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A Novel Dynamic Financial Conditions Index Approach Based on Accurate Online Support Vector Regression

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Abstract

In this paper, we construct a novel dynamic financial conditions index (DFCI) for China based on accurate online support vector regression (AOSVR), and the constructed DFCI is evaluated on future inflationary pressures. The research results indicate dynamic effect of financial variables on DFCI in time-varying economic and financial environment, verifying the dynamic nature of the weights in our DFCI. On the whole, in our DFCI exchange rate, stock price, and money supply have the push-down effect on DFCI, taking negative dynamic weights. Housing price has the pull-up effect on DFCI, taking positive dynamic weights. The effect of interest rate on DFCI is erratic, taking sign-changed dynamic weights. The Granger causality test results show the superior performance ability of our DFCI compared with the FCI constructed based on SVR.

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Keywords: Macroeconomic; Monetary policy; Financial conditions index; Accurate online support vector regression; Dynamic.

1. Introduction

Financial Conditions Index (FCI) [1], a weighted average of the short-term interest rate, the exchange rate, house price, and share price, that is extended from Monetary Conditions Index (MCI) [2], has commonly been used as a composite measure of the stance of monetary policy in open economies. As an important indicator for macroeconomic and the formulation of monetary policy, FCI has been received extensive research in the past decade [3-5]. For the construction of FCIs, there are mainly three methods to estimate the weights of the respective asset price in an FCI: simulations with large-scale macroeconomic model [6], vector auto regression (VAR) model [7], and reduced-form demand equations [8]. Different from these econometric methods, support vector regression (SVR) [9], a data mining method developed from structural learning theory, has achieved good performance ability in a wide variety of applications [10-12]. Recently, Wang et al. [13] have used SVR construct FCI for China, showing good performance ability.

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However, for the above methods, the weights of the variables are all fixed in the entire sample period. It may be unsuitable in the time-varying economic and financial environment. Of course, nothing about monetary policy or its assessment is simple, and the link between financial conditions and economic activity evolves over time. Therefore, the dynamic weights are more suitable for the time-varying environment. For time-varying environment, Ma et al. [14] have proposed accurate online support vector regression (AOSVR) by solving SVR online that has achieved good performance ability in a wide of dynamic environment applications [15-16].

In this paper, we construct dynamic financial conditions index (DFCI) for China based on AOSVR. In our DFCI, the dynamic weights are obtained by estimating AOSVR on output, which is an important objective in the field of monetary policy. Further, in order to evaluate our DFCI whether is an useful indicator, our DFCI is evaluated on inflation, which is another important objective in the field of monetary policy. The money supply is the intermediate target of monetary policy operations, and plays an important role in formulation, implementation and conduction of monetary policy in China [17]. The money supply maybe affect output and inflation, therefore, we construct two DFCIs based on AOSVR with money supply or not. As a comparison, we also construct two FCIs based on SVR. The research results indicate dynamic effect of financial variables on DFCIs in time-varying economic and financial environment, verifying the dynamic nature of the weights in our DFCIs, and show the superior performance ability of our DFCIs compared with the FCIs.

The rest of this paper is organized as follows: Section 2 briefly introduces FCI, DFCI, and AOSVR methodologies. Section 3 presents the dynamic financial conditions index for China based on AOSVR. Evaluation of dynamic financial conditions index is given in Section 4. Some conclusions and remarks are drawn in Section 5.

2. Methodologies

2.1. Dynamic financial conditions index

The general constructed strategy of FCI [1] is as follows:

$$FCI_t = \sum_{i=1}^{n} w_i(q_{it} - \bar{q_{it}}) \tag{1}$$

where q_{it} is the price of asset i in period t, $\bar{q_{it}}$ is the long-run trend or equilibrium value of the price of asset i in period t, $t = 1, 2, \cdots, T$, w_i is the relative weight given to the price of asset i in the FCI, and $\sum_{i=1}^{n} |w_i| = 1$.

However, the FCI is static due to the same w_i during the T period. In order to reflect the time-varying of FCI, a dynamic FCI (DFCI) [17] can be constructed as follows:

$$DFCI_t = \sum_{i=1}^{n} w_{it}(q_{it} - \bar{q_{it}}) \tag{2}$$

where w_{it} is the relative weight given to the price of asset i in period t for the $DFCI_t$, and $\sum_{i=1}^{n} |w_{it}| = 1$.

In fact, how to calculate the dynamic weight of each variable in DFCI is one of the key problems. To obtain the dynamic weights in DFCI, accurate online support vector regression, a data mining method, will be introduced in the next subsection.

2.2. Accurate online support vector regression

Suppose given a training data set $T = \{(x_1, y_1), (x_2, y_2), \cdots, (x_l, y_l)\}$, where $x_i \in X \subset R^n$, $y_i \in Y \subset R$, and l is the number of samples in the training data set, the classical SVR [9] searches for an optimal regression function:

$$f(x) = \omega^T \phi(x) + b \tag{3}$$

where $\omega \in R^n$ is weight vector, $\phi(x)$ is a mapping function which maps input space X into hyper space F, and $b \in R$ is constant. To measure the empirical risk, the ε-insensitive loss function:

$$L^{\varepsilon}(x, y, f) = |y - f(x)|_{\varepsilon} = \begin{cases} 0 & \text{if } |y - f(x)| \leqslant \varepsilon \\ |y - f(x)| - \varepsilon & \text{others} \end{cases} \tag{4}$$

is considered that sets a nonnegative ε tube around the data, within which errors are discarded. By introducing the regularization term $\frac{1}{2}\|\omega\|^2$ and the slack variables ξ and η, the primal problem of SVR can be expressed as follows:

$$\begin{aligned} \min_{\omega,b,\xi_i,\eta_i} \quad & \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{l}(\xi_i + \eta_i) \\ \text{s.t.} \quad & y_i - f(x_i) \geqslant -\varepsilon - \xi_i \\ & f(x_i) - y_i \geqslant -\varepsilon - \eta_i \\ & \xi_i, \eta_i \geqslant 0, i = 1, \cdots, l \end{aligned} \tag{5}$$

where C is a positive parameter determining the trade-off between the empirical risk and the regularization term [18-20].

The solution of (5) can be obtained by introducing Lagrange multipliers and solving the dual optimization problem as follows:

$$\begin{aligned} \min_{\alpha,\alpha^*} \quad & \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} Q_{ij}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) + \varepsilon\sum_{i=1}^{l}(\alpha_i + \alpha_i^*) - \sum_{i=1}^{l} y_i(\alpha_i - \alpha_i^*) \\ \text{s.t.} \quad & \sum_{i=1}^{l}(\alpha_i - \alpha_i^*) = 0 \\ & 0 \leqslant \alpha_i, \alpha_i^* \leqslant C, i = 1, \cdots, l \end{aligned} \tag{6}$$

where $Q_{ij} = \phi(x_i)^T\phi(x_j) = K(x_i, x_j)$, $K(x_i, x_j)$ is a kernel function, α_i and α_i^* are Lagrange multipliers. The regression function (3) can be written as follows:

$$f(x) = \sum_{i=1}^{l} K(x_i, x)(\alpha_i - \alpha_i^*) + b \tag{7}$$

However, batch implementation of SVR is static, which is inefficient in the dynamic setting. For the dynamic situation, Ma et al. [14] have proposed accurate online support vector regression (AOSVR).

In order to further analysis, according the corresponding KKT conditions of (6), the whole training data set is divided into three subsets: support vectors S, remaining vectors R, and the error vectors E as follows:

$$\begin{aligned} S &= \{i|0 < |\theta_i| < C\} \\ R &= \{i|\theta_i = 0\} \\ E &= \{i||\theta_i| = C\} \end{aligned} \tag{8}$$

where $\theta_i = \alpha_i - \alpha_i^*$ is the coefficient difference of the solutions α and α^* of (6).

For the dynamic situation, when a newly collected sample X_t is added to the training data set, AOSVR will immediately update itself according to the new sample X_t's location relative to the current model until the new sample X_t can be assigned to one set of S, E, R. The basic idea is to change the coefficient θ_{X_t} corresponding to the new sample X_t in the largest allowed discrete steps to meet the KKT conditions, at the same time, ensure the existing samples before t period continue to satisfy the KKT condition at each step. The incremental algorithm can start from an already defined situation, and the detailed online update equations can be seen from [14].

3. Dynamic financial conditions index for China based on AOSVR

3.1. Data

The most commonly used financial variables to construct FCI [1,3] include real interest rate (rr), real effective exchange rate (reer), real stock price (rsp), and real housing price (rhp). In China, the money supply is the intermediate target of monetary policy operations, and plays an important role in monetary policy formulation, implementation, and conduction [17]. Since the money supply maybe affect output and inflation, here we consider two cases with money supply or not. The sample period of the analysis is from January 2001 to September 2014. The monthly data are used for all the financial variables.

For the inflation, consumer price index (CPI) is represented. For CPI, the monthly data are calculated using the ring data fixing December 2000 with 100 as the base period. For gross domestic product (GDP), the monthly data are converted from quarterly GDP by using quadratic-match sum function in Eviews. For interest rate, the monthly data are represented by 7-day interbank offered rate. The monthly data of real effective exchange rate released by Bank for International Settlements (BIS) are adopted in this paper. For stock price, the monthly data are represented by the price of Shanghai Composite Index closed at the end. The monthly data of housing price are represented by national housing climate index. Money supply is represented by broad money (M2). The data of consumer price index, gross domestic product, and national housing climate index are taken from the National Statistic Bureau of China (http://www.stats.gov.cn/), the data of interest rate, stock price, and M2 are obtained from the People's Bank of China (http://www.pbc.gov.cn/), the data of real effective exchange rate are obtained from BIS (http://www.bis.org/). Based on Goodhart and Hofmann [1], the long-run trend values of all the financial variables are obtained by HP filter with a smoothing parameter of 14400. The gap values of all the financial variables are calculated by real value minus long-run trend value, shorted by rgdpgap, rrgap, reergap, rspgap, rhpgap, and rm2gap, respectively. In order to reduce the influence of the data size difference, the gap values of all the financial variables are standardized.

3.2. Construction

In this subsection, we use AOSVR construct the dynamic financial conditions index for China. We define the dynamic FCI without M2 as DFCI1, and with M2 as DFCI2. Define the dynamic input variables be $X_t = \{x_{it}\}$, where for DFCI1, $X_t = (x_{rrgap,t}, x_{reergap,t}, x_{rspgap,t}, x_{rhpgap,t})$, and for DFCI2, $X_t = (x_{rrgap,t}, x_{reergap,t}, x_{rspgap,t}, x_{rhpgap,t}, x_{rm2gap,t})$, and the dynamic output variables be $Y_t = rgdpgap_t$, $t = 1, 2, \cdots, 165$. The corresponding regression function of our objective is as follows:

$$f(X_t) = \omega_t^T \phi(X_t) + b_t \tag{9}$$

The dynamic ω_t and b_t are obtained online from AOSVR implemented in MATLAB 7.0 [21]. The optimal fixed parameter C is obtained through searching from the set $\{2^{-8}, \cdots, 2^8\}$, and the optimal fixed parameter ε is obtained from 0.01 to 0.1. The Root Mean Squared Error (RMSE) is used to choose the optimal fixed parameters by evaluating the performance, which is defined as follows:

$$RMSE = \sqrt{\frac{1}{l}\sum_{i=1}^{l}(y_i - \hat{y}_i)^2} \tag{10}$$

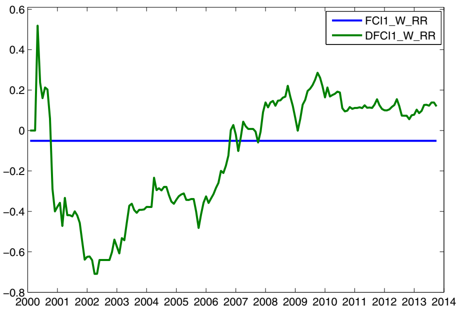
where y_i is the true value and $\hat{y}_i$ is the predicted value. For DFCI1, the weight vector $\omega_t = (\omega_{rrgap,t}, \omega_{reergap,t}, \omega_{rspgap,t}, \omega_{rhpgap,t})^T$, and for DFCI2, $\omega_t = (\omega_{rrgap,t}, \omega_{reergap,t}, \omega_{rspgap,t}, \omega_{rhpgap,t}, \omega_{rm2gap,t})^T$. In order to ensure ω_t correspond with the financial variables, the linear kernel where $\phi(x) = x$ is used here. Accordingly, the weight vector $\omega_t = \sum_{i=1}^{t} \theta_i X_i$. The dynamic weight w_{it} of financial variable i in period t is defined as follows:

$$w_{it} = \frac{\omega_{it}}{\sum_{i=1}^{n} |\omega_{it}|} \tag{11}$$

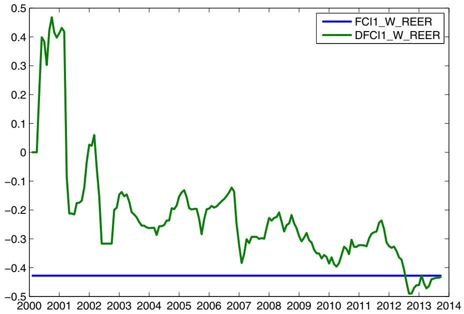
where $n = 4$ for DFCI1, $n = 5$ for DFCI2, and $t = 1, 2, \cdots, 165$.

3.3. Analysis of dynamic weights

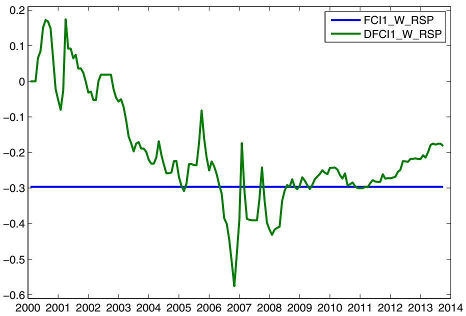
The dynamic weights of the financial variables in DFCI1 and DFCI2, which are obtained based on output at the period t from AOSVR, are shown in Figures 1 and 2, respectively. As a comparison, we also construct two static FCIs based on SVR, FCI1 without M2 and FCI2 with M2, and the static weights are also given. In Figures 1 and 2, the weights of financial variables correspond to their gap values. It can be seen from Figures 1 and 2 that, as



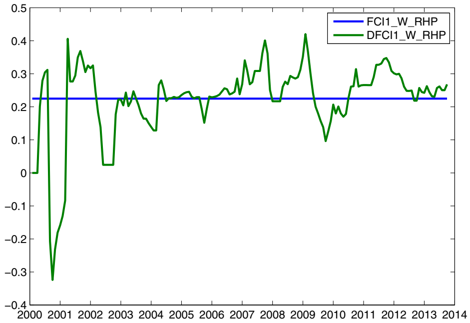
(a) FCI1-DFCI1-W-RR



(b) FCI1-DFCI1-W-REER



(c) FCI1-DFCI1-W-RSP



(d) FCI1-DFCI1-W-RHP

Fig. 1. (a) The weights of RR; (b) The weights of REER; (c) The weights of RSP; (d) The weights of RHP.

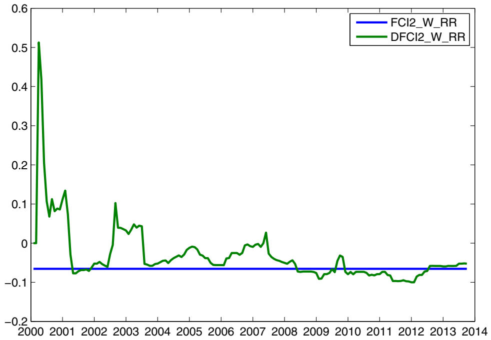
time goes on, the signs and absolute values of the weights in DFCIs are time-varying greatly compared with those in FCIs. The research results indicate dynamic effect of financial variables on DFCIs in time-varying economic and financial environment, verifying the dynamic nature of the weights in our DFCIs. For DFCI1, from Figure 1, we can find that the weights of RR varied from 0.5 to −0.7 rapidly, then fluctuated up to 0.2 gradually. It may be related to management system of Chinese interest rate. Different from RR, the weights of REER varied from 0.4 to −0.2 rapidly, then fluctuated down to −0.5 gradually. It may be related to Chinese floating exchange rate and rising exchange rate with fluctuations. The weights of RSP varied from 0.18 to −0.58, then fluctuated up to −0.2. The weights of RHP varied from 0.3 to −0.3 rapidly, then fluctuated from 0 to 0.4. For DFCI2, from Figure 2, we can find that the weights of RM2 varied from 0 to −0.58 rapidly, then fluctuated to −0.3. Compared DFCI1 with DFCI2 from Figures 1 and 2, it can be seen that the rough varied trends of the weights of REER, RSP and RHP are similar. There is no doubt that the fact of the weights changed in DFCI2 is related to added RM2, illustrating that RM2 affects DFCI. On the whole, in our DFCIs exchange rate, stock price, and money supply have the push-down effect on DFCIs, taking negative dynamic weights. Housing price has the pull-up effect on DFCIs, taking positive dynamic weights. The effect of interest rate on DFCIs is erratic, taking sign-changed dynamic weights, and it may be related to management system of Chinese interest rate and added RM2.

4. Evaluation of dynamic financial conditions index

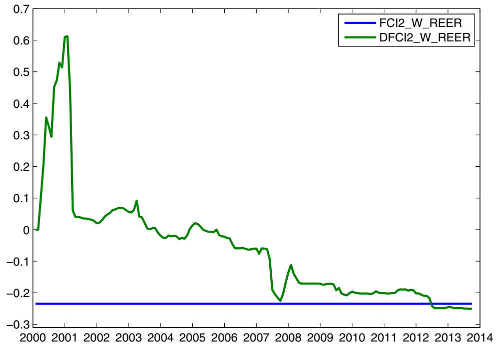
The dynamic weights in our DFCIs are estimated on output which is an important objective in the field of monetary policy. Meanwhile, inflation is another important objective. In this section, we check whether the DFCIs are useful indicators for future inflationary pressures further.

4.1. Dynamic financial conditions index and inflation

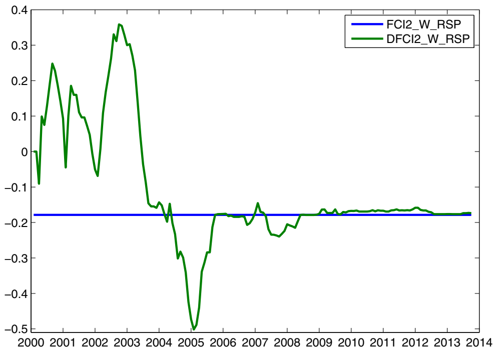
In this subsection, Figure 3 shows FCI1 and FCI2 which are constructed based on (1), DFCI1 and DFCI2 which are constructed based on (2), and the growth rate of CPI (CPIR). The zero horizontal line represents zero



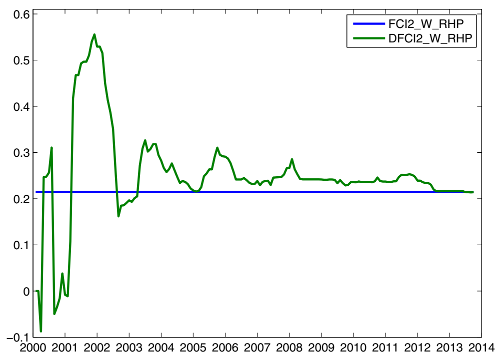
(a) FCI2-DFCI2-W-RR



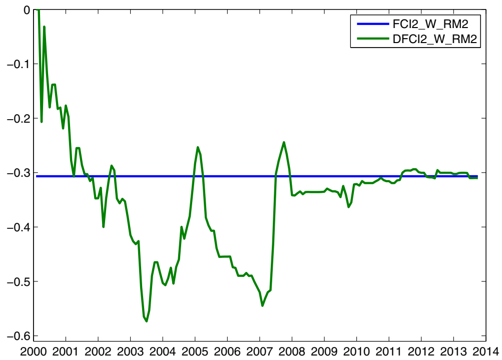
(b) FCI2-DFCI2-W-REER



(c) FCI2-DFCI2-W-RSP



(d) FCI2-DFCI2-W-RHP



(e) FCI2-DFCI2-W-RM2

Fig. 2. (a) The weights of RR; (b) The weights of REER; (c) The weights of RSP; (d) The weights of RHP; (e) The weights of RM2.

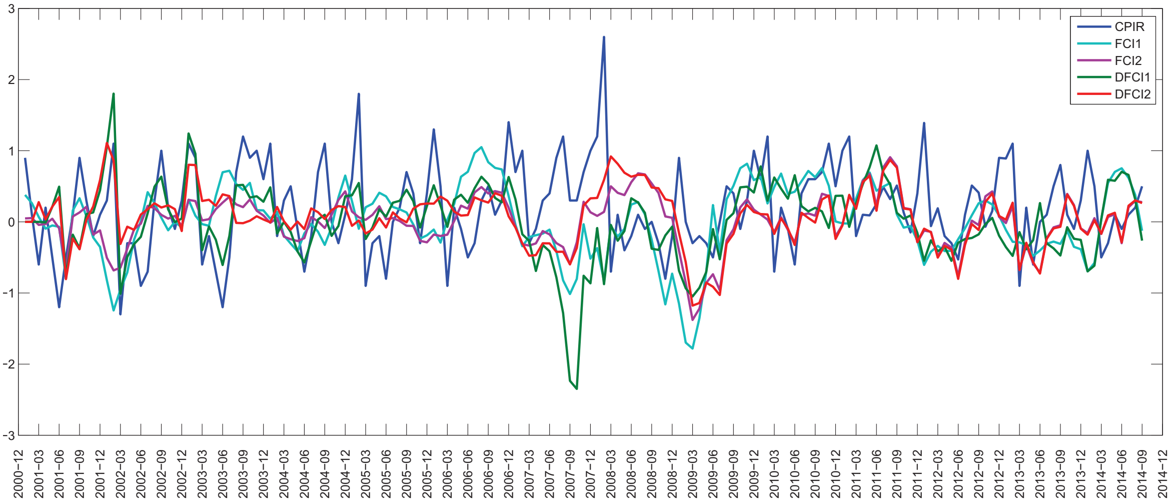


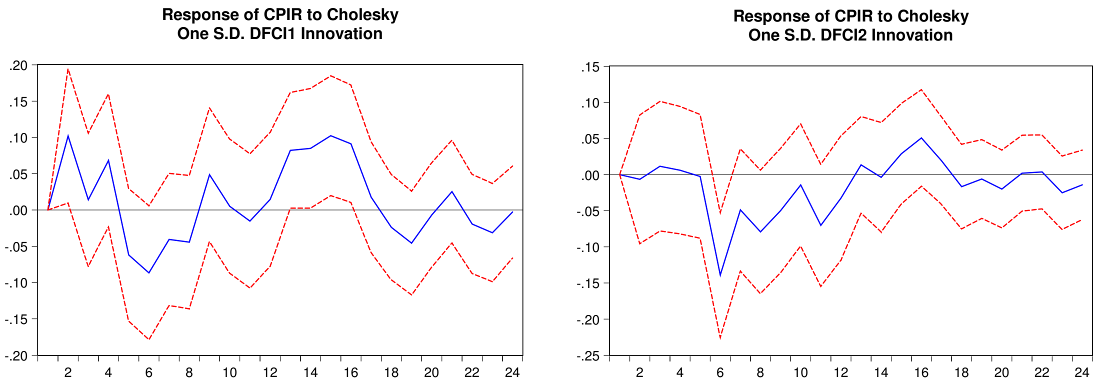
Fig. 3. CPIR, FCI1, FCI2, DFCI1, and DFCI2.

inflation and an equilibrium of easing and tightening financial conditions. Above the zero, it represents inflation and easing financial conditions, and below the zero, it represents deflation and tightening financial conditions. From Figure 3, it can be seen that the trend of DFCI1 is roughly consistent with that of DFCI2. On the whole, both DFCI1 and DFCI2 lead CPIR. We can also find that DFCI2 has smaller fluctuations than DFCI1, illustrating that RM2 is an appropriate indicator to add to DFCI.

It is worth noting that there are some big turning points of DFCIs anastomosis with the major economic and financial events: (I) Shanghai Cooperation Organization was born in June 2001 and China joined WTO in November 2001. They added driving force to economic development of China. At the same time, we can find DFCIs varied from tightening financial conditions to easing financial conditions quickly. (II) SARS virus was endemic in early 2003. It brought a negative impact on economic development of China, and we can find DFCIs fluctuated from easing financial conditions to tightening financial conditions. (III) Government of China suppressed the house price in 2006. As a result, we can find DFCIs varied from near equilibrium to tightening financial conditions quickly. (IV) The housing price in China rose contrarian in 2007. With real estate continually bubbling, house price in China constantly pushed to new high points, which led CPIR rise up to the highest point rapidly. It can be seen that DFCIs varied from tightening financial conditions to easing financial conditions rapidly, which were earlier than CPIR. (V) Subprime crisis exacerbated and global financial crisis broke in 2008. Affected by the subprime crisis and global financial crisis, China's economy received a huge impact. At the same time, it can be seen that DFCIs varied from easing financial conditions to equilibrium quickly, then drop to tightening financial conditions rapidly. (VI) European debt crisis broke from December 2009. Firstly, affected by Greek debt crisis which broke in December 2009, China's economy continued to slump. At the same time, we can find that DFCIs fluctuated from equilibrium to tightening financial conditions slowly. With European debt crisis exacerbated in 2011, DFCIs drop to tightening financial conditions rapidly, which were earlier than CPIR. The above analysis confirms the rationality of our constructed DFCIs from one side.

4.2. Granger causality test

In this subsection, we carry out the Granger causality test to examine whether lagged values of the FCIs or DFCIs help to predict current CPI inflation. The optimal lag order is 12 that is selected based on AIC (Akaike's Information Criterion), SC (Schwarz Criterion) and LR (Likelihood Ratio) criteria. Table 1 reports the results. From Table 1 we can find that: for FCI1, the null hypothesis 1 of no causality is rejected at the 1% level, however, the null hypothesis 2 is also rejected at the 5% level; for FCI2, the null hypothesis 3 is not rejected, however, the null hypothesis 4 is rejected at the 10% level; for DFCI1 and DFCI2, the null hypothesis 5 and 7 are rejected at the 5% and 10% level, respectively, meanwhile, the null hypothesis 6 and 8 are all not rejected. Therefore we



(a) (b)

Fig. 4. (a) Impulse responses of inflation CPIR to DFCI1 shock; (b) Impulse responses of inflation CPIR to DFCI2 shock.

conclude that the lagged DFCIs contain significant information for future inflation over and above the information already contained in lags of inflation itself.

Table 1. Granger causality test for the FCIs and DFCIs.

No.	Null hypothesis	F	P	No.	Null hypothesis	F	P
1	FCI1 does not Granger Cause CPIR	2.4481	0.0066***	2	CPIR does not Granger Cause FCI1	2.0638	0.0237**
3	FCI2 does not Granger Cause CPIR	1.4192	0.1652	4	CPIR does not Granger Cause FCI2	1.7810	0.0579*
5	DFCI1 does not Granger Cause CPIR	1.8624	0.0450**	6	CPIR does not Granger Cause DFCI1	1.3362	0.2061
7	DFCI2 does not Granger Cause CPIR	1.7023	0.0734*	8	CPIR does not Granger Cause DFCI2	1.1441	0.3309

Note: ***, **, and * mean the P value is significant under 1%, 5%, and 10% significance level, respectively.

4.3. Impulse responses

In this subsection, the impulse responses of inflation CPIR to DFCIs shock based on bivariate VARs are computed, and Figure 4 displays the results. The optimal lag order is 12 selected based on AIC, SC and LR criteria. The DFCIs shock are identified based on a standard Cholesky factorisation ordering CPIR first. From Figure 4, it can be seen that the responses of CPIR to Cholesky one S.D. DFCI1 innovation reach the maximum 0.102 after 2 and 15 months, and reach the minimum −0.087 after 6 months; the responses of CPIR to Cholesky one S.D. DFCI2 innovation reach the maximum 0.051 after 16 months, and reach the minimum −0.139 after 6 months.

5. Conclusions

In this paper, we have constructed dynamic financial conditions index (DFCI) for China based on AOSVR for the time-varying economic and financial environment. Obtaining dynamic weights by estimating AOSVR on output, we construct two DFCIs with money supply or not, respectively. In order to evaluate the DFCI whether is an useful indicator, the DFCI is evaluated on inflation further. The research results indicate dynamic effect of financial variables on DFCIs and show the superior performance ability of our DFCIs compared with the FCIs based on SVR. On the whole, in our DFCIs exchange rate, stock price, and money supply have the push-down effect on DFCIs, taking negative dynamic weights. Housing price has the pull-up effect on DFCIs, taking positive dynamic weights. The effect of interest rate on DFCIs is erratic, taking sign-changed dynamic weights. However, with Chinese interest rate being market-oriented, the dynamic effect of interest rate on DFCI will be explicit and important. With RMB being internationalized (to promote it, we proposal to establish Developing Country International Trade Cooperative Organization taking China as the core with the construction of One Belt and One Road) and capital being globalized, to extract the nonlinear DFCI, the nonlinear kernel where the mapping function

$\phi(x)$ can be expressed will be studied in the next work. Moreover, there are many other financial variables affecting DFCI from the theoretical or practical perspective, to extract the financial variables effectively by the methods of feature selection [22-25] will be studied further.

Acknowledgments

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