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The Casual Relationship between China's Financial Stress and Economic Policy Uncertainty: A Bootstrap Rolling-Window Approach

Xin Li[1], Rundong Zhang[2*], Jin Wang[1]

[1]Department of Finance, Ocean University of China, Qingdao, China
[2]Information Technology Company, Jiangsu Port Group, Nanjing, China
Email: lixin9462@stu.ouc.edu.cn, *zhangrundong@portjs.cn, wangjin123321123@163.com

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Abstract

This study explores the causal relationship between China's financial stress and economic policy uncertainty. Considering structural changes in two series, we find that long-run nexus using full-sample data are unstable, suggesting that causality tests cannot be relied upon. Then, we employ a time-varying rolling window estimation to re-examine the dynamic causalities. The empirical results show that financial stress has both positive and negative impacts on economic policy uncertainty in several sub-periods, meanwhile, economic policy uncertainty has the same effects on financial stress in China, which illustrates that the time-varying causality exists between two variables. These findings indicate that the government should make the formulation of macroeconomic policies stable and strengthen the supervision of financial markets, including the guidance of the public reasonable expectations, which are critical to the economic development in China.

Keywords

Financial Stress, Economic Policy Uncertainty, Time-Varying Causality, Rolling Window

1. Introduction

Economic policy uncertainty (EPU) and financial risk have been the most important issues in economics and finance recently. Financial risk management is difficult at the best of times, especially in times of economic policy uncertainty

[1]. Sum (2012) also indicates that financial stress (FS) and EPU play an important role in the economic growth and recovery of the overall economy [2]. Corporations, consumers, and financial institutions become highly reluctant to make any investment, spending, and lending decision when a high level of FS is observed in the economy [3]. The reason why making those decisions is that the credit costs for economic entities will increase significantly during the situation of financial instability. In addition, when the macro-economy appears to become more uncertain, economic entities are more likely to suspend their investment projects, and to decrease their production capacity, they would reduce personnel scale and stop employing new employees as well. When investors and consumers are exposed to a higher degree of EPU, their willing of investment and consumption will be discouraged [4]. Unavoidably, the delay in investment and consumption might have a negative impact on economic recovery and growth [5].

Moreover, EPU is also highly correlated with the cost of finance; the higher cost of finance is negatively associated with firms' capital expenditure and investments [6]. A range of studies notes that there exists a negative relationship between investment and consumption (e.g. [7] [8]). Although FS and EPU play important roles in explaining economic growth and recovery, there is very limited literature examining the relationship between these two variables. Regarding to this, this paper aims to complement previous studies, to examine whether the inherent relationship exists between EPU and FS.

China has been the world's second largest economy since 2010, with an average annual economic growth rate of 9.6 percent during 2006-2015. Actually, the performance of China's economy, as well as government policy conditions and financial market development, has never been more associated with the global economic system than it is nowadays. However, Chinese economy is facing structural reformation, and the speed of economic growth rate has been slow down due to this giant economy is stepping into the deep water of the reform and opening up. Two direct reasons are the increasing policy uncertainty and lack of adequate economic reforms since 2006. In other words, the blurry direction of the economic policy has roiled the development of Chinese financial markets over the past years. More recently, Chinese stock market experienced great volatility and Shanghai Securities Composite Index is nearly halved in 2015. The outbreak of the stock market crisis has a severe impact on Chinese financial market. The implement of Circuit Breaker in 2016 aggravates the financial market fluctuations.

By using the economic policy uncertainty index (or financial stress index), a wide range of researches detect the relationship between EPU (or FS) and economic activities [9]-[18]. For example, Cevik *et al.* (2013) utilize a Vector auto-regression (VAR) model to investigate the nexus between FS and economic activities among five European countries and confirm that there is a significant linkage between FS and economic activities [13]. Reboredo and Uddin (2016) apply a quantile regression approach to investigate the impact of FS and policy uncertainty on the energy and metals markets [14]. Their empirical results show that financial stress has a better interpretation for commodity return than policy uncertainty. Moveover, Aboura and Roye (2017) firstly develop French financial stress index and then detect FS and economic dynamics in France, revealing that lower economic activity are linked with significantly high financial stress [15]. Therefore, they suggest that financial stress index can work as an indicator of measuring the stability of the French financial market. In term of the relationship between EPU and economic and financial activities, Dakhlaoui and Aloui (2016) apply a rolling approach to investigate the interactive nexus between the volatility of BRIC stock market and EPU, and they notice that a time-varying relationship exists between them and this correlation tends to be highly volatile during global economic recession [16]. Based on the DCC-MIDAS model, Fang *et al.* (2017) propose that EPU has a positive effect on the crude oil and the U.S. stock market in the long-term [17]. Besides, Raza *et al.* (2018) utilize nonparametric causality-in-quantiles estimation to examine whether EPU has influence on gold prices, and their findings demonstrate that EPU is able to trigger gold prices movements in all selected countries [18].

Although there exist a substantial number of studies investigating the relationship between EPU (or FS) and economic activities, only three of them have combined EPU and FS together directly. Sum (2012) applies the VAR estimation to detect the symmetric causality relationship between EPU and FS in U.S., of which empirical results indicate that EPU and FS are interactive with each other [2]. However, she concerns full-sample nexus only, and which is susceptible to misleading results and conclusion in the present of parameter instability resulting from structural changes in the relationships. Afterwards, Sun *et al.* (2017) re-examine the relationship between EPU and FS from the multi-scales perspective in U.S., and they find that the long-run trends of EPU and FS are highly correlated with each other, while the correlation of the two variables for short-run fluctuates drastically [19]. In addition, Liow *et al.* (2018) pay their attention to investigating dynamics between EPU and FS in the multi-country context and they find that EPU spillovers lead FS spillovers across seven countries [20]. Overall, the existed studies have made contributions to the research of the relationship between EPU and FS. However, this study is still necessary because only few previous studies have discovered the relationship between China's financial stress (CNFS) and EPU before. Especially in recent years, China develops rapidly and the economic development of China stands a pivotal position in the world, meaning that the economic stability and financial development in China are particularly important for the current situation. This study also provides vital information to the current literature and contributes to the further understanding of the causal relationship between FS and EPU.

The main contribution of this study to the existing literatures lies in the following parts. First of all, different from Sum's research which (2012) only considers a linear full-sample relationship between EPU and FS [2], this study considers structural changes in each variable and the time-varying effects between them. More comprehensive consideration of the non-linear impacts of EPU (FS) on changes of FS (EPU) will make the results more reliable. Specifically, this paper applies a bootstrap rolling window estimation to identify the time-varying relationship between EPU and FS, which sheds new light on the previous literature merely considering the linear transmission. To our knowledge, this paper is one of the first studies to employ a time-varying approach to analyse this subject. Second, this paper specifically investigates the dynamic nexus between EPU and FS in China context, which might have implications on financial stability and conduct of economic policies for policymakers and in turn, help to the health macroeconomic and financial development in China.

The empirical results of this paper reveal that CNFS has both positive and negative impacts on EPU in several sub-periods; meanwhile, EPU has the same effects on CNFS, which illustrates that the time-varying causality exists between two variables. Specifically, this study finds that both positive (from 2002.01 to 2002.09) and negative effects (from 2012.10 to 2012.11 and 2015.08 to 2015.09) exist between EPU to CNFS. On the other hand, CNFS has a negative impact on EPU in 2001.11-2002.12, 2010.01-2010.05 and 2011.01-2011.05, while it switches to a positive relationship in 2008.04-2008:07, 2008.09-2009.07 and 2015.07-2016.02. Moreover, it is interesting to be observed that EPU has a weak and brief influence on CNFS compared to the effects of CNFS on EPU. These findings indicate that the linear model estimations in previous literatures are not suitable to seize the actual relationship between EPU and CNFS, which therefore may lead to misunderstanding of the dynamics of two variables.

The rest of this work is organized as follows. Firstly, Section 2 discusses linkages between financial stress and economic policy uncertainty. Then, Section 3 introduces the methodology implemented in this paper. Afterwards, Section 4 describes the corresponding data. Section 5 talks about the empirical results of this research. Finally, the conclusion of this paper will be discussed in Section 6.

2. Linkages between Financial Stress and Economic Policy Uncertainty

As a typical financial risk status, financial stress or financial instability can affect economic policy through various channels. From a macro perspective, Rodrik (1991) argues that monetary policy, fiscal policy and regulatory policy uncertainty can adversely impact the macroeconomics [8]. Especially during the global economic depression period, the worldwide economies will frequently change their economic policies to treat external shocks, after that EPU would increase generously. The domestic EPU is highly likely to force authorities changing policies no matter whether they are willing to do that, containing fiscal policies, monetary policies, exchange rate policies and so on. And then, the volatility of financial market may increase due to currency supply changes, interest rates float, or the volatile stock market. If such circumstance occurs in China, the healthy development of its financial markets may be hindered.

From the microscopic point of view, when there is a high degree of uncertainty in the economy, companies are likely to delay their investment projects, and reduce their production capacity, as well as lay off existing employees, and freeze the employment of new employees [4]. When investors and consumers perceive a higher degree of EPU, they are reluctant to conduct further investment and consumption. The delay in investment and spending can have a negative impact on economic recovery and growth [5]. EPU is also highly correlated with the cost of finance; the higher cost of finance is negatively associated with firms' capital expenditure and investments [6]. As a result, it is possible to increase financial market volatilities.

From the other side, economic policy is not pre-determined but changes with economic conditions variation, and which would affect or partially shape the expectation of market participants. Furthermore, the financial stress index could provide valuable information as a heightened index helps modify economic policies to decrease the uncertainty [21]. In episodes of high financial stress, firms hesitate to invest or are reluctant to hire new workers. This effect is sometimes called the "wait-and-see effect" [4]. At the same time, the expectation and action of market participants will affect the economic variables of government policy formulation. The volatility of financial market on the macroeconomic fluctuations will in turn affect the formulation of economic policies, thus sub-market policy-oriented uncertainty lead to EPU increase.

3. Methodology

3.1. The Bootstrapping Full-Sample Causality Tests and Stability Test

To investigate the causal relationship between CNFS and EPU, we apply the two-variable Granger non-causality test based on the VAR framework here. Moreover, this paper utilizes the *RB*-based modified-*LR* approach [22] to detect the nexus between CNFS and EPU in China's context. Besides, in order to show the *RB*-based modified-*LR* causality test, the bivariate VAR (p) process is considered as follows:

$$\begin{bmatrix} CNFS_{1t} \\ EPU_{2t} \end{bmatrix} = \begin{bmatrix} \varphi_{10} \\ \varphi_{20} \end{bmatrix} + \begin{bmatrix} \varphi_{10}^{(L)} \varphi_{12}^{(L)} \\ \varphi_{21}^{(L)} \varphi_{22}^{(L)} \end{bmatrix} \begin{bmatrix} CNFS_{1t} \\ EPU_{2t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \tag{1}$$

where CNFS and EPU indicate FS and EPU, respectively. $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})'$ follows a zero mean, independent, white noise process with non-singular covariance matrix. $\phi_{ij}(L) = \sum_{k=1}^{p+1} \phi_{ij,k} L^k$, $i, j = 1,2$ and L is the lag operator ($L^k x_t = x_{t-k}$). Besides, the optimal lag length p can be determined by the Schwarz Information Criteria (SIC).

However, the underlying full sample may have structural changes. Consequently, the full-sample causality between two series tends to be unstable [23]. To overcome this problem, this paper utilizes the *Sup-F, Mean-F* and *Exp-F* tests [24] to examine the parameters' stability in the short-term, while the parameters' stability in the long-term is examined with the L_c test [25].

3.2. The Bootstrap Rolling-Window Causality Test

To overcome the parameter non-constancy in the short- and long-term and avoid pre-test biases, we follows Balcilar *et al.*(2010) to apply the sub-sample bootstrap rolling window causality estimation [26]. Setting a sub-sample rolling window with l observations, the full sample with T observations can be changed to a series of $T–l$ sub-samples, that is to say, $\tau - l + 1, \tau - l, \cdots, T$ for $\tau = l, l+1, \cdots, T$. The window size is the precision of estimations, and it controls the number of observations. Definitely, a large window size can improve the accuracy while may reduce the representativeness of heterogeneity. On the contrary, a small window size may increase the representativeness while decreasing the accuracy of estimation. In this study, we choose a window size of 24 months[1].

4. Data

The monthly data of China EPU used in this paper are obtained from the Economic Policy Uncertainty Index website [27]. Moreover, in term of the CNFS, we refer to Sun and Huang (2016) to build the latest CNFS[2] index [28], because China's government does not offer an official CNFS index. The corresponding data come from China Economic Information Network (CEIN), People's Bank of China (PBoC), and the National Bureau of Statistics (NBS). The sampling data ranges from 1995.01 to 2017.06 due to the availability of the EPU index, which includes the period of Asian financial crisis in 1997, the World Financial Crisis in 2008, and Chinese stock market's great volatility in 2015. **Figure 1** plots the CNFS and EPU change with time.

According to **Figure 1**, it clearly shows that the change of CNFS and EPU with time in China. On one hand, during the period of Asia financial crisis and subprime crisis, the FS increased extraordinarily rapidly. CNFS in these periods were much greater than the average level, and we can also notice that CNFS's extreme value in Asia financial crisis is higher than in global financial crisis. That to say, the impact of the Asian financial crisis on China's financial industry is greater than the impact of the global financial crisis on China's financial sector. The similarities between those two variables are that both CNFS and EPU decreased to the average level after the recession. In 2005, the China begun to implement a floating exchange rate system, causing huge fluctuations in the financial market, therefore, the index of CNFS fluctuated to extreme point again. Moreover, Chinese stock market experienced a great fluctuation and Shanghai Securities Composite Index fell nearly half in 2015. The outbreak of the stock

[1]We also use a lager window size of 36 and a smaller window size of 12 months to test, but find the results are changed very little.

[2]The variables employed in constructing CNFS for China include non-performing-loans ratio, deposits-to-loans ratio, exchange rates and foreign reserves, stock index. We employ equal-variance weighting to construct an overall CNFS for China's financial system.

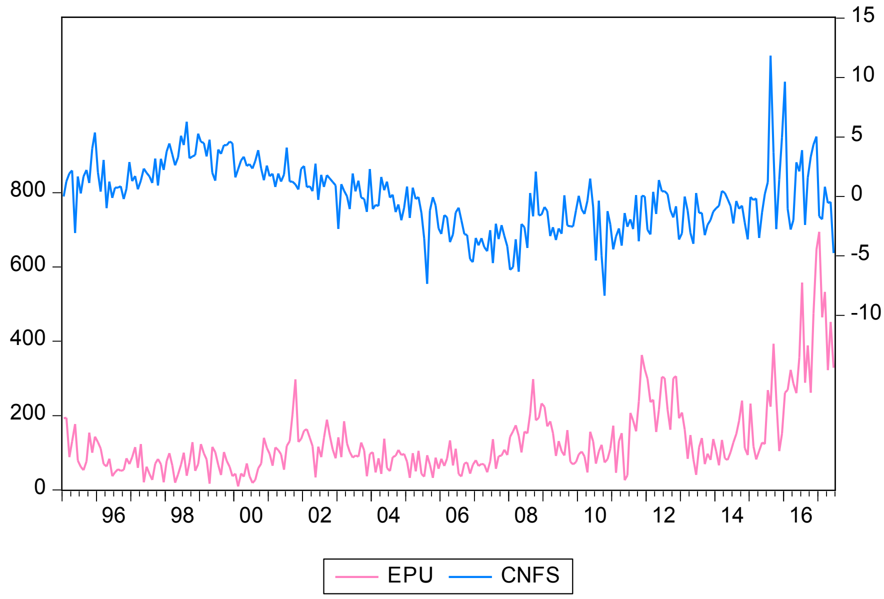

Figure 1. The comparison between CNFS and EPU.

market crisis in China has a huge impact on Chinese financial market, and in this year, the index of CNFS reached the largest extreme value in recent years, meaning that Chinese financial condition faced a larger pressure than ever. On the other hand, **Figure 1** also indicates that EPU got its extreme value in 2001.10. However, after China joining in the WTO, China's economy has integrated into the world in one piece and this important milestone-like event contributes to the increasing development of China's economy. The growth of economy climbed up year by year afterwards, and China's GDP grew steadily and its growth rate remained above 8% until the subprime mortgage crisis breaking out in 2007. According to this, the EPU decreased to the average level slowly from 2001 to 2007. In 2008, the EPU increased to nearly 300 again, which was its second extreme value. After the global crisis, the EPU decreased sharply from 2008 to 2011. However, the EPU increased again to reach its third extreme value in only 5 months after 2011.06. More recent years, it is obvious that China's EPU remained in high positions since the outbreak of the stock market crisis in 2015. In 2017.01, the EPU reached the highest point, which was around 700, the maximum in the observation period.

5. Empirical Results

Before testing the full-sample causal relationship between the two variables using the VAR model, we utilize ADF-test to examine the stationarity of the CNFS and EPU. **Table 1** shows that the ADF-Test cannot able to reject the null hypothesis of nonstationarity for two series in levels while it can reject the null hypothesis when the series are in their first differences. Overall, these results indicate that CNFS and EPU in China are nonstationary processes in levels but attain stationary in their first differences, that to say, they are $I(1)$ series.

Table 1. Univariate unit root tests (with constant).

Variable	Levels	First Differences
	ADF	ADF
CNFS	−2.245	−15.054***
EPU	−2.065	−14.053***

Note: ***indicates significance at the 1%.

In order to examine the causal relationship between CNFS and EPU, bivariate VAR models were then constructed as Equation (1). The optimal lag length selected based on SIC is 3. **Table 2** display the Granger causality results in full-sampling period, utilizing the *RB* bootstrap-based modified-*LR* causality approach. From the bootstrapping *p*-values, it is clear to notice that CNFS does Granger cause EPU, but EPU does not Granger cause CNFS. This finding is inconsistent with the existing literature [2] [19] [20] which indicate that CNFS and EPU Granger-cause each other or EPU does Granger cause FS with unidirectional. This conflict probably has to do with the data examined and the methodology used, as well as the effect of structural changes in different countries.

However, taking structural changes into account, parameters in the above VAR models estimated using full-sample data in China may tend to be time-varying. Thus, the causality test with constant parameters in the equation across the full sampling period is unreliable [29]. According to this argument, we attempt to investigate the stability of parameter and then find whether two series exist structural changes. According to Andrews and Ploberger, we utilize the *Sup-F*, *Mean-F* combined with *Exp-F* tests [24] to detect the each parameter stability in the above VAR models. Moreover, we also apply the L_c test of Nyblom (1989) here to examine for all parameters in the whole VAR system [25].

Table 3 represents the corresponding results. Specifically, the results of *Sup-F* tests are registered in the first row, suggesting that it has a one-time sharp shift in the CNFS and EPU at the 1% level. The *Mean-F* and *Exp-F* tests are shown in the second and third rows, which indicates that equations from CNFS, EPU and the overall VAR system may change gradually over time. In addition, the L_c statistics test also supports that parameters change with time-varying in the whole VAR system. Therefore, these findings confirm that the parameters of the overall VAR model utilizing full-sampling data are unstable due to the presence of structural changes. Overall, these results in **Table 3** imply that the result of full-sampling correlation between EPU and CNFS cannot be relied upon.

Considering structural changes, we apply the bootstrap rolling window approach to re-examine the dynamic nexus between CNFS and EPU. Different from the full-sampling investigation, this estimation detects the correlation between CNFS and EPU tend to be more reliable due to taking structural changes and the time-varying effect into account in each sub-sample, which is different

Table 2. Full-Sample granger causality tests.

Test	H_0: *CNFS* does not Granger cause *EPU*		H_0: *EPU* does not Granger cause *CNFS*	
	Statistics	*p*-values	Statistics	*p*-values
Bootstrap *LR* Test in China	8.615***	0.000	1.787	0.150

Note: *** indicates significance at the 1%.

Table 3. Parameter stability tests.

	CNFS Equation		*EPU* Equation		*VAR* System	
	Statistics	Bootstrap *p*-value	Statistics	Bootstrap *p*-value	Statistics	Bootstrap *p*-value
Sup-F	57.176***	0.000	38.199***	0.000	64.355***	0.000
Mean-F	28.193***	0.000	24.498***	0.000	48.931***	0.000
Exp-F	25.088***	0.000	16.010***	0.000	29.704***	0.000
L_b^c					7.335***	0.005

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

from previous estimations. In the sub-sample relationship test of the rolling window, we apply the *RB*-based modified-*LR* approach to investigate the dynamic nexus between CNFS and EPU. The null hypothesis of the estimation means that EPU does not Granger cause CNFS and vice versa. Based on the VAR models in Equation (1) and utilizing the rolling sub-sample data within twenty-four-months observations, we estimate the bootstrap *p*-values of *LR*-statistics. For each sub-sample, Figures 2-5 show all the rolling estimation of the bootstrap *p*-values and corresponding coefficients.

Specifically, Figure 2 indicates that rolling bootstrap *p*-values of *LR* statistics estimated utilizing sub-samples data. According to Figure 2, we can see that the null hypothesis of CNFS does not Granger cause EPU can be rejected at 10 percent significance level in several sub-sample periods, including 2001.11-2002.12, 2008.04-2008.07, 2008.09-2009.07, 2010.01-2010.05, 2011.01-2011.05, 2015.07-2016.02. Figure 3 illustrates the rolling estimates of the magnitude of the effect that CNFS has on EPU. Particularly, it describes that CNFS has a negative impact on EPU in 2001.11-2002.12, 2010.01-2010.05 and 2011.01-2011.05, while it exists a positive relationship in 2008.04-2008.07, 2008.09-2009.07 and 2015.07-2016.02. As we can see from Figure 1, in 2001, the change of CNFS is decreased and the fluctuation of EPU deviates from this trend, CNFS has a negative impact on EPU during this period. Until the period between 2008.04 and 2009.07, CNFS has a positive impact on EPU. During this time, both developed and emerging economies face the global financial crisis and most country's economic policies exist great uncertainty, including China. Liow *et al.* (2018) point that the EPU of China and six advanced economies of G7 reached extreme value during the periods of Lehman Brothers bankruptcy shocks and subsequent

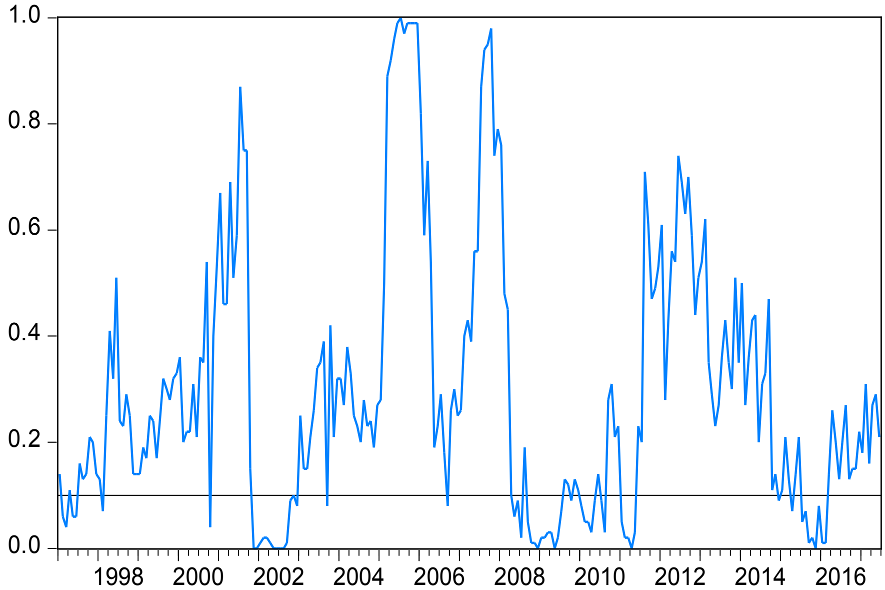

Figure 2. Bootstrap *p*-value: CNFS does not Granger cause EPU.

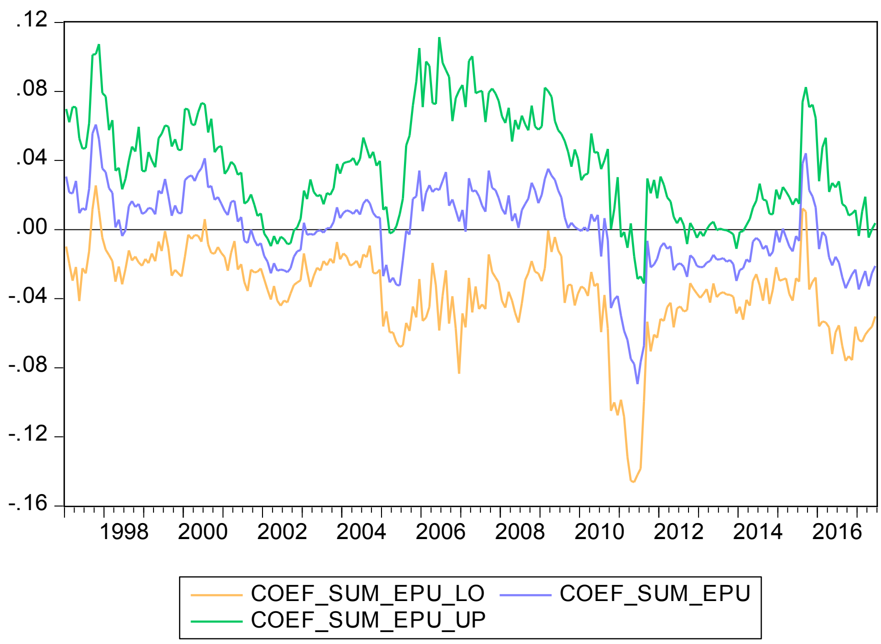

Figure 3. The sum of coefficients for EPU as dependent.

global economic recession [20]. Later after 2010, CNFS has a negative impact on EPU again. In 2015, the outbreak of the stock market crisis in China has a large impact in its financial market, and in this year, the index of CNFS reaches the largest extreme value in recent years. And EPU increased rapidly at the same time. In general, the bootstrap sub-sample rolling estimates in **Figure 2** and **Figure 3** indicate that the CNFS has both a positive and negative impact on EPU.

Figure 4 shows that the rolling bootstrap *p*-values of *LR* statistics with the null hypothesis that EPU does not Granger cause CNFS. **Figure 5** illustrates the

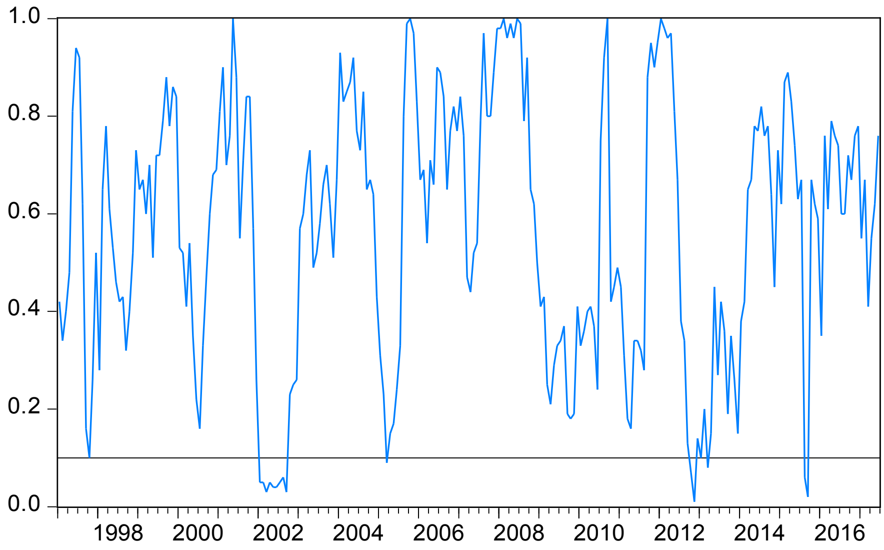

Figure 4. Bootstrap *p*-value. EPU does not Granger cause CNFS.

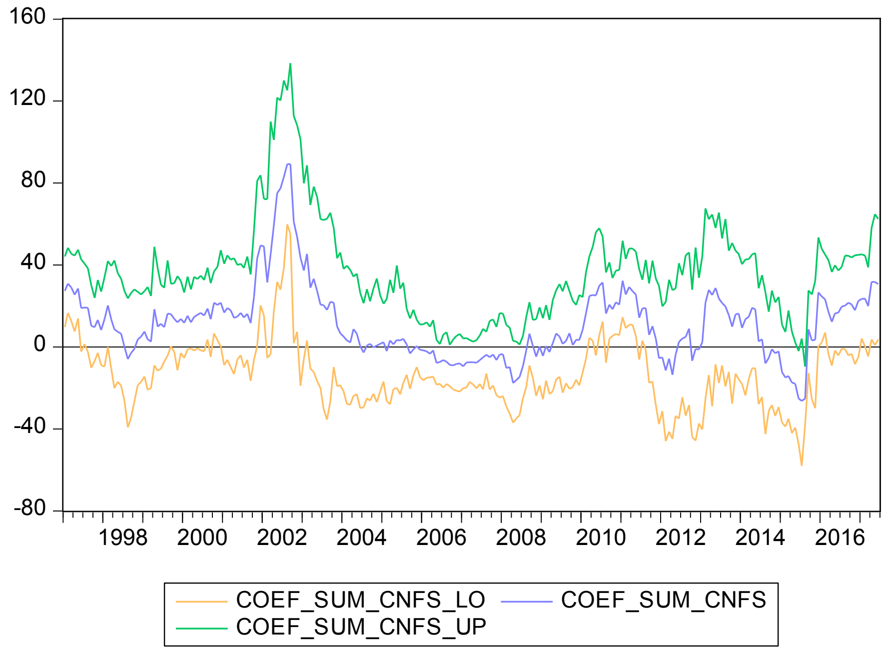

Figure 5. The sum of coefficients for CNFS as dependent.

bootstrap estimates of the rolling-window coefficients for the impact of EPU on CNFS in China. From **Figure 4**, it is clearly shown that the null hypothesis is rejected significantly in some time periods (2002.01-2002.09, 2012.10-2012.11, 2015.08-2015.09), but the lengths of time are all short. That to say, EPU has a weak and brief effect on CNFS compared to CNFS influencing on EPU. In **Figure 5**, it can be clearly observed that both positive (2002.01-2002.09) and negative effects (2012.10-2012.11 and 2015.08-2015.09) exist from EPU to CNFS. From **Figure 1**, we can conclude that the trend of EPU is reduced during the period 2002.01-2002.09, which means China has a good economic situation during this time. As we all known, China joined the WTO in 2001, and China's economic performance appears to be in a good situation when joining the WTO after one year. The annual GDP hit more than 1.4 trillion dollars, up 8% over the previous year and the per capita GDP is close to 1000 dollars. Moreover, the total import and export exceeded 600 billion dollars. All of the developments imply that China is facing smaller FS than the other period. In general, the relationship between EPU and FS in China is not always consistent with the view that FS and EPU Granger-cause each other [2]. It is actually acceptable as China has experienced economic restructuring and structural changes in financial market among the past few decades. Therefore, the relationship between EPU and FS in China is not stable over time and even showed a short-term deviation from the positive link.

6. Conclusions

This study investigates the causal relationship between CNFS and EPU utilizing a bootstrap full-sample Granger causality test and sub-sample rolling window causality estimation in China. The full-sample Granger causality test provides no evidence that EPU can cause CNFS in China. However, taking the presence of structural changes in full-sample data into consideration, parameter stability tests find that in the short-run, relationships between EPU and CNFS are unstable. Then, we utilize the bootstrap sub-sample estimation, and we find that there are bidirectional causal relationships. Although the relationship between EPU and CNFS in China is not stable over time and even exhibits short-run deviations from the positive link, it actually fits well with the fact that China has experienced economic transitions and structural changes in economics. This study provides some implications for the market regulators and the government. The authority should make the formulation of macroeconomic policies stable and strengthen the supervision of financial markets, including the guidance of the public reasonable expectations, which are critical to the economic development in China.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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