de-trending the data using the H-P filter technique. In fact, the cyclical component of GDP as a typical representative for the business cycle originates from many empirical research studies that approve its ability to reasonably reflect the economic fluctuations (for example, Galí, 2011). In what follows, the stock market cycle is denoted as *sto-cyc*, and the business cycle is denoted as *bus-cyc*. The sample period of this paper spans from 1992Q1 to 2016Q3, which can sufficiently cover the ups and downs of the real economy and the remarkable volatilities in the Chinese stock market.

Figure 1 shows the time-series plot of the cyclical fluctuations in GDP and stock price in China. As seen, the business cycle and stock market cycle are closely correlated across the sample period. For some sub-periods, for instance, 1999-2004 and 2007-2008, we can observe that they are positively correlated. However, for the sub-periods 2004 to 2006 and 2014 to 2015, they appear to be negatively correlated. Likewise, we also note that the lead-lag relationship between the business cycle and stock market cycle evolves with time. These intuitive findings affirm our confidence in using the rolling-window sub-sample causality test that takes the time-variations into account when examining the causal linkage between the business cycle and stock market cycle in China.

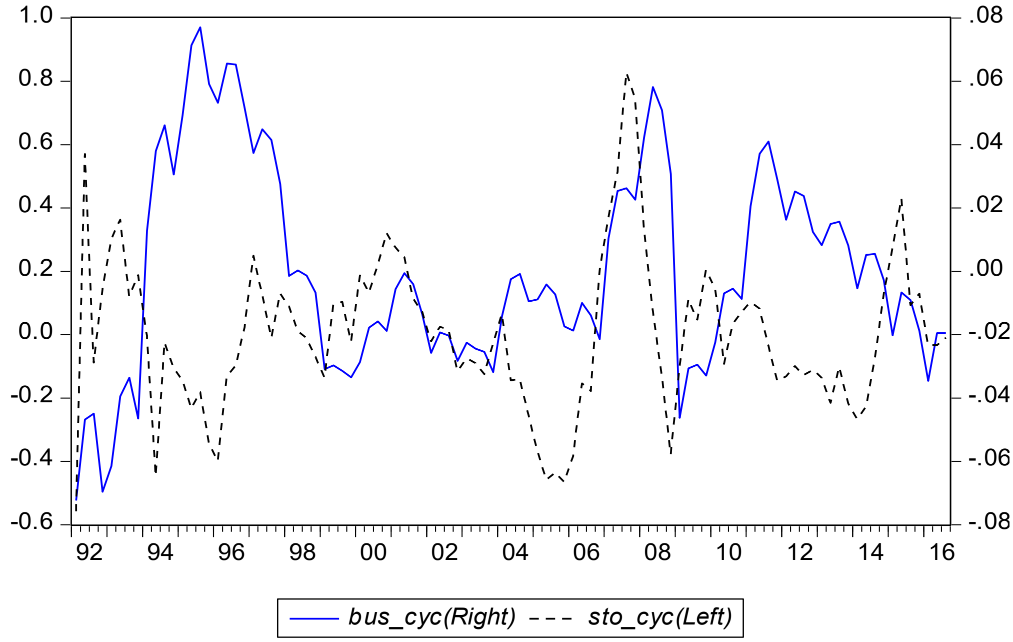

Figure 1. The time-series plot of the cyclical fluctuations in GDP and stock prices of China

Figures 2-3 depict the business cycles and stock market cycles turning points identified based on the GDP and stock price series by using the modified BBQ algorithm[2]. The BBQ algorithm is a classical method for periodic division. Note that we use the monthly stock prices instead of the quarterly data to estimate the stock market cycle turning points. That's because that more detailed information with respect to stock price variations that are masked by the quarterly data can be well identified by the monthly data. As shown in Figure 2 on page 42, China has experienced six full business cycles (trough to trough) across the sample period, with frequencies from 8 to 28 quarters. In the second cycle, the 1997 Asian financial crisis led to a long recession lasting for 17 quarters, i.e., from 1996Q1 to 2000Q1. Owing to the onset of the recent global financial crisis and the deepening of its effects on China's economy, the fifth cycle has the shortest duration of 9 quarters (from 2007Q2 to 2009Q2). During this cycle, the expansion culminated in 2008 Q3 (the peak), and the recession only lasted for 3 quarters. The latest cycle can be detected between 2009Q3 and 2016Q2, and has the longest duration of 28 quarters (7 years). Within this cycle, the peak was reached in the fourth quarter of 2011, and then the recession which lasted for 18 quarters starts. Hereafter, China's economy rebounded in the second quarter of 2016, and starts a recovery.

In Figure 3, we can observe that the stock market cycle has a much higher frequency than the business cycle. The shortest bull-bear cycle lasted for less than 2 quarters, while the longest cycle lasted for 12 quarters (3 years). In particular, before the 1997 Asian financial crisis, a bull market

[2] In this paper, the recession (expansion) is defined by two consecutive quarterly or five consecutive monthly declines (increases) in GDP or stock price, respectively. The trough of business cycle/stock market cycle is considered to be the ending of the recession, where is the starting point of expansion at the same time. The code for the modified BBQ (MBBQ) algorithm was written by James Engel and is available at http://www.ncer.edu.au/data/data.jsp.

lasting for 5 quarters can be detected. However, with the onset of the crisis, the stock market crashed since the second quarter of 1997. Similarly, a long-lasting bull-bear market cycle, which lasted for 28 quarters, can also be identified before and after the recent global financial crisis. During this cycle, the peak was reached in the fourth quarter of 2007, and then the severe crash reoccurred. The latest stock market collapse began with the popping of the stock market bubble at the end of the second quarter of 2015, and lasted for about 2 quarters. Hereafter, China's stock market began a recovery starting with the second quarter of 2016.

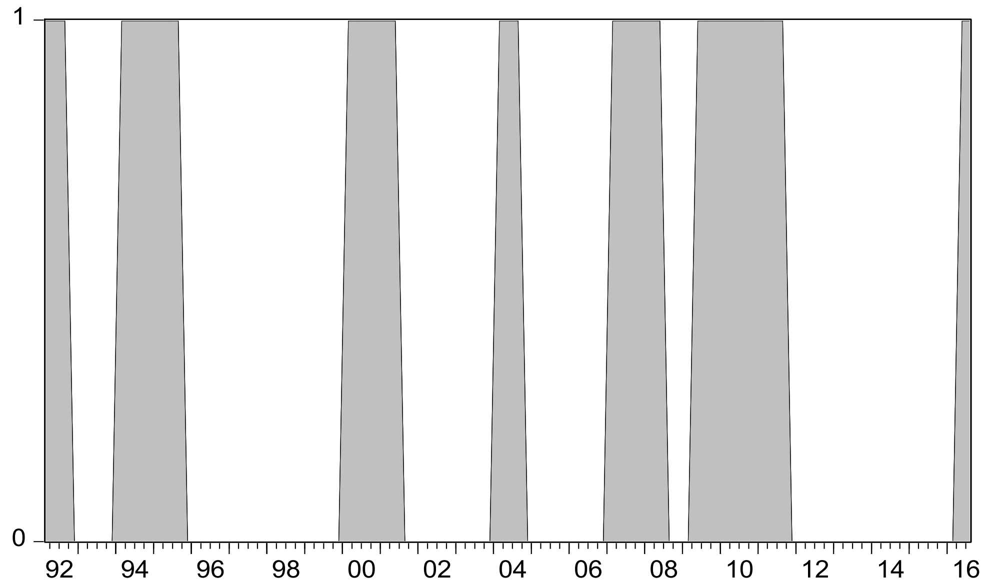

Figure 2. The business cycle turning points of China between 1992Q1:2016Q3
Note: Expansions are shaded in light grey.

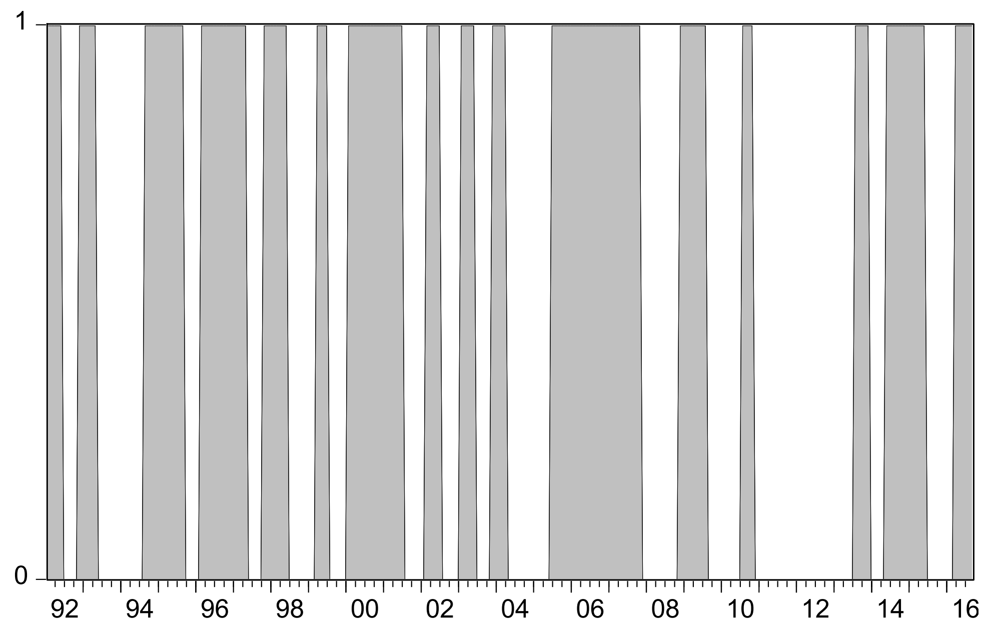

Figure 3. The stock market cycle turning points of China between 1992Q1:2016Q3
Note: Expansions are shaded in light grey.

5. Empirical Results

We first test for stationarity of the underlying data using the ADF test developed by Dickey and Fuller (1981), and the MZ_a test proposed by Phillips and Perron (1988). The results of these tests are reported in Table 1(A) and 1(B).

Table 1(A). Augmented Dickey-Fuller (ADF) unit root test results

Series	**Constant** [a]	***p*-value**	**None** [b]	***p*-value**
sto-cyc	-2.913**	0.048	-2.934***	0.004
bus-cyc	-4.136***	0.001	-4.134***	0.000

Notes: *** and ** indicate significance at the 1% and 5% levels, respectively.

[a] This is a one-sided test with the null hypothesis that a unit root exists; The 1% and 5% significance critical values are -3.499 and -2.892, respectively.

[b] This is a one-sided test with the null hypothesis that a unit root exists; The 1% and 5% critical values are -2.590 and -1.944, respectively.

Table 1(B). Phillip-Perron unit root test results

Series	**Constant** [a]	***p*-value**	**None** [b]	***p*-value**
sto-cyc	-5.262***	0.000	-5.281***	0.000
bus-cyc	-3.106**	0.029	-3.117***	0.002

Notes: *** and ** indicate significance at the 1% and 5% levels, respectively.

[a] This is a one-sided test with null hypothesis that the series is stationary; The 1% and 5% significance critical values are -3.498 and -2.891, respectively.

[b] This is a one-sided test with null hypothesis that the series is stationary; The 1% and 5% significance critical values are -2.589 and -1.944, respectively.

As seen, the ADF test statistics reject the null hypothesis of nonstationarity for all series at the original levels. The MZ_a tests are also able to reject the null hypothesis of nonstationarity for all series at the original levels. That is, the two tests both suggest that the *sto-cyc* and *bus-cyc* series are stationary processes.

Next, we construct the bivariate VAR model as equation (5). The optimal lag-length based on SIC is 1. After conducting the *RB* based modified-*LR* full-sample causality test, we report the corresponding results in Table 2. We observe that the null hypotheses that *bus-cyc* does not Granger cause *sto-cyc* fail to reject at the 10% significance level while the null hypotheses *sto-cyc* does not Granger cause *bus-cyc* can be rejected at the 10% level. This means that there exists a unidirectional causality from the stock market cycle to business cycle in China. Obviously, this result is inconsistent with our theoretical model and the previous literature (e.g., Fama, 1990; Luintel and Khan, 1999; Muhammad and Rasheed, 2002; Singh, 2010), which suggests there is bidirectional causality between the stock market and real economy. This conflict may be related to the data examined and the methodology used as well as the effects of structural changes.

To confirm the validity of our full-sample results, we subsequently conduct the *Sup-F, Mean-F* and *Exp-F* tests and the *Lc* test to check for the parameters stability in the bivariate VAR model formed by the full-sample data. The corresponding results are reported in Table 3. The results show that all the three tests can be rejected at less than the 5 percent level of significance in the *sto-cyc* equation and the VAR(1) system. Meanwhile, for the *bus-cyc* equation, the *Sup-F* and *Exp-F* tests can be rejected at less than the 10 percent level of significance. This indicates that the parameters of the VAR model comprising full-sample data are unstable due to the existence of structural changes, and hence, the results of the full-sample causality test are unreliable.

Table 2. Full-sample Granger causality tests

Tests	H_0: *bus-cyc* does no Granger cause *sto-cyc*		H_0: *sto-cyc* does not Granger cause *bus-cyc*	
	Statistics	***p*-value**	**Statistics**	***p*-value**
Bootstrap *LR* Test	5.942^{**}	0.018	2.811	0.104

Notes: We calculate p-values using 2,000 bootstrap repetitions. ** indicates significance at the 5% level.

Table 3. Parameter stability tests

Tests	*sto-cyc* Equation		*bus-cyc* Equation		VAR(1) System	
	Statistics	Bootstrap *p*-value	Statistics	Bootstrap *p*-value	Statistics	Bootstrap *p*-value
Sup-F	41.201^{***}	0.000	18.544^{**}	0.044	38.251^{***}	0.001
Mean-F	13.889^{***}	0.001	6.471	0.207	20.301^{***}	0.003
Exp-F	16.652^{***}	0.000	5.886^{*}	0.057	15.568^{***}	0.000

Notes: We calculate *p*-values using 2,000 bootstrap repetitions. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

As a consequence, we employ the rolling-window approach and the *RB* based modified-*LR* causality test to re-examine the causality between the stock market cycle and business cycle in China. Concretely, we estimate not only the bootstrap *p*-values of *LR*-statistics, but also the magnitude of the stock market cycle on the business cycle and that of the business cycle on the stock market cycle using the rolling sub-sample data comprising 24-quarter observations[3]. All these rolling estimates are reported in Figures 4 and 5. Note that after trimming 24-quarter observations from the beginning of the full sample, the rolling estimates move from 1998Q1 to 2016Q3.

Figure 4(A) presents the rolling bootstrap p-values of the *LR*-statistic with the null hypothesis that *sto-cyc* does not Granger cause *bus-cyc*. We pay more attention to the *p*-values lower than 0.1 (the part below the red line). As seen, the null hypothesis can be rejected at the 10 percent significance level over the sub-periods 2004Q2 to 2006Q4 and 2013Q3 to 2014Q4. Figure 4(B) shows the rolling estimates of the magnitude of the effect of *sto-cyc* on *bus-cyc*.

[3] Although an interpretation for the selection of the 24-quarter window size has been mentioned earlier, we still implemented different bootstrap rolling-window causality tests using 20- and 28-quarter window sizes and estimated the magnitude of the effect of the business cycle on the stock market cycle and that of the stock market cycle on the business cycle. The results are proved rather similar to those from the causality test based on the 24-quarter window size, which further indicates that the results based on the 24-quarter window size are robust. Specifically, the details of these results are available upon request.

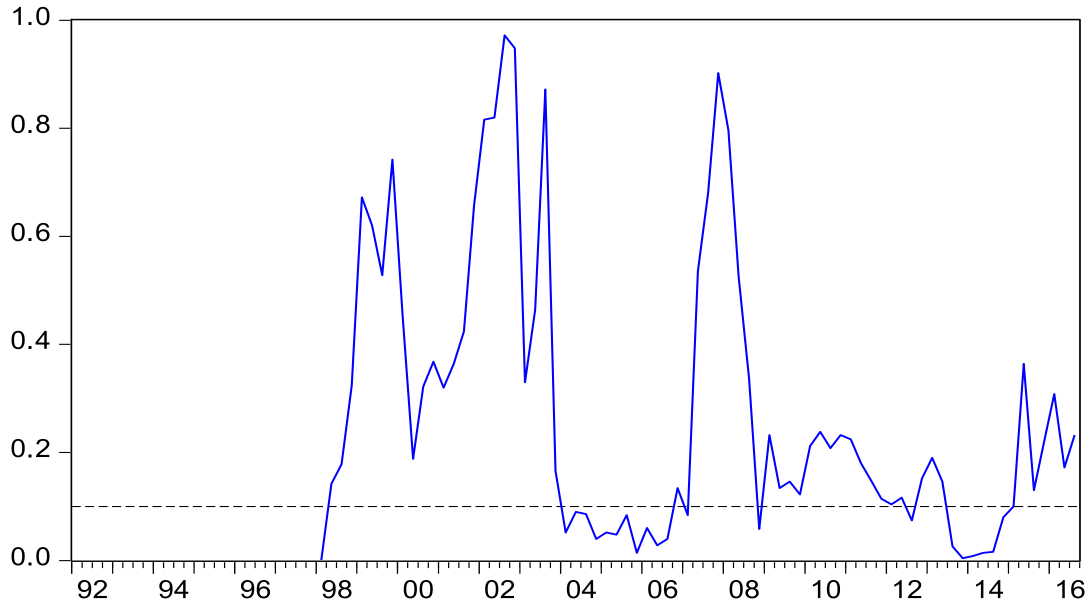

Figure 4(A). Bootstrap p-values testing the null hypothesis that *sto-cyc* does not Granger cause *bus-cyc*

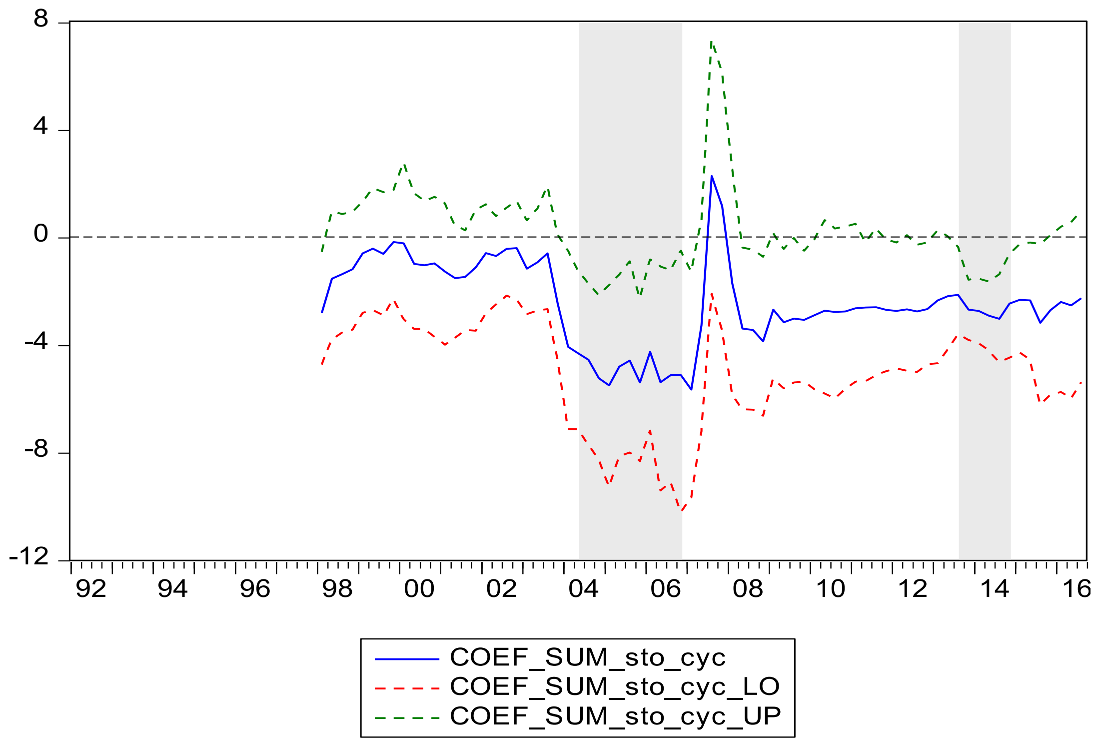

Figure 4(B). Bootstrap estimates for the sum of the rolling coefficients for the impact of *sto-cyc* on *bus-cyc*

Figure 5(A) on page 46 shows the rolling bootstrap p-values of *LR*-statistics estimated using sub- samples data testing the null hypothesis that *bus-cyc* does not Granger cause *sto-cyc*. We also pay more attention to the *p*-values lower than 0.1 (the part below the red line). Clearly, we can find that there exists causality from the business cycle to the stock market cycle over the sub-periods 2002Q3- 2004Q2 and 2008Q3-2014Q4 for China.

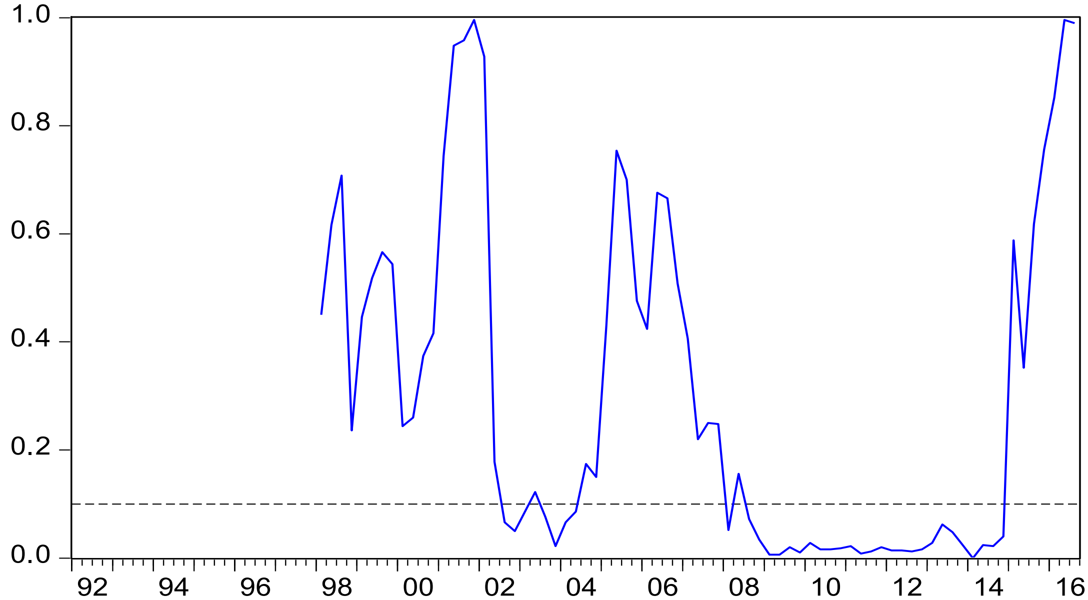

Figure 5(A). Bootstrap p-values testing the null hypothesis that *bus-cyc* does not Granger cause *sto-cyc*

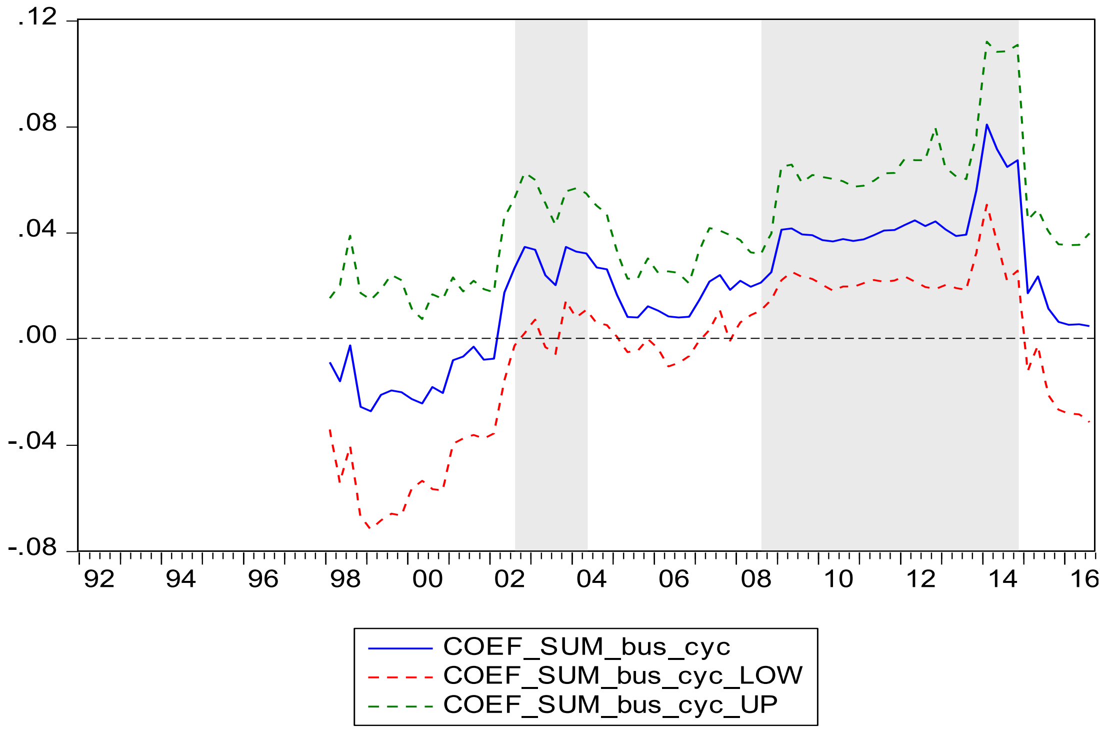

Figure 5(B). Bootstrap estimates for the sum of the rolling coefficients for the impact of *bus-cyc* on *sto-cyc*

Figure 5(B) shows the bootstrap estimates of the sum of the rolling-window coefficients for the impact of *bus-cyc* on *sto-cyc*. As is seen, the business cycle has a significant positive impact on the stock market cycle during those sub-periods. The intuition behind the positive effect is that when the economic downturn occurs, the future cash flow and discount rate will cause massive uncertainties, which will result in sharp fluctuations in the stock market; otherwise, when the economy enters into recovery, the government tends to promote a bull market in order to stimulate the economic growth. This fits well the facts of China. During the sub-period 2002Q3 to 2004Q2, China witnessed a significant economic slowdown. At the same time, the stock market was trapped in a prolonged bear market. For the sub-period 2008Q3 to 2014Q4, the real economy underwent a business cycle from expansion to recession, while the stock market showed the opposite. Our finding also confirms that the causality from the business cycle to the stock market cycle in China is time-varying. In addition, this is obviously quite different from the result of the full-sample causality test that suggests no causality from the business cycle to the stock market cycle in China and the conclusions drawn from the existing literature that argues the causality from economic growth to stock market development is stable across the sample period (for example, Binswanger, 2000; Odhiambo, 2009). Finally, compared to the weak effect of the stock market cycle, the business cycle has a much stronger effect on the stock market cycle, reflecting the important role of economic fundamentals in explaining the stock market fluctuations in China. This finding is greatly consistent with DeStefano (2004), Odhiambo (2009) and Zhu and Zhu (2014) who also find that business cycles help to predict stock market developments. Though our theoretical analysis and recent empirical studies highlight the role of monetary policy in stock market fluctuations (for example, Marfatia, 2014; Babajide, *et al.*, 2016; Hong, *et al.*, 2018), the present study provides a direct line linking stock market cycle formation and development to business cycle dynamics.

6. Conclusion

The aim of this paper is to shed light on the causal relationship between the stock market cycle and business cycle in China. The data cover the period from 1992Q1 to 2016Q3. We employ both the bootstrap full-sample Granger causality test and the bootstrap rolling-window sub-sample causality test. The bootstrap full-sample causality test suggests that there exists unidirectional full-sample causality from the stock market cycle to the business cycle in China. Then, considering structural changes in the underlying data, we conduct a parameter stability test and find that the parameters in the VAR models comprising our full-sample data are unstable. Therefore, the bootstrap rolling-window sub-sample causality test is well advised.

Using a 24-quarter rolling window size, we find that the causality between the stock market cycle and business cycle does exhibit substantial time variations in China. Specifically, there is a negative causality from the stock market cycle to the business cycle during two sub-periods, 2004Q2-2006Q4 and 2013Q3-2014Q4, and a positive causality from the business cycle to stock market cycle over the other two sub-periods, 2002Q3- 2004Q2 and 2008Q3-2014Q4. Moreover, the effect of the stock market cycle on the business cycle is weaker than that of the business cycle on the stock market cycle. This implies that stock market volatility is not the main factor driving the business cycle dynamics; conversely, business cycle dynamics can exert a larger impact on the formation and development of stock market cycle in China. These findings conflict with the results of the full-sample causality test, but fits well with DeStefano (2004) and Zhu and Zhu (2014) who also presented that business cycles help to predict stock market developments.

Our findings have important implications for policymakers and investors in China. First, based on the above conclusions, stock market participants should take the time-varying nature in the causal relationship between the business cycle and stock market cycle into consideration and predict the volatility of the stock market through analysis of economic conditions, so as to rationally plan their own investment decisions and reduce risk losses. Second, a stock market boom seems unlikely to stimulate economic growth at least in the near term, although the Chinese government hopes it would. To enhance the importance of the stock market to economic growth, the Chinese government should reduce its control or intervention and develop a stock market that operates in accordance with market rules and favors a better allocation of resources. Third, owing to the relatively strong effect of the business cycle on the stock market cycle, maintaining stable economic growth can be helpful for restoring the confidence of investors and reinvigorating the current stock market of China.

The above conclusions appear to be robust. However, our analysis is studied with bivariate variables. In fact, the causal relationship between the stock market cycle and business cycle may be affected by other economic variables. A number of interesting studies have found that there is an increasing connection of domestic stock markets with global financial market conditions, such as stock market volatilities of other integrated economies (Graham, *et al*., 2012; Marfatia, 2017; Zhang, *et al*., 2014), exchange rates (Chkili, *et al.*, 2014) and investor sentiment (Ni, *et al*., 2015). In light of the empirical evidence, in future research we may further study the causal relationship between the stock market cycle and business cycle by including the global financial market connections to enhance the persuasiveness of the paper. In the mean time, a limitation of this research is that it only focuses on China and lacks an international comparison. Hence, further research may investigate the causal relationship between the stock market cycle and business cycle from an international perspective in order to determine whether there exists a general law in the interaction of the stock market cycle and business cycle.

References

[1] Andrés, J., López-Salido, J. D., & Nelson, E. (2009). "Money and the natural rate of interest: structural estimates for the united states and the euro area", *Journal of Economic Dynamics and Control*, 33(3): 758-776.

[2] Andrews, D. W. (1993). "Tests for parameter instability and structural change with unknown change point", *Econometrica*, 61(4): 821-856.

[3] Andrews, D. W., & Ploberger, W. (1994). "Optimal tests when a nuisance parameter is present only under the alternative", *Econometrica*, 62(6): 1383-1414.

[4] Arias, J. E., Caldara, D., & Rubio-Ramírez, J. F. (2019). "The systematic component of monetary policy in SVARs: an agnostic identification procedure", *Journal of Monetary Economics*, 101 (January): 1-13.

[5] Babajide, A., Isola, L., & Somoye, R. O. (2016). "Stock market response to economic growth and interest rate volatility: Evidence from Nigeria", *International Journal of Economics and Financial Issues*, 6(1): 354-360.

[6] Balcilar, M., Ozdemir Z., & Arslanturk Y. (2010). "Economic growth and energy consumption causal nexus viewed through a bootstrap rolling window", *Energy Economics*, 32(6): 1398-1410.

[7] Binswanger, M. (2000). "Does the stock market still lead real activity?--an investigation for the G-7 countries", *Financial Markets & Portfolio Management*, 15(15): 15-29.

[8] Bloom N. (2009). "The impact of uncertainty shocks", *Econometrica*, 77(3): 623-685.

[9] Bloom, N., Floetotto, M., Jaimovich, N., Saporta, E. I., & Terry, S. (2012). "Really uncertain business cycles", *NBER Working Papers*, 41(4): 8-18.

[10] Canova, F., & Menz, T. (2011). "Does money matter in shaping domestic business cycles? An international investigation", *Journal of Money, Credit and Banking*, 43(4): 577-607.

[11] Carlston, B. (2018). "Can stock market liquidity and volatility predict business cycles?", *Studies in Economics and Finance*, 35(1): 81-96.

[12] Chen, S. S. (2009). "Predicting the bear stock market: macroeconomic variables as leading indicators", *Journal of Banking & Finance*, 33(2): 211-223.

[13] Chkili, W., & Nguyen, D. K. (2014). "Exchange rate movements and stock market returns in a regime-switching environment: Evidence for BRICS countries", *Research in International Business and Finance*, 31(May): 46-56.

[14] Choudhry, T., Papadimitriou, F. I., & Shabi, S. (2016). "Stock market volatility and business cycle: evidence from linear and nonlinear causality tests", *Journal of Banking & Finance*, 66 (May): 89-101.

[15] Cochran, S. J., & DeFina, R. H. (1995). "Duration dependence in the U.S. stock market cycle: A parametric approach", *Applied Financial Economics*, 5(5): 309-318.

[16] DeStefano, M. (2004). "Stock Returns and the Business Cycle". *The Financial Review*, 39 (4): 527-547.

[17] Dickey, D. A., & Fuller, W. A. (1981). "Likelihood ratio statistics for autoregressive time series with a unit root", *Econometrica*, 49(4): 1057-1072.

[18] Emilios, G., & Evangelos, G. (2015). "On the stock market liquidity and the business cycle: a multi-country approach", *International Review of Financial Analysis*, 38 (March): 44-69.

[19] Fama E. F. (1990). "Stock returns, expected returns, and real activity", *Journal of Finance*, 45(4): 1089-1108.

[20] Galí, J. (2011). "On the role of technology shocks as a source of business cycles: some new evidence", *Journal of the European Economic Association*, 2(2-3): 372-380.

[21] Gordon, M. J. (1963). "Optimal investment and financing policy", *The Journal of Finance*, 18(2): 264-272.

[22] Graham, M., Kiviaho, J., & Nikkinen, J. (2012). "Integration of 22 emerging stock markets: a three-dimensional analysis", *Global Finance Journal*, 23(1): 34-47.

[23] Granger, C. W. (1996). "Can we improve the perceived quality of economic forecasts?", *Journal of Applied Econometrics*, 11(5): 455-473.

[24] Harman, Y. S., & Zuehlke, T. W. (2007). "Nonlinear duration dependence in stock market cycles", *Review of Financial Economics*, 16(4): 350-362.

[25] Harris, R. D. F. (1997). "Stock markets and development: a re-assessment", *European Economic Review*, 41(1): 139-146.

[26] Hong, H., Chen, N., O'Brien, F., & Ryan, J. (2018). "Stock return predictability and model instability: Evidence from mainland China and Hong Kong", *The Quarterly Review of Economics and Finance*, 68 (May): 132-142.

[27] Kim, M. K., & Zumwalt, J. K. (1979). "An analysis of risk in bull and bear markets", *Journal of Financial & Quantitative Analysis*, 14(5): 1015-1025.

[28] Luintel, K., & Khan, M. (1999). "A quantitative reassessment of the finance-growth nexus: evidence from a multivariate VAR", *Journal of Development Economics*, 60(2): 381-405.

[29] Lunde, A., & Timmermann, A. (2004). "Duration dependence in stock prices: an analysis of bull and bear markets", *Journal of Business & Economic Statistics*, 22(3): 253-273.

[30] Marfatia, H. A. (2014). "Impact of uncertainty on high frequency response of the US stock markets to the Fed's policy surprises", *The Quarterly Review of Economics and Finance*, 54(3): 382-392.

[31] Marfatia, H. A. (2017). “A fresh look at integration of risks in the international stock markets: A wavelet approach”, *Review of Financial Economics*, 34(1): 33-49.

[32] Miao, J. J., Wang, P. F., & Xu, W. F. (2015). “A Bayesian dynamic stochastic general equilibrium model of stock market bubbles and business cycles”, *Quantitative Economics*, 6(3): 599-635.

[33] Muhammad, N., Rasheed, A., & Husain, F. (2002). “Stock prices and exchange rates: are they related? Evidence from south Asian countries”, *Pakistan Development Review*, 41(4): 535-550.

[34] Næs, R. , Skjeltorp, J. A. , & Ødegaard, B. A. . (2011). “Stock market liquidity and the business cycle,” *The Journal of Finance*, 66(1): 139-176.

[35] Ni, Z. X., Wang, D. Z., & Xue, W. J. (2015). “Investor sentiment and its nonlinear effect on stock returns—new evidence from the Chinese stock market based on panel quantile regression model”, *Economic Modelling*, 50 (November): 266-274.

[36] Odhiambo, N. M. (2009). “Electricity consumption and economic growth in South Africa: a trivariate causality test”, *Energy Economics*, 31(5): 635-640.

[37] Pagan, A. R., & Sossounov, K. A. (2003). “A simple framework for analyzing bull and bear markets”, *Journal of Applied Econometrics*, 18(1): 23-46.

[38] Paul, B., & Franck, P. (2006). “Stock prices, news, and economic fluctuations”, *American Economic Review*, 96(4): 1293-1307.

[39] Pesaran, M., & Timmermann, A. (2005). “Small sample properties of forecasts from autoregressive models under structural breaks”, *Journal of Econometrics*, 129(1-2), 183-217.

[40] Phillips, P. C., & Perron, P. (1988). “Testing for a unit root in time series regression”, *Biometrika*, 75(2): 335-346.

[41] Prabheesh, K. P., & Vidya, C. T. (2018). “Do business cycles, investment-specific technology shocks matter for stock returns?”, *Economic Modelling*, 70 (April): 511-524.

[42] Singh, D. (2010). “Causal relationship between macro-economic variables and stock market: a case study for India”, *Pakistan Journal of Social Sciences*, 30(2): 263-274.

[43] Williams, J. B. (1938). *The Theory of Investment Value*. Cambridge, MA: Harvard University Press.

[44] Wu, Y., John, G. P., Jing S., & Wei X. (2007). “Chinese stock market cyclical regimes: 1991-2006”, Economics Letters, 97(3), 235-239.

[45] Zhang, B., & Li, X. M. (2014). “Has there been any change in the co-movement between the Chinese and US stock markets?”, *International Review of Economics & Finance*, 29 (January): 525-536.

[46] Zhu, Y., & Zhu, X. (2014). “European business cycles and stock return predictability”, *Finance Research Letters*, 11(4): 446-453.