Construction of China's financial conditions index in the post-crisis era

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Received 15 October 2019
Revised 15 October 2019
Accepted 15 October 2019

Abstract

Purpose – The purpose of this paper is to summarize different methods of constructing the financial conditions index (FCI) and analyze current studies on constructing FCI for China. Due to shifts of China's financial mechanisms in the post-crisis era, conventional ways of FCI construction have their limitations.

Design/methodology/approach – The paper suggests improvements in two aspects, i.e. using time-varying weights and introducing non-financial variables. In the empirical study, the author first develops an FCI with fixed weights for comparison, constructs a post-crisis FCI based on time-varying parameter vector autoregressive model and finally examines the FCI with time-varying weights concerning its explanatory and predictive power for inflation.

Findings – Results suggest that the FCI with time-varying weights performs better than one with fixed weights and the former better reflects China's financial conditions. Furthermore, introduction of credit availability improves the FCI.

Originality/value – FCI constructed in this paper goes ahead of inflation by about 11 months, and it has strong explanatory and predictive power for inflation. Constructing an appropriate FCI is important for improving the effectiveness and predictive power of the post-crisis monetary policy and foe achieving both economic and financial stability.

Keywords Credit availability, Time-varying weight, TVP-VAR model, Financial conditions index (FCI)

Paper type Research paper

1. Introduction

Triggered by the US subprime mortgage crisis, the 2008 global financial crisis sent huge adverse shocks to economic and financial stability of countries around the world and greatly impacted monetary policies. Theories and practice of monetary policies changed during and after the crisis. Monetary policy theories started to focus on how financial sector growth affected economic activities. Before the crisis, the financial market was generally regarded as a mere derivative of the real economy, facilitating economic functioning; it was also believed that achieving price and output stability could help promote financial stability. As the financial sector evolves, however, it can directly impact normal functioning of the real economy. Hence, it is necessary to conduct a detailed study of post-crisis mechanisms of the financial sector. Besides, unconventional monetary policies have started to be implemented in practice. In the pre-crisis era, most of the central banks in developed financial markets followed the Taylor rule in designing conventional monetary policies, i.e., they provided banks or the interbank market with nominal short-term interest rates. The conventional monetary policies helped sustain rapid growth and low inflation for a fairly long period of time. However, the financial system was

The authors benefited from useful comments and took suggestions of anonymous reviewers in improving the paper. The authors are fully responsible for the paper.

heavily undermined after the crisis, limiting the effectiveness of the conventional monetary policies. As a result, central banks turned to a series of unconventional monetary policies to address consequences of the financial crisis.

Output and price stability are certainly conducive to the economy. Yet the crisis shows that monetary policies focusing only on these goals may not produce sound economic outcomes. To ensure the effectiveness of monetary policies, central banks have to pay attention to the functioning of the financial sector. However, due to complexity of the financial system, its post-crisis disruption and lagged transmission, tracking the development of the financial sector has become increasingly difficult. As a result, constructing an effective index for measuring financial conditions offers useful information for central banks to develop and implement monetary policies.

When central banks use monetary policy tools to intervene economic activities, there is a long lag between policy tools and ultimate goals and the two are not directly related. Thus, it is useful to use another variable that sits between policy tools and ultimate goals. The intermediate variable refers to an economic variable or indicator that has close and stable relationship with the ultimate goals and is capable of responding to changes in monetary policies. Generally speaking, the key advantage of an intermediate goal is to help central banks respond to systemic shocks by adjusting policy tools more rapidly and accurately than having the ultimate goals as the only reference.

Before the financial crisis, developed financial markets tend to use the nominal short-term interest rate as the intermediate goal. Thanks to sound financial system, policy tools can exert full impact on the real economy by influencing the short-term interest rate. For instance, the US Federal Reserve adjusts the federal funds rate or conducts open market operation to affect the short-term interest rate. Given that China's financial market remains unsophisticated and interest rate liberalization is still under way, China's central bank is inclined toward quantitative monetary policy tools or direct control and so it chooses intermediate goals with corresponding traits. Sheng and Wu (2008) believe that China's intermediate goals of monetary policies are credit scale and M2. Jiang *et al.* (2005) find that the impact significance of credit, M2 and M1 on prices and output are on a declining order while the impact on stability increases in sequence. Given the development of China's financial system and new changes after the financial crisis in particular, it becomes clear that focusing on money circulation and credit alone has its limitations, as some relevant studies put forward the concept of credit traps. Benmelech and Bergman (2012) believe that under special circumstances, when the central bank injects liquidity into the banking system, banks might rationally stock liquidity instead of extending loans. This leads to lack of corporate liquidity, lower investment level and depressed collateral values, rendering the monetary policy ineffective. Therefore, selecting a more comprehensive and reasonable intermediate goal is absolutely required for enhancing the effectiveness of monetary policies.

Based on monetary policy transmission, financial conditions index (FCI) is developed as an index that integrates the channels of interest rate, exchange rate and asset price. FCI can reflect the overall picture of the financial sector, respond to changes of central banks' monetary policies and create impacts on the real economy, meeting the criteria of an intermediate goal of monetary policies. Many studies find FCI as an effective tool in measuring financial circumstances and predicting output or inflation, thus an appropriate candidate for the intermediate goal.

China's financial market lags behind in its development and faces regulatory gaps. After the crisis, many problems arise in the financial market, creating headwinds to economic development. Given China's economic slowdown in the post-crisis era, it is necessary to improve the central bank's effectiveness in using monetary policies for macro-control and accurately track changes in the financial sector. Thus, developing China's FCI has great theoretical and practical significance.

2. The literature on FCIs

FCI has been developed on the basis of monetary condition index (MCI). First proposed by Bank of Canada in 1990s, MCI is the weighted average of changes in short-term interest rate and exchange rate from their values in a base period. Taking into account both interest rate and exchange rate channels, MCI aims to provide information on the stance of economic and monetary policies. Changes in MCI indicate the extent of easiness of current monetary conditions compared with the base period. Simple and easy to understand, MCI is widely used by central banks, international organizations and financial institutions. However, as modern finance grows in complexity and size, there is increasing attention on how financial indicators such as asset price affect the economy. Unable to describe the financial market, MCI is no longer suitable as an intermediate goal. In contrast, FCI introduces financial conditions indicators that impact the economy and subject to monetary policies, thus extending traditional measurement of policy stance and offering a more comprehensive insight into economic and financial conditions. Goodhart and Hofmann (2001) are the first to develop FCI using short-term interest rate, effective real exchange rate, housing price and stock price. Lack (2003) believes that FCI performs better than traditional MCI in tracking and predicting output and inflation. Gauthier *et al.* (2004) find that Canada's FCI outperforms MCI in many areas based on calculations.

The theoretical basis for FCI to be an intermediate goal is the theory of monetary policy transmission. Early studies find that apart from traditional channels of interest rate and exchange rate, asset and stock prices play an important role in monetary policy transmission through wealth effect and credit channels. The effectiveness of asset price transmission remains controversial. Asset price is essential in the transmission mechanism in theory but empirical studies produce different results. Many studies find that stock returns possess little predictive information for future output (Fama, 1981; Stock and Watson, 1999; Estrella and Mishkin, 1998). According to Goodhart and Hofmann (2002, 2003), stock prices cannot predict inflation in 17 developed nations; yet housing and stock prices of G7 nations have significant impact on the output gap.

Zhang (2002) thinks that bond risk premium has strong predictive power for future output. There are different views concerning bank credit channel. Bernanke and Gertler (1995) believe that quantitative credit channels exist under the condition of financial friction. Kishan and Opiela (2000) think that the USA and other developed nations have bank credit channel. Thornton (1994) holds the view that financial liberalization could weaken bank credit channel. Since the financial crisis, due to zero lower bound and financial system collapse, traditional transmission channels that developed economies always rely on have lost effectiveness. Relevant studies give more attention to the importance of channels such as asset price. According to Adrian and Shin (2010), decline in asset prices leads to higher leverage for financial institutions. They, in turn, sell assets to pay off debts and lower the leverage, which leads to further asset price decline and more damaging impact on the economy. Gertler and Karadi (2011) believe that decline in asset prices undermines the balance sheet of the financial sector, reduces the ability to absorb deposits, increases loan rates and lowers investment and output.

Constructing FCI is aimed to measure the total impact of financial variables and their lagging factors on economic activities. The key issue lies with choosing variables and determining weights. Regarding variables, FCI, based on monetary policy transmission, usually consists of financial variables such as interest rate, exchange rate, stock wealth, interest rate spread and housing price. Generally, the choice of explanatory financial variables depends on their statistical significance in the model. After the financial crisis, some scholars introduce lending standards to illustrate non-price credit conditions (Swiston, 2008; Guichard and Turner, 2008). Under different FCIs, description of financial condition changes may differ due to different composition of the financial variables. Bernanke and Blinder (1992) find that short-term interest rate has a certain degree of predictive power for output and inflation. Introducing exchange rate channel helps to capture the way relative prices of imports and exports affect aggregate demand. Gauthier *et al.* (2004) think that the exchange channel is particularly important for small and open economies. In comparison with short-term interest rate, long-term interest rate is less directly impacted by monetary policies. However, long-term interest rate is more relevant to financing decisions of companies and families. Gauthier *et al.* (2004) also find that bond risk premium can significantly explain Canada's output. Goldman Sachs and Morgan Stanley add term spreads in FCI and many studies find that term spreads carry more predictive content for inflation than short-term interest rate. Generally, FCI also includes proxy variables of the stock market, with stock price as the most straightforward one. The inclusion of housing price has caused some controversy. Some studies find that housing price has more explanatory and predictive power than stock price (Goodhart and Hofmann, 2002; Mayes and Viren, 2001), while some researchers construct the US FCI without including the variable of housing price (Guichard and Turner, 2008; Matheson, 2012). The recent trend is to expand FCI variables and add more impact factors to enhance FCI's ability to indicate the effect of monetary policies.

In terms of weights, they are generally determined based on the impact of financial conditions on economic growth and inflation. Current literature mainly adopts two approaches to determine the weights of FCI variables.

The first approach is economic modeling used to explain the role of asset prices in the transmission mechanism. Goodhart and Hofmann (2003) summarize three methods of estimating GDP response to financial variable shocks. They are reduced-form aggregate demand equations, simulation in a large-scale macro-econometric model, and vector autoregression (VAR) impulse response functions.

A typical reduced-form aggregate demand model includes an IS equation relating the output gap to interest rates, exchange rates and other asset prices, and a Phillips Curve relating inflation to the output gap. The model has the advantage of reflecting impact of all potential transmission channels on the real economy and creating a framework for modeling the monetary policy and other shocks. Many researchers use the method to build FCI (Gauthier *et al.*, 2004; Goodhart and Hofmann, 2002; Mayes and Viren, 2001; Batini and Turnbull, 2002). However, its simplified assumption that all financial variables are exogenous to each other and to the real economy may lead to estimation bias or identification problems.

Simulation in a large-scale macro-econometric model uses impact of financial variable shocks on economy to estimate weights of financial variables. The method captures key structural traits of the economy and takes into account interplay of all variables. Dudley and Hatzius (2000) use the method to construct FCI. However, macro-econometric models used by organizations such as central banks do not include extensive financial variables; and asset prices such as stock price have a limited role in such models. Macro-econometric models that fail to capture real financial circumstances tend to perform poorly. Some post-crisis research builds an independent financial sector in the macro-econometric model by introducing factors such as financing constraints, collateral and credit spreads, paying attention to the impact of asset price shocks on financial stability and real economy. Beaton *et al.* (2009) construct the US FCI using an improved version of the method and study the US financial landscape under the zero interest rate.

For VAR impulse response functions, weights are calculated using several-period lagged impulse responses of output or inflation to shocks of financial variables. Gauthier *et al.* (2004) and Swiston (2008) use VAR to calculate FCI. Goodhart and Hofmann (2002) use VAR method that includes all variables in the reduced-form aggregate demand equation and one-period lagged world oil prices as an exogenous variable. Relative weights are calculated based on average impact of asset price shocks on inflation over the following 12 quarters. There have been improvements in relevant studies. One improved method is generalized impulse response.

Gauthier *et al.* (2004) suggest using generalized impulse response functions to calculate weights. Orthogonalized impulse responses are not invariant to the reordering of the variables in the VAR, but generalized impulse responses are, and resulting weights are more stable. Feng *et al.* (2012) construct China's FCI using generalized impulse response. A second method is time-varying weights. Fixed weights are incapable of reflecting structural changes of economic and financial conditions. To address the defect and reflect structural changes, one remedy is to estimate weights based on multiple shorter periods, but this may result in series that are too short and unreliable estimation. Some relevant studies build the time-varying parameter vector autoregressive (TVP-VAR) model. A representative study uses TVP-VAR model to analyze Japanese monetary policies (Nakajima *et al.*, 2011). Chinese scholars have followed the method to build FCI for China (Deng *et al.*, 2016).

The second approach is based on the ability of key indicators and their various combinations to predict output or inflation. As pioneers of the approach, Stock and Watson (2003) identify 38 individual indicators sourced from bivariate models and calculate medians and trimmed means of forecasts. They find that combination forecasts are more accurate than many univariate and bivariate benchmark models. English *et al.* (2005) construct a factor model consisting of 30–50 financial variables for the USA, the UK and Germany. The factors and their lagged values are used to predict output gap and inflation. Through factor analysis and selection of financial variables for weighted linear combination, the approach helps test the common structures of the variables and eliminate the "noise" of irregular movements of particular variables at a certain time. The approach comes with the advantage of not relying on any model. However, it does not allow time-varying weights and weights of individual variables are unknown.

Application of FCI is an issue that deserves attention. Beaton *et al.* (2009) use FCI to demonstrate that US financial conditions have huge detrimental impact on GDP growth during the crisis. They also find that monetary easing policies adopted by the Federal Reserve are not enough to offset tightened financial conditions. Guichard and Turner (2008) use FCI to measure whether financial conditions are tightened or eased compared with historical average of effective policy rates. Swiston (2008) applies FCI to measure the contribution of financial shocks to growth in a particular quarter. Institutions such as Goldman Sachs and Morgan Stanley believe that FCI can predict output growth in the following quarters and estimate future progress of monetary policies. FCI is a powerful tool for central banks. Central banks can use FCI to measure and evaluate financial conditions of economies in an all-around way and obtain leading information about economic prospects. In time of shocks, changes of FCI can offer information relating to market interpretation of the shocks and expectations of future monetary policies. Diao and Zhang (2012) find that by introducing Taylor rule, FCI can better describe how interest rates respond to financial conditions. These studies show that a well-developed FCI can serve as an intermediate goal of the central bank.

There could be problems associated with FCI as well. One problem comes from construction method. First, weights are estimated from the model and the explanatory power is limited by the model assumption. Second, FCI includes variables that affect output and inflation at different speeds. Developing FCI of a certain point in time overlooks its temporal dynamics. Third, there could be institutional changes or structural shifts during the sample period. Parameters are unstable and changes in financial impulse transmission are not identified in FCI. Finally, variables of FCI are generally considered exogenous variables in the derived weighted model, yet non-exogeneity of regression factors can lead to simultaneity bias. There is a second problem with FCI. FCI that only includes financial asset prices is questioned concerning its effectiveness in indicating financial conditions. Financial conditions manifest themselves through changes in financial asset prices, but they depend on credit supply and demand. For instance, higher interest spread that is caused by rising credit demand for productive investments suggests future economic expansion. In comparison, higher interest spread that is caused by shrinking credit supply due to reluctance in lending suggests economic slowdown in the future. Distinguishing change of credit demand from that of credit supply is particularly important in the post-crisis environment filled with uncertainties and asymmetric information. Current FCIs generally fail to take this into consideration.

In China, studies on FCI start late and usually draw on existing research in terms of FCI variables and technical methods. Regarding selection of variables, the basic way is to add a number of financial variables besides interest rate and exchange rate. For example, Chen and Zhou (2004) suggest adding M2 to FCI. Dai and Zhang (2009) construct FCI by introducing Shanghai Composite Index into VECM model. Given special traits of China's financial system and limited liberalization of financial variables, FCI constructed on these variables cannot fully reflect financial conditions and may well mislead development of monetary policies. Later studies start to focus on realities and include different variables that can reflect China's financial conditions. Variables such as foreign reserve (Diao and Zhang, 2012) and social financing volume (Xu and Zheng, 2013) are introduced into FCI. Xu and Ouyang (2014) use non-human wealth ratio as a variable and the resulting FCI has sound predictive power for consumer price index (CPI). Furthermore, there has been extensive research on FCI construction methods and weights. Feng and Wang (2006) use VAR model to construct FCI; Lu and Liang (2007) apply OLS to estimate variables' impact on the reduced-form aggregate demand equation and the reduced-form excess demand equation to determine weights in FCI. Wang *et al.* (2011) construct FCI based on the model of simultaneous equations. Guo and Yang (2012) use two sub-samples before and after the crisis and construct FCI based on the VAR model. Through comparative studies, they find that housing price and stock price have relatively great impact on inflation and such impact differ before and after the crisis. Yu and Yu (2013) use time-varying parameters state space model to estimate FCI weights. Qu and Zhu (2016) make use of TVP-FAVAR model to construct FCI, which has strong explanatory and predictive power for future inflation. Deng *et al.* (2016) construct FCI based on TVP-VAR model and find that shocks from financial conditions to inflation and economic fluctuations have significant asymmetry. In general, FCI studies in China grow fast but remain immature on the whole. First, they inherit basically the same variables from previous research, i.e. the five variables of interest rate, exchange rate, stock price, housing price and M2. The only difference lies with the choice of nominal variables, real variables or gaps. Second, estimated weights differ a lot. One explanation is that estimated results are very sensitive to sample period and China's economic and financial structures change constantly. Third, current studies fail to fully reflect China's special financial mechanisms and regulatory requirements and they lack investigation into non-financial variables. Finally, FCI construction mainly relies on fixed weights, while time-varying weights are less applied. As a result, they fail to capture dynamic impacts of financial shocks.

3. Empirical study

3.1 Improving on FCI construction

Based on the literature review, I believe that developing China's FCI requires improvements on three aspects. First, China's economic and financial reform leads to structural changes, making it more reasonable and effective to use dynamic weights as opposed to fixed weights. Second, to leverage advantages of the impulse response function, I suggest expanding or optimizing VAR method. Third, China's development conditions need to be factored in when selecting variables.

Advantages of the impulse response function could be summarized as follows. First, it has little involvement with economic theories and uses empirical data to estimate weights.

Second, it allows more interplay among variables. Third, it alleviates estimation bias or identification problems. Fourth, it captures the ability of economic growth to respond to changes in variables. Building on the advantages, the paper extends the VAR impulse response function to TVP-VAR approach. Fixed weights are replaced with time-varying weights to better show temporal dynamics of FCI. Estimated on the basis of variable data of a time period, fixed weights fall short of manifesting structural changes of the economic and financial conditions in the period. To reflect such structural changes, an alternative is to estimate weights based on a number of shorter periods. However, this might lead to series that are too short and unreliable VAR estimates. Time-varying weights can address these problems.

In terms of variable selection, an important extension of post-crisis studies is introducing credit availability (CA), which measures lenders' willingness to provide funds at the market interest rate. Bassett *et al.* (2014) make credit standards a new indicator of credit supply. They find that the shock of tightened credit standards leads to a substantial decline in output and undermines the capacity of businesses and households to borrow from banks; it also results in wider credit spreads and eased monetary policies. CA is closely related to credit supply and relatively independent of factors affecting credit demand. In identifying overall financial conditions, CA offers supplementary data about credit price and quantity. However, selecting a proxy variable for CA is a difficult issue. According to my observation, current studies in China have not introduced CA as an FCI variable. One reason is limited investigation into non-financial factors. A second reason is lack of universally accepted statistical indicators for CA in China. In an attempt to share views on this issue, the paper uses "banker confidence index"[1] as proxy for CA and constructs an FCI that includes the variable of CA.

Banker confidence index is chosen as proxy for CA due to four reasons. First, the paper draws on the ideas of Swiston. He looks into outcomes of the Federal Reserve's Senior Loan Officer Opinion Survey on lending standards, and uses professionals' subjective judgment on lending difficulty as a proxy variable for CA. Inspired by this, I turn to banker confidence index that derives from a comprehensive survey of senior management in China's banks. The index is highly relevant to real economic activities and the financial market. Second, in the post-crisis financial market, partial institutional failure and irrational factors lead to distortion of indicators. CA measured by financial indicators alone cannot reflect real lending difficulty in the credit market. Last but not least, phenomena such as credit traps and safe asset traps might distort credit behavior of banks and other financial institutions. In such cases, credit allocation does not follow financial indicators, so measurement of credit conditions should not be limited to financial indicators. In summary, banker confidence index is indeed an effective proxy for CA.

Novelty of the paper is shown in three aspects. First, the pater adopts TVP-VAR method in developing dynamic weights of FCI, giving full consideration to potential changes of all FCI variables before and after the crisis. Second, the paper selects FCI variables based on China's mechanism of monetary policy transmission. It gives attention to banks' crucial status in the credit market and introduces banker confidence index for the first time. Third, FCI developed in the paper has explanatory and predictive power for financial conditions' impact on inflation.

3.2 FCI equations and theoretical basis

FCI is the weighted average of gaps for all component variables:

$$\mathrm{FCI}_t = \sum_{i=1} \omega_i \left(s_{it} - s_{it}^*\right), \tag{1}$$

$$\omega_i = \theta_i / \sum_{i=1} |\theta_i|. \tag{2}$$

In the equations above, s_{it} refers to value of variable i at the time of t. s_{it}^* refers to the long-term equilibrium value of variable i at the time of t. It follows that $(s_{it}–s_{it}^*)$ indicates deviation of variable i from long-term equilibrium, or gap. ω_i refers to weight allocated to the gap of variable i. θ_i refers to inflation response to one-unit shock of variable i gap. Orthogonalized impulse response functions vary greatly to reordering of variables. To avoid this issue, the paper adopts a generalized impulse response function that is unaffected by reordering of variables. In addition, θ_i is defined as the sum of lagged values of generalized impulse response to shocks.

A simple deduction of the theoretical basis of FCI is given as follows.

Relationship between output gap and inflation is derived from the sticky price model:

$$p = p^e + a(Y - Y^e)p - p - 1 = p^e - p - 1 + a(Y - Y^e)\pi = \pi^e + a(Y - Y^e).$$

The relationship between variables and inflation could be discussed on this basis. The first variable is interest rate:

$$\text{Output } Y = C + I.$$

Interest rate impacts the output through investment. With other conditions unchanged, the deviation of interest rate from equilibrium could be calculated as follows:

$$\pi - \pi^e = a(Y - Y^e) = a[I(r - r^e + r^e) - I(r^e)] = f(r - r^e).$$

The second variable is exchange rate, defined as relative price levels of two countries. With other conditions unchanged, the deviation of exchange rate from equilibrium could be calculated as follows:

$$E = p/p'p = p'Ep - p^e = p'(E - E^e)\pi - \pi^e = p'(E - E^e).$$

The third variable is asset price, which impacts inflation in two ways. First, asset price itself is a part of the price level and deviation from the equilibrium directly causes inflation changes:

$$p = \theta p_a + (1 - \theta)p'p - p^e = \theta\left(p_a - p_a^e\right)\pi - \pi^e = \theta\left(p_a - p_a^e\right).$$

The second is related to wealth effect. Higher asset prices increase family and business wealth and promote consumption and investment:

$$\pi - \pi^e = a(Y - Y^e) = a\left[C(p_a) - C\left(p_a^e\right)\right] + a\left[I(p_a) - I\left(p_a^e\right)\right] = g\left(p_a - p_a^e\right).$$

The last variable is the amount of money. Given equilibrium of monetary supply and demand:

$$M = L(r, Y)M - M^e = k(Y - Y^e) - h(r - r^e)M - M^e = (\pi - \pi^e)k/a - hf^{-1}(\pi - \pi^e).$$

As shown above, deviation of the variables from equilibrium has impacts on inflation. The principle of constructing FCI is integrating impacts from the deviation in order to effectively reflect changes in financial conditions.

3.3 Variables selection and data processing

In addition to traditional FCI variables, such as interest rate, exchange rate, stock price and housing price, the paper introduces the variable of monetary supply that is used as the intermediate goal of China's monetary policy. The introduction enhances link between FCI and the monetary policy. As a novel experiment, the paper adds CA as a variable.

After the financial crisis, monetary policy transmission becomes less effective and financial institutions are less likely to lend due to unfavorable economic landscape and prospects. Introducing the non-financial variable of CA helps to describe current financial conditions more fully. All financial variables in the paper are inflation adjusted.

Regarding data selection and processing, a total of 240 samples of monthly data are collected from January 1997 till December 2016. For CPI, data from January 2011 till December 2016 are sourced from the IMF International Financial Statistics database and the remaining data are calculated based on monthly year-on-year data from the CEInet Statistics Database. 2010 is the base year when CPI equals 100. Inflation (INF) is monthly year-on-year CPI minus 100. Real interest rate (*R*) equals weighted average of seven-day interbank interest rates minus inflation. Real exchange rate (ER) is real effective exchange rate of RMB. Real stock price (SP), real housing price (HP) and real money supply (*m*) are calculated by dividing the closing Shanghai Composite Index at the end of the month, real estate climate index and M2 by corresponding CPI, respectively. Current studies have not identified a universally accepted proxy variable for CA in China. Considering the importance of banks in China's credit system, banks' willingness to lend has a direct impact on corporate access to loans. Factoring in statistical availability at the same time, the paper designates banker confidence index as the proxy variable for CA. Since only quarterly data of the index from 2007 Q1 are available, I turn to Eviews 8.0 linear function for frequency conversion, translating quarterly data from 2007 Q1 to 2016 Q4 into monthly data. For the data mentioned above, the real effective exchange rate RMB is taken from BIS and the remaining data are from the CEInet Statistics Database.

Variable gaps are then calculated from the data. The paper uses HP-filterto get long-term equilibrium value of all series and sets the smoothing coefficient of monthly data as 14.400. Furthermore, seasonal adjustments are made to variables such as exchange rate and stock price. Since the variables might have large seasonal variation, x12 procedure is used to eliminate such variation. Real interest rate gap (R_gap) is the periodic series based on HP-filtered real interest rates. For real exchange rate gap (ER_gap), real stock price gap (SP_gap), real housing price gap (HP_gap) and real monetary supply gap (m_gap), data are HP-filtered get trend series and x12 procedure is used to get seasonally adjusted figures before deducting trend series.

Augmented Dickey–Fuller (ADF) test of the series above shows that inflation, CA and all gaps are smooth series (see Table I).

3.4 Constructing FCI

The paper centers on constructing FCI with time-varying weights. To better showcase advantages of time-varying weights, I start with constructing an FCI with fixed weights for comparison. Fixed weights of sub-samples are also calculated. Changes of weights in

Table I.
ADF test results

Variables	Test formats (c, t, p)	t-Statistics	Critical value	Unit root test
INF	(c, t, 1)	−3.57	−3.43**	Smooth
R_gap	(0, 0, 2)	−6.21	−2.58***	Smooth
ER_gap	(0, 0, 3)	−4.04	−2.58***	Smooth
SP_gap	(0, 0, 4)	−5.90	−2.58***	Smooth
HP_gap	(0, 0, 8)	−4.72	−2.58***	Smooth
m_gap	(0, 0, 10)	−5.07	−2.57***	Smooth
CA	(c, 0, 4)	−2.73	−2.58*	Smooth

Notes: c means inclusion of constants, t means inclusion of trend terms, while 0 means non-inclusion of constants or trend terms. p refers to lags selected according to AIC principle. ADF test adopts MacKin-non-critical values. *,**,***Significant at the 10, 5 and 1 percent levels, respectively sub-samples show that using a single weight for a relatively long period is unreasonable as it fails to accurately track structural changes of the financial conditions. Time-varying weights are thus preferred to fixed weights.

3.4.1 Fixed weights. First, the entire sample is used to estimate fixed weights. Data series of CA are too short so they are not included in the model. Following AIC principle and FPE principle, a lag order of 4 is set as optimal for VAR model. According to the AR Roots Graph, all characteristic roots fall in the unit circle. This shows VAR (4) is stable and it can be used for impulse response analysis, as indicated by Figure 1. Figure 1 also shows that a unit of positive shock from real exchange rate gap has negative impact on inflation from Lag 1 to Lag 22, with the biggest impact in Lag 7 (−0.1533). RMB appreciation leads to decline of net exports; lower aggregate demand alleviates inflationary pressure. Shock from real monetary supply gap starts to have a positive impact on inflation from Lag 4 and the impact reaches peak in Lag 15 (0.2916). Impact of monetary supply on inflation is very stable. The shock of real housing price has negative impact on inflation in the first seven lags. However, it turned positive from Lag 7 to Lag 31, which goes against the normal pattern. Real stock price gap has unstable impact on inflation; inflation rises immediately after the shock and the impact remains positive until Lag 18. Inflation makes significant negative movements in later lags.

Among all impulse response weights above, only the weight of real exchange rate gap is negative while the rest are positive, which goes against economic patterns. For instance, it is unreasonable that real interest rate gap has positive impact on inflation. Such a result is closely related to China's realities. Starting from 1996, China officially makes monetary supply the intermediate goal, and so monetary supply has a very stable impact on inflation during the sample period. Managed exchange rate ensures relative stability of currency value and exchange rate exerts stable impact on inflation during the sample period. The other three variables are different. Interest rate liberalization is still under way, stock market is to be further developed and real estate market is vulnerable to speculations. As a result, the three variables produce highly unstable impact on inflation, which may violate general rules. In this case, simply using fixed weights to describe changes in financial conditions of the last 20 years is rather inappropriate. Structural shifts of the financial market in each lag change the variables' impact on inflation and therefore weights have to be adjusted accordingly.

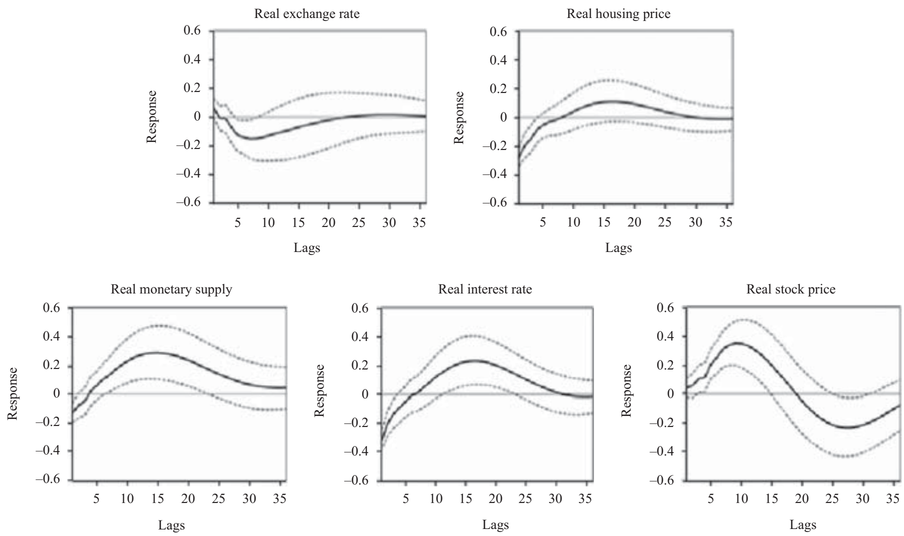

Figure 1.
Generalized impulse response of inflation to all variables

Sub-samples are used to calculate weights and compare their changes in each lag. Pre-crisis period is defined as from January 1997 to December 2016 and post-crisis period from January 2007 to December 2016. Weights are calculated as previously described (see Table II).

Comparison with Table II shows that real interest rate gap and real stock price gap register the largest weight changes before and after the crisis. Weight changes of real interest rate gap suggest variation of the interest rate transmission. Pre-crisis interest rate gap has a limited yet normal impact on inflation. However, post-crisis interest rate gap displays an abnormal positive correlation with inflation, as lower interest rate does not turn around the declining trend of inflation. Weight of real stock price gap also varies greatly. Higher stock price could promote inflation, suggesting that asset price transmission is relatively effective. The weight of real housing price gap remains unchanged. Negative impact of real exchange rate gap on inflation narrows down. It might be explained by RMB liberalization and the fact that lower inflation caused by appreciation is set off by capital influx. The weight of real monetary supply gap declines after the crisis. It suggests weakened ability of the central bank to control inflation through monetary supply.

Figure 2 shows the predictive effect of FCI for inflation. With the increase of lagged length, the correlation coefficients of the three FCI series and inflation all rise before going down. For overall FCI and pre-crisis FCI, their correlation coefficients with inflation peak in Lag 12, reaching 0.51 and 0.62, respectively. For post-crisis FCI, correlation coefficient with inflation peaks in Lag 10, reaching 0.75. In particular, the correlation coefficients for post-crisis FCI are above 0.6 from Lag 8 to Lag 13, indicating that post-crisis FCI has the highest predictive power for the inflation of the fourth quarter. Both pre-crisis FCI and post-crisis FCI perform better than overall FCI in predicting inflation.

Hence, using a single weight for a long period of time cannot accurately reflect structural changes of financial conditions. Assigning different weights for different periods enhances effectiveness of FCI. This leads to application of time-varying weights.

Variables	Entire sample	Pre-crisis sample	Post-crisis sample
R_gap	0.23	−0.11	0.28
ER_gap	−0.13	−0.21	−0.06
SP_gap	0.09	−0.27	0.30
HP_gap	0.06	0.07	0.07
m_gap	0.49	0.34	0.29

Notes: Calculation of weight coefficients is based on the sum of generalized impulse responses to shocks across 36 lags. I choose to cover 36 lags because changes of generalized impulse responses become stable around Lag 36. If the lag length is too short, impact of shocks might not be fully reflected, which could lead to wrong conclusions

Table II.
Weights of gaps in different samples

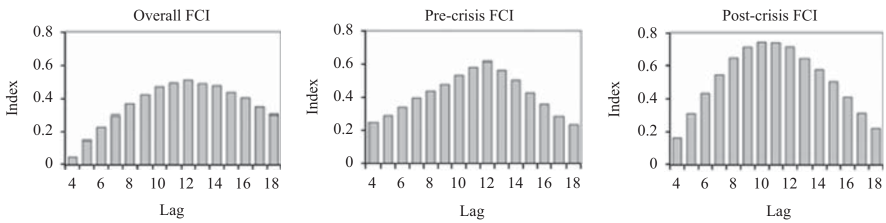

Figure 2.
Correlation coefficients of FCI with fixed weights and inflation across lags

3.4.2 Time-varying weights and introduction of credit availability. Time-varying weights are estimated to better describe dynamic changes of economic and financial conditions. In addition, CA is introduced in FCI to factor in non-financial factors.

FCI weights are defined as time-varying as opposed to fixed:

$$\omega_{it} = \theta_{it} / \sum\nolimits_{i=1}^{n} |\theta_{it}|. \tag{3}$$

Time-varying weights are calculated based on VAR model. The paper follows the method by Nakajima (2011):

$$\begin{aligned} &\mathrm{y}_t = C_t + B_{1t}\mathrm{y}_{t-1} + \cdots + B_{\mathrm{st}}\mathrm{y}_{t-s} + e_t \\ &e_t \sim N(\cdot)\,0,\ \ \boldsymbol{\Omega}_t. \end{aligned} \tag{4}$$

Equation (4) holds when $t = s+1, \ldots, n$. y_t is the $k \times 1$ vector of inflation, CA and financial variable gaps. $B_{1t}, \ldots, B_{st}$ are $k \times k$ matrices of time-varying coefficients. $\boldsymbol{\Omega}_t$ is the $k \times k$ matrix of time-varying covariance.

Suppose $\boldsymbol{\Omega}_t = A_t^{-1} \sum_t \sum_t A_t'^{-1}$. A_t is the lower triangular matrix with the diagonal element equal to 1. $\sum_t = \mathrm{diag}\ (\sigma_{1t}, \ldots, \sigma_{kt})$.

β_t is defined as the row vector of $B_{1t}, \ldots, B_{st}$:

$$\mathrm{a}_t = \left(\mathrm{a}_{1t}, \ldots, \mathrm{a}'_{qt}\right),$$

where a_t is the column vector of A_t's lower triangular element:

$$h_t = (h_{1t}, \ldots, h_{kt}), \ \ h_{it} = \ \log\ \sigma_{it}^2.$$

Time-varying coefficients follow the random walk process:

$$\beta_{t+1} = \beta_t + u_{\beta t} a_{t+1} = a_t + u_{at} h_{t+1} = h_t + u_{ht}.$$

In the equation above, $e_t = A_t^{-1} \sum_{t\varepsilon t}$. Σ_a and Σ_h are diagonal matrices:

$$\beta_{s+1} \sim N\left(\mu_{\beta 0}, \sum\nolimits_{\beta 0}\right),\ \ a_{s+1} \sim N\left(\mu_{a0},\ \ \sum\nolimits_{a0}\right),\ \ h_{s+1} \sim N\left({}_{\mu} h_0,\ \ \sum h_0\right).$$

where $(\Sigma_a)_i$ and $(\Sigma_h)_i$ are the ith diagonal elements of the matrix.

Their default prior values as follows:

$$\begin{aligned} &\left(\sum \beta\right) - 2_i \sim \mathrm{Gamma}(20, 10 - 4), \\ &\left(\sum a\right) - 2_i \sim \mathrm{Gamma}(4,\ \ 10 - 4), \\ &\left(\sum h\right) - 2_i \sim \mathrm{Gamma}(4, 10 - 4). \end{aligned} \tag{5}$$

The paper uses MATLAB to run the Markov chain Monte Carlo algorithm provided by Nakajima. Bayesian analysis of the time-varying coefficient is applied to get time-varying impulse responses of inflation to simulated shocks of all remaining variables in 30 lags. The impulse responses are then used in Equation (3) to get time-varying weight series of all variables[2].

Figure 3 shows that weights of all FCI variables vary significantly with time, suggesting the time-varying nature of variables' impacts on inflation in different time periods. Specifically, weights of real stock price gap, real housing price gap and real monetary supply gap are significant and stable, with the exception of 2008–2009 and 2011–2012, when inflation rapidly declines and the weights dramatically deviate from the long-run trend. This suggests the three variables have great impacts on inflation. For real interest rate gap and real exchange rate gap, their weights fluctuate on a low level, suggesting limited impact on inflation. In the two periods of rapid inflation decline, weights are adjusted accordingly and they show fairly strong predictive power for inflation.

It is interesting to observe the changing weight of CA, the non-financial variable. On the whole, the weight tends to move around −0.1. However, in the two periods of rapid inflation decline, weight surges to positive values. In the 2008–2009 period, CA decline could partially explain the declining inflation. Due to shocks of the financial crisis, banks become reluctant to lend. Lower market liquidity bears negatively on economic activities and leads to lower inflation. In the 2011–2012 period, CA declined as the Chinese central bank raised the required reserve ratio for six consecutive times and adjusted upwards the benchmark deposit rate three times in the year of 2011, greatly constraining credit supply in the market. But in most of the time after crisis, CA is negatively correlated with inflation, suggesting banks' increased appetite for lending and slow yet steady decline of inflation. Such a trend, I believe, shows that China's deflationary risks might come from capital borrowers rather than suppliers. After the tumble in 2007, the banker confidence index moved upward despite volatilities, but the declining trend of inflation was not reversed. Banks became more willing to lend and yet enterprises had a low demand for capital, which might be explained by lower capital returns and uncertain economic prospects. If CA declines, the problem could be worsened, as shown by the substantial decline of inflation in 2008–2009 and 2011–2012 periods. Therefore, following changes of CA weights help us understand the meaning of inflation movements in the post-crisis era and offer guidance for adjustment of monetary policies.

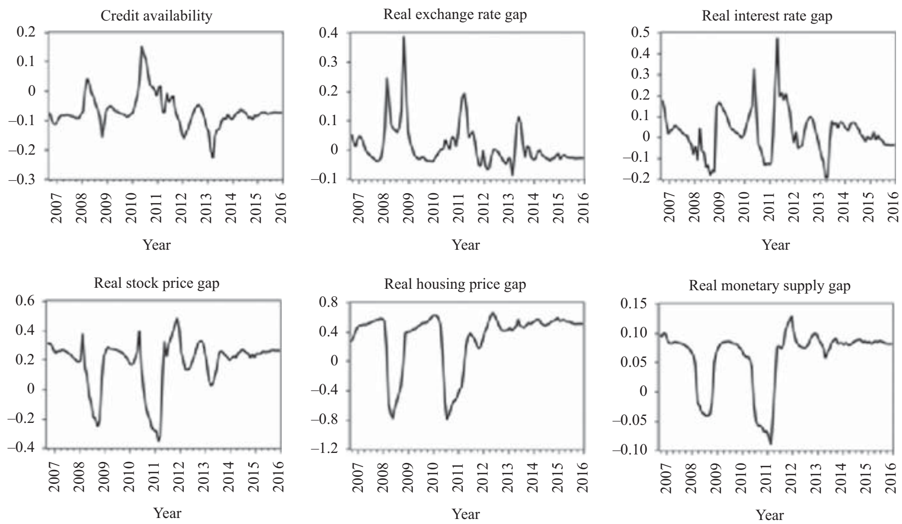

Figure 3.
Time-varying weights of variables in FCI

Weight series above are used as inputs for Equation (1) to construct FCI with time-varying weights. Trend lines of FCI and inflation are presented together in Figure 4, which shows a high level of synchronization between the FCI with time-varying weights and the post-crisis inflation.

In the next step, correlation coefficients of FCI and inflation across different lags are calculated (Figure 5). Lagged values of FCI are highly correlated with inflation and the correlation coefficient reaches the peak of 0.698 in Lag 11. The peak is slightly smaller than that of FCI with fixed weights, which stands at 0.75. For FCI with fixed weights, it has the highest correlation with inflation in Lag 10; however, correlation coefficients in other lags fall far below the peak. In contrast, FCI with time-varying weights has notably higher

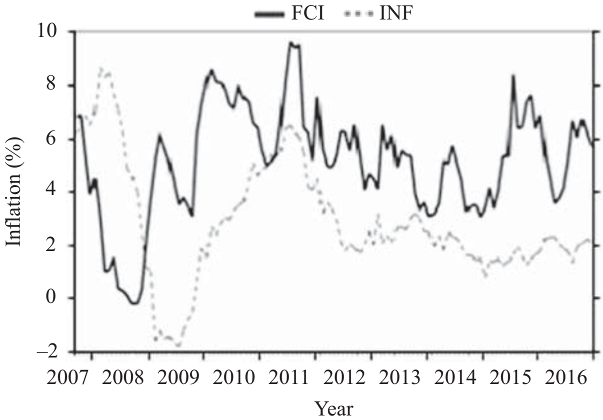

Figure 4.
Trend lines of FCI and inflation

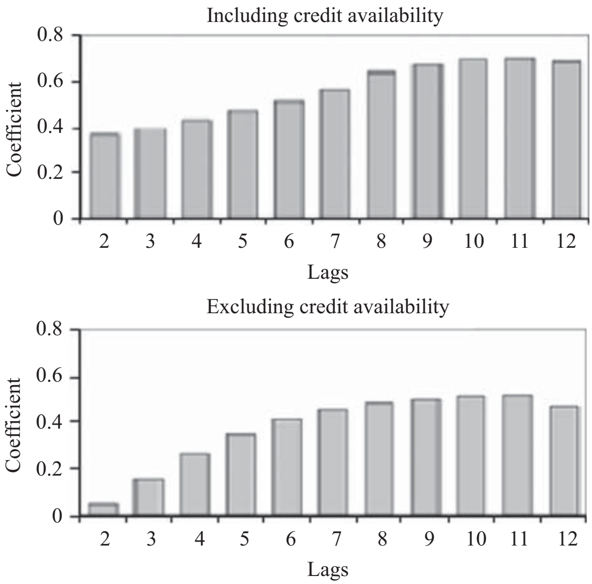

Figure 5.
Correlation coefficients of FCI and inflation across lags

correlation with inflation across different lags. In other words, FCI with time-varying weights is a more reliable predictor for inflation.

To understand the role of CA in FCI, the paper uses the method described above to calculate time-varying FCI without the variable. Correlation coefficient between the FCI and inflation is shown in Figure 5. Inclusion of CA significantly enhances the correlation of FCI and inflation, improves the maximum correlation coefficient and the overall predictive power. It demonstrates that introducing the non-financial variable that indicates bank willingness to lend has realistic relevance to construction of FCI.

In the next step, I will elaborate on the FCI with time-varying weights and the inclusion of CA.

First, Granger causality test is run (Table III). Figure 3 shows that when there is a lag order of 1–2, FCI and inflation are each other's Granger cause. When there is a lag order of 6–9, FCI is the one-way Granger cause of inflation with p-value smaller than 0.1. This suggests that FCI can significantly impact short-term inflation and FCI is able to make sound prediction of inflationary changes in the next nine lags.

Next, I build a smooth series that contains only FCI and inflation to build a VAR model[3]. Based on AIC principle and bivariate VAR model, the paper impulses response of inflation to FCI shocks. LR principle and FPE principle suggest the optimal lag order of 4 and AR root response. Both FCI and inflation series pass the unit root test; Figure 6 shows

Table III.
Granger causality test of FCI and inflation

Null hypothesis: FCI is not the Granger cause of inflation				Null hypothesis: inflation is not the Granger cause of FCI			
Lag order	F-value	p-value	Conclusion	Lag order	F-value	p-value	Conclusion
1	11.04	0.0012	Refuse	1	4.56	0.0349	Refuse
2	4.96	0.0088	Refuse	2	2.38	0.0977	Refuse
3	2.20	0.0928	Refuse	3	0.99	0.3997	Not refuse
4	1.63	0.1726	Not refuse	4	1.66	0.1656	Not refuse
5	1.35	0.2488	Not refuse	5	1.44	0.2488	Not refuse
6	1.88	0.0924	Refuse	6	1.37	0.2364	Not refuse
7	1.86	0.0849	Refuse	7	0.88	0.5259	Not refuse
8	2.14	0.0398	Refuse	8	0.81	0.5924	Not refuse
9	1.75	0.0908	Refuse	9	0.96	0.4774	Not refuse
10	1.44	0.1773	Not refuse	10	0.75	0.6728	Not refuse
11	1.33	0.2251	Not refuse	11	0.72	0.7117	Not refuse
12	0.96	0.4952	Not refuse	12	0.58	0.8490	Not refuse

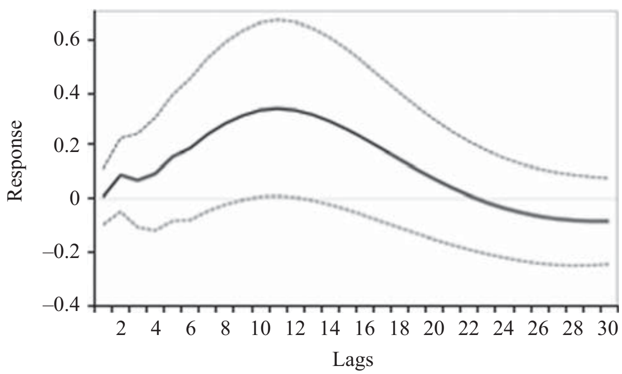

Figure 6.
Generalized impulse response of inflation to FCI

that all characteristic values fall within the unit circle; and VAR (2) model is systemically stable. Figure 6 reports the generalized impulse response of inflation to FCI. The response first increases and then goes down. It peaks in Lag 11 at 0.34 and goes below 0 after Lag 22. The impulse responses of the 30 lags total 3.6. The results show that FCI can produce fairly significant impact on inflation.

Finally, I use regression equation $\pi_t = \beta_0 + \beta_1 \mathrm{FCI}_{t-i} + \varepsilon_t$ to test the predictive power of FCI for inflation. FCI_{t-i} is the i step-ahead value of FCI. Make $i = 0, 1, \ldots, 12$ and we get Table IV.

When $i = 11$, the root mean square error (RMSE) has the smallest value; and R^2 shows that 48 percent of inflation change can be explained by FCI_{t-11}. Meanwhile, AIC and SC have the smallest value when $i = 11$. It can be concluded that the 11-step-ahead value of FCI has the best predictive power for inflation.

The empirical results show that the FCI developed in this paper, with time-varying weights and including the variable of CA, performs well in reflecting post-crisis financial conditions of China. Stock price, housing price and monetary supply are still important variables that impact the functioning of China's financial sector while interest rate and exchange rate play a smaller role. The non-financial variable of CA performs well as it significantly improves the correlation of FCI and inflation across different lags. Furthermore, the paper puts forward the idea that current deflationary risks might come mainly from capital borrowers. Introduction of non-financial variables is a key direction for future studies of FCI. In times of economic and financial volatility in particular, conventional transmission mechanisms become less effective and yet non-financial factors come into play, such as economic expectations, industrial outlooks and willingness to hold excess liquidity. Focusing on financial variables alone cannot render full understanding of change patterns of real economic variables such as inflation.

Derived from TVP-VAR model, time-varying weights of FCI represent a remarkable improvement on the fixed weights widely used in traditional research. By simply comparing correlation coefficients between inflation and two types of FCI, respectively (one with fixed weights and the other time-varying weights) across lags, the paper finds that FCI with fixed weights has dramatic variation while FCI with time-varying weights is smooth and has better performance overall. FCI constructed with time-varying weights is more sensitive to changes in financial conditions, including changes of financial variables themselves as well as changes concerning relative status of variables. Therefore, using time-varying weights is more effective in describing financial conditions.

i	β_1	R^2	AIC	SC	RMSE	MAE
3	0.039**	0.03	4.39	4.44	2.13	1.55
4	0.055**	0.06	4.33	4.38	2.07	1.48
5	0.070***	0.12	4.24	4.29	1.98	1.40
6	0.084***	0.18	4.09	4.14	1.84	1.32
7	0.096***	0.26	3.93	3.98	1.69	1.27
8	0.107***	0.36	3.71	3.76	1.51	1.19
9	0.113***	0.43	3.53	3.58	1.39	1.11
10	0.115***	0.48	3.39	3.44	1.29	1.03
11	0.113***	0.48	3.34	3.39	1.26	1.01
12	0.109***	0.45	3.38	3.43	1.29	1.00

Notes: When i equals 1 and 2, the correlation coefficients are not significant and not listed in the table. **,***Significant at the 5% and 1 percent levels, respectively

Table IV. FCI's predictive power for inflation

4. Conclusions

The paper selects six financial and non-financial variables (interest rate, exchange rate, stock price, housing price, monetary supply and CA), leverages TVP-VAR model to determine time-varying coefficients of variables, and thereby constructs China's FCI in the post-crisis era. The paper also investigates into the explanatory and predictive power of the FCI for China's inflation after the financial crisis.

The FCI constructed in the paper has sound explanatory and predictive effect for inflation, as supported by empirical data. The correlation coefficient between FCI and inflation reaches 0.698 in Lag 11. In addition, Granger causality test shows that FCI is the Granger cause of inflation in the next nine lags. VAR (2) model built on FCI and inflation suggests that generalized impulse response of inflation to FCI reaches the maximum of 0.34 in Lag 11 and that impulse responses in 30 lags total 3.6. The 11-step-ahead value of FCI has the best predictive power and is able to explain 48 percent of the inflation change. The results above prove the FCI constructed in the paper is ahead of inflation by 11 months and it has sound explanatory and predictive power for inflation.

Constructing an appropriate and improved FCI helps to effectively monitor changes in financial conditions, as well as reflect and predict trends of the real economy. As the financial market is yet to fully recover after the crisis, using FCI as reference helps the monetary authority to better understand functioning of the financial sector in the oversight and policy-making process, enhance effectiveness and predictive power of monetary policies, and achieve both economic and financial stability.

Notes

1. Banker confidence index is based on surveys targeting senior management of all types of banks in China (including foreign-invested commercial banks), i.e. headquarter chiefs, presidents of first-tier and second-tier bank branches, or vice presidents in charge of credit business.
2. The paper sets a lag order of 8 for the VAR model. The resulting weight series, starting from September 2007, is slightly shortened compared with original data series but this does not have a clear impact on results.
3. Smoothness of inflation has been tested above. The ADF test format for FCI is (0, 0, 6). *t*-Statistics is equal to −3.07 and it is significant at 1 percent level.

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