



THE EFFECTIVENESS OF CHINA'S MONETARY POLICY: BASED ON THE MIXED-FREQUENCY DATA



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ABSTRACT

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After the period of rapid growth, the Chinese economy has entered the “new normal” stage. This is a sign of the expected slowdown in economic growth. In the course of development, has the effectiveness of China’s monetary policy changed? Which of quantity and price rule monetary policies is more suitable for China’s economy? Very few researches focus on these questions, and this paper constructed a novel Mixed-Frequency Bayesian Factor Augmented Vector AutoRegression (MF-BFAVAR for short) model by combining the dynamic factor model, mixed-frequency spirit, Bayesian estimation, and factor augmented vector autoregression to find the answer. And we applied three different frequencies of data, in order to get the best estimated results. The conclusion is that price rule monetary policy is suitable for the period of steady development, and when economic growth suffers fluctuations, quantity rule monetary policy has better performance. Therefore, monetary policymakers should formulate the most effective policy based on different situations.

Contribution/ Originality: This study is one of the very few researches on the effectiveness of China’s monetary policy under the “new normal” situation. And we construct a novel methodology framework, MF-BFAVAR, which is, as far as we know, the first time to take advantage of the dynamic factor model, mixed-frequency spirit, Bayesian estimation and factor augmented vector autoregression at the same time. Unlike the existing literature, we applied data at three different frequencies (quarterly, monthly and daily) in our estimation.

1. INTRODUCTION

China, as one of the world’s most notable economies, has achieved amazing economic development. Since the year of 2014, the growth rate of China’s GDP has been turned from “high” to “medium high”. One obvious sign is that expected growth rate of GDP have been downshifted from around 10% to a 6-7%. The Chinese President Xi Jinping applied the term “new normal” to describe the situation in 2014. Since then, it has been used not only to describe slower economic growth, but also to describe the changes taking place in China’s economy generally, such as intelligent manufacturing, poverty eradication, stricter environmental regulations (Abdul-Rahaman & Yao, 2019; Aizenman, Chinn, & Ito, 2016; Chen & Groenewold, 2019; Mi et al., 2017).

The “new normal” of Chinese economy is a hot topic, and related research is growing rapidly. However, there are very few researches on the changes of effectiveness of Chinese monetary policy under the condition of “new normal” (Abdul-Rahaman & Yao, 2019; Aizenman et al., 2016; Kang, 2018; Zhang, Chen, Fan, & Wang, 2018). In

China's latest 14th five-year development plan, the important role of monetary policy in macroeconomic regulation and control has once again become prominent. Prior to the 2008 financial crisis, China has formed a monetary policy framework that is primarily based on quantity rule and supplemented by price rule. At the same time, China has spared no effort to promote the process of marketization of interest rates (Zhao, Wang, & Deng, 2019). In 2015, the marketization of interest rates was basically completed, which provided favorable conditions for the effective implementation of price rule monetary policy (Ausloos, Ma, Kaur, Syed, & Dhesi, 2019; He, Leung, & Chong, 2013; Tan, Ji, & Huang, 2016). In fact, since the reform and opening up, China's economic structure has undergone several tremendous changes. In the course of decades of development, the effectiveness of China's monetary policy has also changed alongside with the rapid economic growth. Since the Chinese economy entered the "new normal" situation, has the effectiveness of different monetary policies changed in response? Which monetary policy rule should be selected as the main implementation one in the future? This paper is trying to give the answer.

However, doing research on China's monetary policy is not easy, due to the not very satisfactory quality of statistical data, such as the lack of long-term historical data. And the rapid institutional and structural changes that China has undergone also have an impact on the quality (Fernald, Spiegel, & Swanson, 2014; He et al., 2013; Liu, Song, & Huang, 2019). Moreover, in previous studies, the common macroeconomic data used in analysis with low statistical frequency usually. GDP, as an example, is quarterly frequency. Limited by the statistical frequency, many useful indicators of economy cannot be included in the analysis model. Although there are some attempts to use mixed frequency data, the data used for research contains only two kinds of statistical frequencies (e.g. monthly-quarterly or weekly-monthly). Insufficient indicators will not reflect the full picture of economy status. Therefore we design a novel MF-BFAVAR (Mixed Frequency Bayesian Factor Augmented Vector Autoregression) method with three kinds of frequency data (quarterly-monthly-daily) to solve the data problems, in order to get better estimation. Our results show that the price rule monetary policy had a better performance for the whole-time span and the period with steady economic growth. While the quantity rule monetary policy could inject power for the period of volatile economic growth.

The follow-up content of our paper is designed as follows. Section 2 is literature review, which details the research progress in related areas. Section 3 introduces the innovative methodology adopted in this paper. Section 4 shows the data we used and the empirical results we got. At last, Section 5 is conclusion.

2. LITERATURE REVIEW

As mentioned above, the "new normal" of Chinese economy is a hot topic. Through a systematic review of existing literature, Tung (2016) made a detailed analysis of the opportunities and challenges that China's future development facing with the "new normal" situation, from many perspectives including foreign exchange reserves and financial development, regional economic integration and development, large-scale scientific and technological innovation and upgrading. Chen and Groenewold (2019) design a framework that combines the VAR model and Blanchard-Quah identification procedure to identify the primary cause affecting China's economic slowdown. And their results show that the slowdown has been mainly supply-driven.

However, there are very few researches on the changes of effectiveness of Chinese monetary policy under the condition of "new normal". Zhang et al. (2018) propose an innovational time-varying parameter vector autoregression, combined with data mining technology, to investigate the time-varying effectiveness characteristics of China's monetary policy, with monthly data. The empirical estimation results of Kang (2018) show that since 2013, the implementation effectiveness of China's monetary policy has changed. The reason is that supply-side structural adjustments and deleveraging of local government debt have resulted in slacks in aggregate demand. The international situation is becoming more complex and changeable, and China's monetary policy still faces the policy trilemma. The dual-track interest rate system has also led to a lack of clarity in the transmission mechanism of monetary policy. Abdul-Rahaman and Yao (2019) constructed a VEC model so as to analyze the

impact of the “new normal” on Chinese economy and various sectors. The conclusion of the study shows that the gradually tightening monetary policy will have very little effect on economic development in the long run, but the decrease in savings will have an adverse effect on it in the short term. The liberation reform will promote the appreciations of the RMB to a certain extent.

Turn to the methodology. The typical VAR model is one of the most popular tool in the area of monetary policy. But it has many shortcomings. Limited by the degree of freedom, the typical VAR model can only contain a few variables. But we cannot count on one official statistical indicator to perfectly reveal entire information (such as GDP and output, CPI and inflation). This greatly affects the estimation performance of the model. The FAVAR model constructed by [Bernanke, Boivin, and Elias \(2005\)](#) using a structural VAR model combined with the factor analysis model for large scale of data makes up for these shortcomings. The main advantage of the FAVAR model is that it can get rid of the limitation of the number of variables in the traditional VAR model while maintaining the general VAR analysis function. Furthermore, the FAVAR model, which can accommodate much more information, is more similar with the real situation central banks and policymakers face, and can minimize the problem of mismeasurement. In addition, the FAVAR model focuses more on reflecting the trend of a set of indicators, and high quality of data is not required. Due to the quality of Chinese statistics is not very well, the FAVAR model is much suitable for our demands. Moreover, many previous literatures have proven that the FAVAR model performs well in empirical estimation, even for relatively reliable data ([Bernanke et al., 2005](#); [He et al., 2013](#)). Therefore, the FAVAR model has been widely used, especially in the macroeconomics area, and extended many novel models.

[Mumtaz and Surico \(2009\)](#) followed the FAVAR method of [Bernanke et al. \(2005\)](#) using a large amount of panel data from 17 industrialized countries to study the global transmission mechanism of anomalous shocks and its impact on the United Kingdom. [Bai and Ng \(2013\)](#) constructed a novel method for extracting latent factors by innovating the principal component analysis approach under restricted conditions, and then proposed a new FAVAR model. [Claeys and Vašíček \(2014\)](#) constructed a new shock conduction monitoring research framework by combining the structural break test and FAVAR model which [Qu and Perron \(2007\)](#) proposed. It also took the sovereign bonds markets of the 16 EU countries as research objects and investigated the transmission Channels of the financial crisis in these bond markets.

There is also no lack of research on China's monetary policy. For example, [Fernald et al. \(2014\)](#) demonstrated the excellent performance of the FAVAR model for research with China's economic data, and used this method to conduct an empirical estimation of the transmission path of China's monetary policy. The results show that increasing bank reserve requirements will reduce economic activity and inflation. Because China's central bank determines changes in interest rates, it has a direct impact on economic activity and inflation. And China's monetary policy transmission mechanism is gradually closer to the Western market economy. In addition to the monetary policy, FAVAR has also been used in many other areas of research, such as identifying coal market shocks ([Chevallier, 2011](#)) exploring factors affecting oil prices ([Aastveit, Bjørnland, & Thorsrud, 2015](#)) and the transmission mechanism of shocks in the cryptocurrency market ([Antonakakis, Chatziantoniou, & Gabauer, 2019](#)).

The FAVAR model also extends many new branches. Integrated with time-varying parameters, as an instant, [Liu et al. \(2019\)](#) constructed the TVP-FAVAR model to study the dynamic changes of China's monetary policy over time. It convinced that China's monetary policy has time-varying characteristic. Price rule and quantity rule have their own advantages, and they should be implemented based on different policy objectives. Since the 2008 global financial crisis, price rule monetary policy has been more suitable for the development of Chinese society.

The Bayesian FAVAR approach combined with the Bayesian Inference and FAVAR, shows a better performance in existing papers. For example, [Gunter and Önder \(2016\)](#) constructed a Bayesian FAVAR model, and used the traffic big data obtained from 10 Google Analytics websites to predict the actual visitors to Vienna. [Serati and Venegoni \(2019\)](#) constructed a new type of Bayesian Time-Varying Parameters FAVAR to study the changing trend of monetary policy effects in the euro area. The conclusion is that both global financial crisis and European

debt crisis have changed the transmission channels of the Eurozone monetary policy, both on price rules (interest rates) or quantity rules (credit). The coordination of fiscal and monetary policies needs to be strengthened in order to exert the best policy results.

Another drawback of the classic VAR model is that it can only do research with the same frequency data, but the statistical frequency of economic data is various. Macroeconomic data are almost quarterly and monthly, while the frequency of financial market statistics is higher. This causes the traditional VAR model to fail to cover more statistical indicators, which will make it difficult to effectively reflect the full picture of the information.

Thus, the Mixed-Frequency VAR method rose in response to these conditions. The spirit of mixed-frequency comes from two articles by [Mariano and Murasawa \(2003\)](#); [Mariano and Murasawa \(2010\)](#). Based on articles that [James and Watson \(1988\)](#); [Stock and Watson \(1989\)](#); [Stock and Watson \(1998\)](#); [Stock and Watson \(2002\)](#) using dynamic factor models to construct consistent factor, Mariano and Murasawa added maximum likelihood estimation to build mixed frequency dynamic factor model that included both monthly and quarterly data. This has also become the origin of various mixed-frequency models, laying a foundation for subsequent related research. Based on these articles, the mixed-frequency model has also been developed in the fields of prediction, shocks identification and transmission. However, whether MF-VAR or MIDAS, the different branching methods, is better have been debated in academia. [Schorfheide and Song \(2015\)](#) integrated the Bayesian method to MF-VAR to construct the Bayesian MF-VAR model with quarterly and monthly data, and compared it with the traditional VAR model and MIDAS regression method. They proved empirically that the new method performed better. [Baumeister, Guérin, and Kilian \(2015\)](#) used the MIDAS regression model and mixed data to explore the linkages between the financial markets and the oil markets. And their results show that the weekly financial market data had a leading significance for the monthly oil price. According to the finding their prediction of the monthly oil price, compared to the MF-VAR model, is considerable better. In sum, it is generally convinced that the effectiveness of the MF-VAR model is limited by the curse of dimensionality, so it is sometimes slightly inferior to that of MIDAS model. However, with the same constraints, the MF-VAR model performs better ([Kuzin, Marcellino, & Schumacher, 2011](#)). Therefore, if the above FAVAR model is introduced, the problem can be solved easily.

Nevertheless, so far, we found that although FAVAR and mixed-frequency factor models both inherit the spirit of [James and Watson \(1988\)](#); [Stock and Watson \(1989\)](#); [Stock and Watson \(1998\)](#); [Stock and Watson \(2002\)](#) the studies using mixed-frequency data combined with FAVAR models is scarce. There are only two articles in the SCI-E and SSCI core database. [Moench and Ng \(2011\)](#) extracted the common component from the mixed-frequency data, and combined with the FAVAR model to explore the connection between US housing and consumption. [Marcellino and Sivec \(2016\)](#) extended the MF-VAR model to the MF-FAVAR model and incorporated Monte Carlo estimation method to reproduce existing researches ([Bernanke et al., 2005](#); [Bernanke, Gertler, Watson, Sims, & Friedman, 1997](#)). These results show that the innovative method improves the ability to identify shocks, avoids biased estimation caused by missing information, and has better calculation results.

In the process of estimating, they both used quarterly and monthly data, just like the previous studies. However, in recent years, a large amount of data is produced in various departments every day, and high-frequency data and big data show a blowout state. The existing method not including higher frequency data will miss many useful information.

Therefore, on the basis of previous empirical experience, this paper constructs a new factor analysis method with three frequencies (quarterly, monthly, daily) data, incorporates Bayesian method, combines the FAVAR model to construct the Bayesian MF-FAVAR model, and uses Chinese data to carry out the empirical research. This novel approach fills the gap of previous studies on the basis of covering information as much as possible. We use this to study the changes in the effectiveness of China's monetary policy under the new normal in order to obtain meaningful research results.

3. METHODOLOGY

In this section, we construct a methodology framework for our empirical estimation. And we gave the novel framework a name MF-BFAVAR (Mixed-Frequency Bayesian Factor Augmented Vector AutoRegression). It integrates mixed-frequency spirit, dynamic factor model, Bayesian method and VAR model.

3.1. Dynamic Factor Model

The dynamic factor model is the method for extracting underlying factors, and we use the presentation way of Fernald et al. (2014) and Liu et al. (2019) in this paper. Let F is a small number of potential factors that we cannot observe from economic activities. X is an N -dimensional multivariate time series vector, which determined by F .

And X is composed of data that we can specifically observe in actual economic activities. And ε is the 0 mean idiosyncratic errors, which is mutually orthogonal stationary process with F . For T periods, the original dynamic factor model can be defined as follows:

$$X_t = \Lambda F_t + \varepsilon_t. \quad (1)$$

In the Equation 1, scale of the vector X_t is much larger than that of the vector F_t . And Λ is the loadings matrix of the indicators X on the factors F . In the dynamic factor model, the factors F are related over time, typically according to a linear autoregression process (as shown in Equation 2):

$$F_t = A(L)F_{t-1} + \eta_t, \quad (2)$$

Where $A(L)$ is the polynomial containing lag operators.

3.2. The Spirit of Mixed-Frequency

As mentioned in the section 2, for the general VAR or FAVAR model, it is not difficult to deal with the same frequency and time span data.

However, due to the different frequencies and time span of macroeconomic statistics, not to mention the quality of Chinese data, it is hard to count on a single statistic indicator to reflect the overall economic status. In addition, because of the different frequencies data cannot be taken, there are some important indicator cannot be considered, which will inevitably lead to the omission of information. Therefore, this paper refers to the method applied by Mariano and Murasawa (2003); Mariano and Murasawa (2010) to introduce the spirit of mixed-frequency into our methodological framework.

Let $X_{1,t}^*$ be the high-frequency latent factor of the observable variable $X_{1,t}$. In this case, $X_{1,t}$ is quarterly data, and $X_{1,t}^*$ are its monthly latent factors. Then the variable $X_{1,t}$ can be observed once every three months, which can be expressed as the geometric mean of its three latent factors. As shown in Equation 3:

$$\ln x_{1,t} = \frac{1}{3}(\ln x_{1,t}^* + \ln x_{1,t-1}^* + \ln x_{1,t-2}^*). \quad (3)$$

And for all t , let $y_{1,t} := \Delta_3 \ln x_{1,t}, y_{1,t}^* := \Delta \ln x_{1,t}^*, y_{2,t} := \Delta \ln x_{2,t}$. Then we can get Equation 4:

$$\begin{aligned} y_{1,t} &= \frac{1}{3}(y_{1,t}^* + y_{1,t-1}^* + y_{1,t-2}^*) + \frac{1}{3}(y_{1,t-1}^* + y_{1,t-2}^* + y_{1,t-3}^*) \\ &= \frac{1}{3}y_{1,t}^* + \frac{2}{3}y_{1,t-1}^* + y_{1,t-2}^* + \frac{2}{3}y_{1,t-3}^* + \frac{1}{3}y_{1,t-4}^* \end{aligned} \quad (4)$$

So $\{y_{1,t}\}$ is an indicator that can be observed every three months, and $\{y_{1,t}^*\}$ is an unobservable indicator.

For all t , let $y_{1,t} := \begin{pmatrix} y_{1,t} \\ y_t \end{pmatrix}$, $\mu = E(y_t)$ and $\mu^* := E(y_t^*)$. We can get Equation 5 and Equation 6:

$$y_t - \mu = H(L)(y_t^* - \mu^*), \quad (5)$$

$$H(L) = \begin{pmatrix} \frac{1}{3}I_{N_1} & O \\ O & 1 \end{pmatrix} + \begin{pmatrix} \frac{2}{3}I_{N_1} & O \\ O & o \end{pmatrix}L + \begin{pmatrix} I_{N_1} & O \\ 0 & o \end{pmatrix}L^2 + \begin{pmatrix} \frac{2}{3}I_{N_1} & O \\ O & o \end{pmatrix}L^3 + \begin{pmatrix} \frac{1}{3}I_{N_1} & 0 \\ O & o \end{pmatrix}L^4, \quad (6)$$

where L is the lag operator. The Equation 5 can be transformed into a Gaussian or General VAR model with p order (as shown in Equation 7),

$$\Phi(L)(y_t^* - \mu^*) = w_t, \{w_t\} \sim IN(0, \Sigma). \quad (7)$$

For $p \leq 5$, we define the state vector as $s_t := \begin{pmatrix} y_t^* - \mu^* \\ \vdots \\ y_{t-4}^* - \mu^* \end{pmatrix}$. The state space representation can be expressed as Equation 8 and Equation 9,

$$s_{t+1} = As_t + Bz_t, \{z_t\} \sim IN(0, I_N), \quad (8)$$

$$y_t = \mu + Cs_t, \quad (9)$$

where $A := \begin{bmatrix} \Phi_1 & \dots & \Phi_{p-1} & \Phi_p \\ & I_{(p-1)N} & & \mathbf{0}_{(p-1)N \times N} \end{bmatrix}$, $B := \begin{bmatrix} \Sigma^{1/2} \\ \mathbf{0}_{4N \times N} \end{bmatrix}$, $C := [H_0 \dots H_4]$. And $\{y_t\}$ is the

mixed-frequency series we calculated. Nevertheless, on account of the missing values of our results, factor extraction cannot be implemented directly. To solve the problem, we referred to the approach in existing studies (Harvey, 1990; Kuzin et al., 2011; Mariano & Murasawa, 2003, 2010) introducing the Kalman filter and smoother to fill the missing values.

Meanwhile, the daily high-frequency data also played a role in our article. However, if the quarterly and monthly data is converted into daily according to the method above, there will be several problems: (i) It is easy to make too much missing data and lead to inaccurate estimations. (ii) The calculation burden is too heavy. Hence, we made an improvement to avoid these problems. That is, monthly is selected as the intermediate frequency, the above formulas are inverted to estimate the latent monthly indicator of the daily data.

3.3. Bayesian Parameters Estimation

Our work referred to the practices of Giannone, Lenza, and Primiceri (2015) and Gunter and Önder (2016) using Bayesian method instead of ordinary least squares (OLS) as the approach of VAR parameter estimation. Under this premise, this paper applied Minnesota or Litterman prior to estimate the parameters of BVAR. The

Minnesota prior is an informative prior that was proposed by Doan, Litterman, and Sims (1984) and Litterman (1986) and gradually became one of the most popular informative priors (Giannone et al., 2015).

Compared with the parameter estimation method applied by the general VAR model, the assumption of Minnesota prior is that the parameters for any VAR equation are random variables that have the characteristic of random walk with drift process. It turns the restrictions on degrees of freedom to that on more distant variable lags (Bańbura, Giannone, & Reichlin, 2010). The use of the informative prior shrinks the unconstrained VAR(p) to a naiver form to obtain a better parameters estimation, which is conducive to better identification and prediction results. In contrast, using uninformative or diffuse priors, such as flat prior, cannot reflect the advantages of Bayesian methods (Giannone et al., 2015).

This paper follows the expression of Lütkepohl (2005) and Gunter and Önder (2016). In Bayesian estimation, it is first assumed a prior probability density function (PDF) $g(\psi)$, and the ψ is a common parameter vector without sample information. Correspondingly, the sample PDF of the ψ with sample information can be given by $f(y|\psi)$, which is similar to the likelihood function $l(\psi|y)$. Let $f(y)$ denote the unconditional sample density, and then we can connect the prior PDF and the sample PDF by the equation:

$$g(\psi|y) = \frac{f(y|\psi)g(\psi)}{f(y)}. \quad (12)$$

Equation 12 is the so-called posterior PDF, which denotes the distribution of ψ under the sample information of y . We also can use the likelihood function and prior PDF to represent it:

$$g(\psi|y) \propto f(y|\psi)g(\psi) = l(\psi|y)g(\psi) \quad (13)$$

The PDF of posterior shown in Equation 13 cannot be computed directly. We should deal with the parameter vector ψ first to obtain the numerical solution. The parameters to be estimated of vector ψ include the parameters of the model and three hyperparameters of BVAR(p). In this paper, we set the overall tightness as 0.1, relative cross-variable weight as 0.99, and 1 for lag decay.

3.4. MF-BFAVAR

Finally, we can establish our FAVAR framework (see Equation 14 and Equation 15) in this paper after the works above, as the instrument to identify the effectiveness of monetary policy shocks:

$$Y_t = B(L)Y_{t-p} + \Gamma F_t + \epsilon_t \quad (14)$$

$$\begin{bmatrix} F_t \\ X_t \end{bmatrix} = A(L) \begin{bmatrix} F_{t-p} \\ X_{t-p} \end{bmatrix} + \eta_t. \quad (15)$$

Where Y_t is the observable monetary policy variable, X_t is the observable variable, and F_t denotes the latent factor extracted base on the dynamic factor model with mixed-frequency spirit. $A(L)$ and $B(L)$ denote lag polynomial with p order and the L is lag operator. ϵ_t and η_t are stochastic disturbances subject to iid. In the process of extracting factors, we followed the approach of existing studies (Kuzin et al., 2011; Mariano & Murasawa, 2003,

2010) by implementing the principal component analysis to obtain the latent factors. At the same time, this article divided the X_t indicators into two groups, to construct the consistency factors of “output” and “inflation”, as Fernald et al. (2014) and Liu et al. (2019) did.

However, information on monetary policy is not perfectly reflected by an observable indicator. Therefore, our paper makes an improvement on the basis of the typical dynamic factor model, and added the potential variable F^y . Hence, the FAVAR equation can be modified to Equation 16:

$$\begin{bmatrix} F_t^x \\ F_t^y \end{bmatrix} = A(L) \begin{bmatrix} F_{t-p}^x \\ F_{t-p}^y \end{bmatrix} + \epsilon_t \tag{16}$$

Where F_t^y is the latent factor of monetary policy (“quantity rule” or “price rule”), F_t^x is $A(L)$ is lag polynomial with p order, and ϵ_t obeys iid. At last, we finished the establishment of the methodology framework, which is the so-called MF-BFAVAR, as the main tool to identify the shocks of the monetary policy. And we used the same model with different lag period to verify the robustness of our methodology.

4. EMPIRICAL RESULTS

4.1. Data Description

We applied the study framework constructed above (MF-BFAVAR), to measure the changes of effectiveness and transmission mechanism of China’s monetary policy in different periods. The data we used is with three frequencies: quarterly, monthly and daily. The time span is from January 2000 to December 2019, covering the periods of the rapid development of China before the global financial crisis, the sharp decline during the crisis, the subsequent rapid recovery, and the “new normal” of economy.

Figure 1 shows the missing values of the indicators we applied. In order to obtain the precise result, it is necessarily to eliminate the effects caused by multiple reasons such as the Chinese Spring Festival. And this article filled in missing values in two ways. For some “output” data, relatively accurate inferences can be made through some relevant indicators.



Figure-1. Missing values of China's macroeconomic indicators.

The missing values of other indicators are filled by the structural time series model and Kalman filter. A R package developed by Moritz and Bartz-Beielstein (2017) was implemented here. And for irregular indicators, such as the deposit reserve ratio, we transferred them to monthly data.

In order to eliminate the effects of price and seasonal changes, this article converts the raw quantitative data into year-on-year growth rates. And all the data is processed by Z-core standardization. The data of the selected 40 indicators details see Table 1-Table 4 are from the China Statistical Yearbook, the database of National Bureau of Statistics of China, and the Choice Economic Database.

Table-1. Description of output indicators.

Output Indicators	For Short	Frequency	First Observation	Last Observation
Power Generation	PG	Monthly	2000M02	2019M12
Industrial Added Value	IP	Monthly	2000M02	2019M12
Fixed Assets Investment	FAI	Monthly	2000M02	2019M12
Export	Exp	Monthly	2000M01	2019M12
Budget Revenue	BR	Monthly	2000M01	2019M12
Total Retail Sales of Consumer Goods	TRSCG	Monthly	2000M01	2019M12
Consumer Confidence Index	CCI	Monthly	2000M01	2019M11
Macro Prosperity Index	MPI	Monthly	2000M01	2019M10
Purchase Management Index	PMI	Monthly	2005M01	2019M12
Total Treight	TF	Monthly	2000M01	2019M11
Crude Steel Production	CSP	Monthly	2000M01	2019M12
Ethylene Production	EP	Monthly	2000M01	2019M12
GDP	GDP	Quarterly	2000Q1	2019Q4
GDP: Secondary Industry	GDP2nd	Quarterly	2000Q1	2019Q4
GDP: Tertiary Industry	GDP3rd	Quarterly	2000Q1	2019Q4
Urban Unemployment Rate	UUR	Quarterly	2002Q1	2019Q4
Disposable Income per Capita	DIC	Quarterly	2013Q1	2019Q4
RMB Exchange Rate (to U.S. Dollar)	ER	Daily	2000/1/1	2019/12/31
Shanghai Composite Index	SHCI	Daily	2000/1/4	2019/12/31
Shenzhen Component Index	SZCI	Daily	2000/1/4	2019/12/31

Table-2. Description of inflation indicators.

Inflation Indicators	For Short	Frequency	First Observation	Last Observation
Consumer Price Index	CPI	Monthly	2000M01	2019M12
Consumer Price Index: Urban	CPIU	Monthly	2000M01	2019M12
Consumer Price Index: Rural	CPIR	Monthly	2000M01	2019M12
Consumer Price Index: Food	CPIF	Monthly	2000M01	2019M12
Consumer Price Index: Non-Food	CPINF	Monthly	2002M03	2019M12
Producer Price Index	PPI	Monthly	2000M01	2019M12
Purchasing Price Index of Raw Material, Fuel and Power	PPIRM	Monthly	2000M01	2019M12
Retail Price Index	RPI	Monthly	2000M01	2019M12
Corporate Goods Price Index	CGPI	Monthly	2000M01	2019M12
Consumer Price Index: in 36 cities	CPI36	Monthly	2000M01	2019M12

Table-3. Description of quantity rule indicators.

Quantity Rule	For Short	Frequency	First Observation	Last Observation
M0	M0	Monthly	2000M01	2019M12
M1	M1	Monthly	2000M01	2019M12
M2	M2	Monthly	2000M01	2019M12

Table-4. Description of price rule indicators.

Price Rule	For Short	Frequency	First Observation	Last Observation
Medium and Long-Term Loan Interest Rate: 3 To 5 Years (Inclusive)	MLLIR	Irregular	2000M01	2015M10
Time Deposit Interest Rate: 1 Year (Full Deposit and Withdrawal) (Month)	RDIR	Irregular	2000M01	2015M10
SHIBOR: Overnight	SHIBOR1d	Daily	2006/10/8	2019/12/31
SHIBOR: 7Day	SHIBOR7d	Daily	2006/10/8	2019/12/31
Chinabond Treasury Maturity Yield: 1 Year	TMY1y	Daily	2002/1/4	2019/12/31
Chinabond Treasury Maturity Yield: 5 Years	TMY5y	Daily	2002/1/4	2019/12/31
CHIBOR: 7 Days	CHIBOR7d	Daily	2004/5/24	2019/12/31

4.2. The Indexes

We used the Kalman filter to integrate the data with mixed frequencies earlier. In this section we use principal component analysis (PCA), another familiar tool of dynamic factor models, to construct the index of each division.

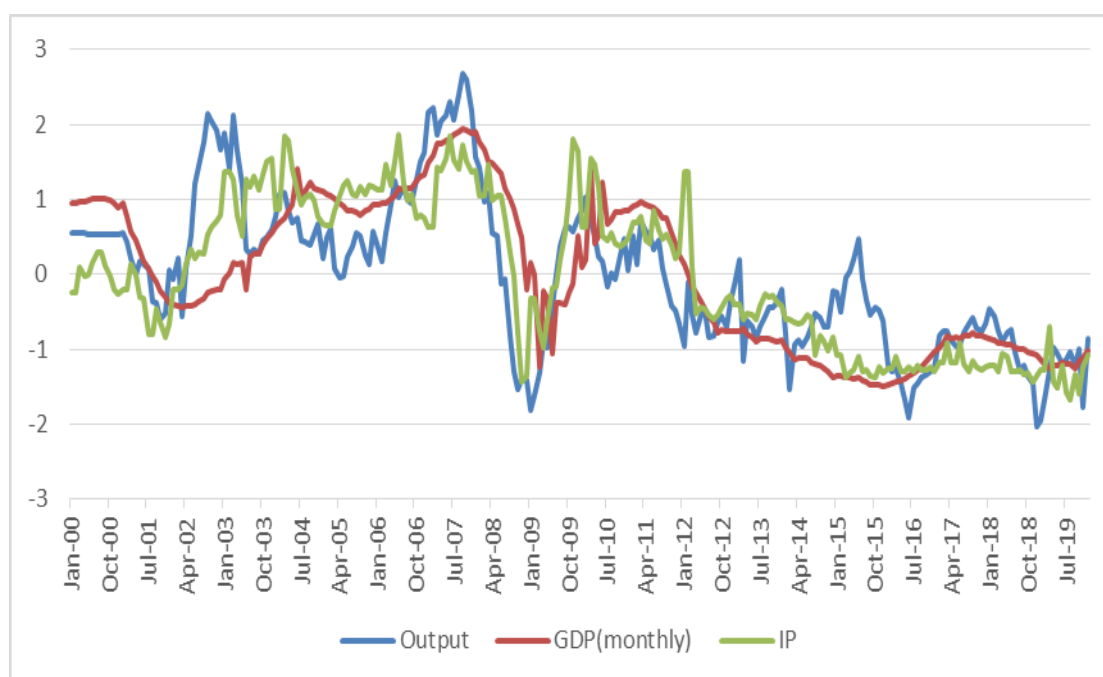


Figure-2. The Comparison of output index, GDP (monthly) and IP.

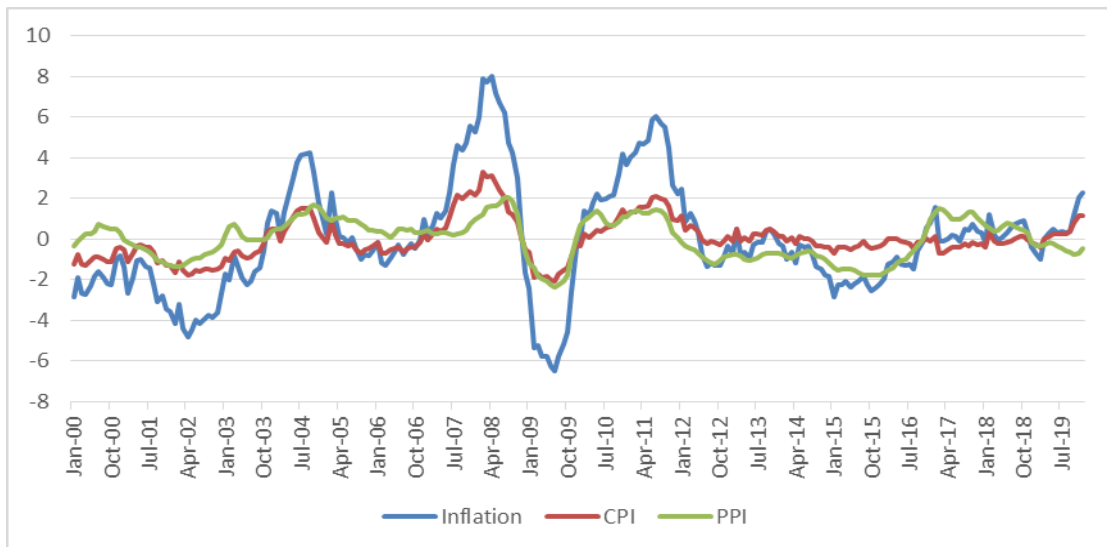


Figure-3. The comparison of inflation index, CPI and PPI.



Figure-4. The comparison of price rule index, SHIBOR7d and MLLIR.

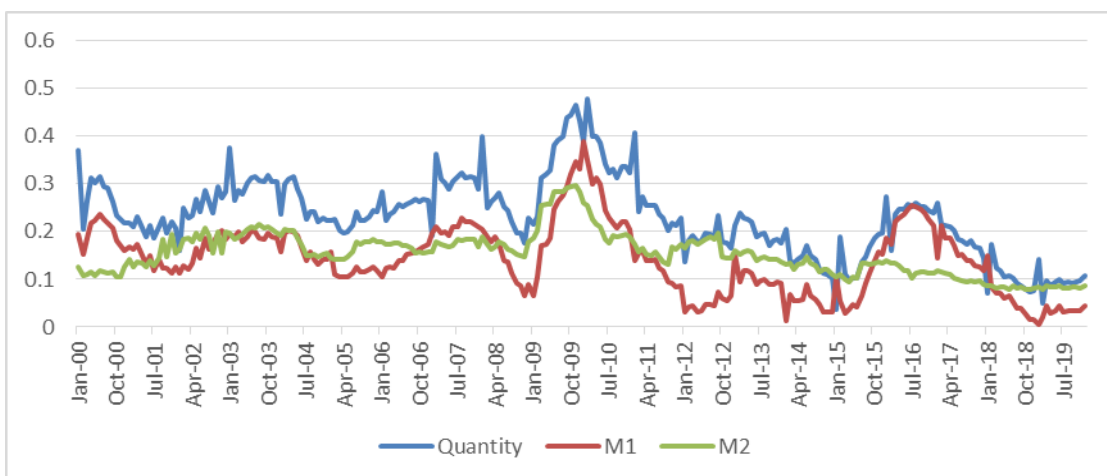


Figure-5. The comparison of quantity rule index, M1 and M2.

Figure 2 - Figure 5 show us the comparisons between the indexes and main indicators of their division. Each index is good to reflect the major trend with slight differences from its main indicator. We theoretically believe that these differences are information on economic activities that cannot be reflected by just one indicator.

4.3. The Results and Discussion

Figure 6 exhibits the impulse response images from the Bayesian FAVAR model by EViews 10.0. They reflect the effectiveness of two rules of monetary policy in different period.

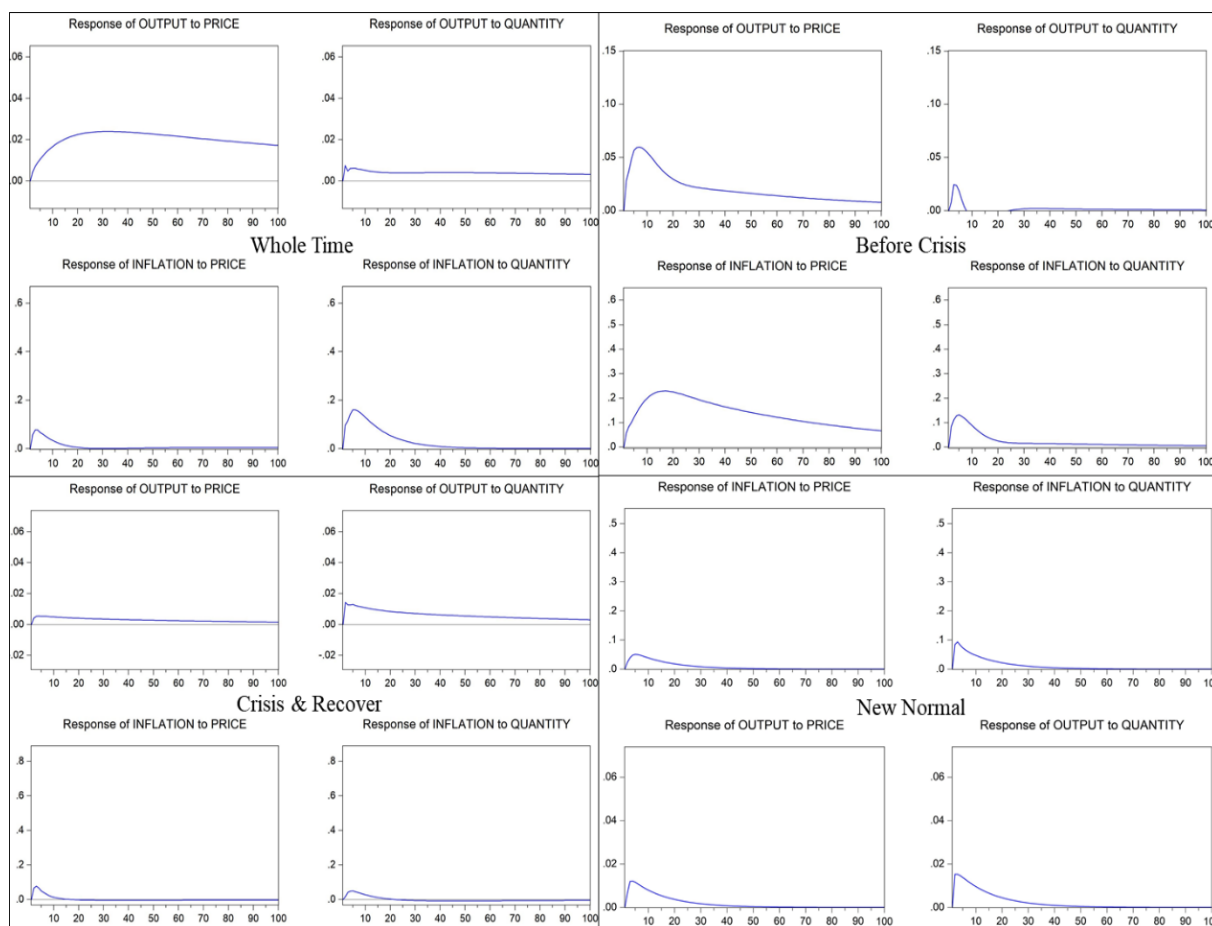


Figure-6. The impulse response results of Bayesian FAVAR in different period.

4.3.1. The Whole Time: 2000-2019

Over the whole-time span, the price rule of monetary policy had a better performance. The response of economic output to a shock of price rule increases from 0 to 0.024, while that of quantity rule increases to about 0.007. And the response of inflation to a shock of price rule increase to 0.078, which is less than 0.161 of quantity rule. For all time, the price rule could accelerate the economic output with less inflation growth.

4.3.2. The Period before the Financial Crisis: 2000-2006

At the beginning of the 20th century, and before the financial crisis, China's economy developed steadily and rapidly for several years. With the continuous progress of market-oriented reforms, the role of price rule monetary policy had become increasingly prominent. As shown in Figure 6, a shock of price rule tools will trigger an increase in economic output of 0.060, which is better than 0.024 of quantity rule. Meanwhile, the contribution of price rule tools (0.230) to inflation is also higher than the quantity rule (0.133).

4.3.3. The Financial Crisis and Recovering: 2007-2014

During this period, China's economic growth experienced sharp fluctuations, and the direct quantity rule monetary policy had better performance. The response of economic output to a shock of quantity rule grows from 0 to 0.014, with only 0.051 increase of inflation. Under the same conditions, the contribution of price rule to output is only 0.005, and brings a slightly higher level of inflation (0.078).

4.3.4. The Period of “New Normal”: 2015-2019

In the period when the China’s economy has just entered the “new normal”, both monetary policies had a positive effect on economic output. Quantity rule tools are more like a double-edged sword, which is slightly better than price rule in promoting output with more increase of inflation. The price rule is more moderate. From the Figure 6, giving a shock to quantity rule will cause an increase on economic output to 0.094, which is higher than 0.051 of price rule. And the inflation also makes a growth of 0.015 that is a little bit higher than 0.012 of price rule.

We can conclude that, the price rule monetary policy was more effective for the entire time span. It means that China’s interest rate marketization process had achieved good results, providing a guarantee for the implementation of price rule monetary policy. This summary also coincides with the conclusion of Fernald et al. (2014) that China’s monetary policy environment is becoming more and more like that of Western economies. Prior to the financial crisis, the advantages of price rule instruments have been highlighted. And during the financial crisis and subsequent recovery phases, more straightforward quantity rule tools are more capable of driving economic recovery. After the Chinese economy entered the “new normal” stage, although the economic growth has declined, the overall development has been relatively stable. Both quantity and price rule policies have demonstrated their own characteristics.

5. CONCLUSION

China’s interest rate liberalization process ensures the effective implementation of price rule monetary policy. Under this premise, in the period of stable and rapid economic development, the effectiveness of price rule tools is better than that of quantity rule. In less favorable situations, such as decline or fluctuation in economic growth, straightforward quantity rule instruments are more likely to reverse the momentum. Different monetary policies have different dynamic effectiveness corresponding to different situations. As a good example, the U.S. Federal Reserve increased its use of quantity rule instruments after the financial crisis. Therefore, facing with volatile economic situation in the future, the monetary policy is not a binary choice. The policy makers should formulate the most effective policies according to different environments. In future, scholars should consider the impact of global economic changes and the simulations of monetary policy in different situations.

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REFERENCES

- Aastveit, K. A., Bjørnland, H. C., & Thorsrud, L. A. (2015). What drives oil prices? Emerging versus developed economies. *Journal of Applied Econometrics*, 30(7), 1013-1028. Available at: <https://doi.org/10.1002/jae.2406>.
- Abdul-Rahaman, A. R., & Yao, H. (2019). China’s new normal and the implications to domestic and global business. *International Journal of Finance & Economics*, 1-15. Available at: <https://doi.org/10.1002/ijfe.1737>.
- Aizenman, J., Chinn, M. D., & Ito, H. (2016). Monetary policy spillovers and the trilemma in the new normal: Periphery country sensitivity to core country conditions. *Journal of International Money and Finance*, 68, 298-330. Available at: <https://doi.org/10.1016/j.jimonfin.2016.02.008>.
- Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2019). Cryptocurrency market contagion: Market uncertainty, market complexity, and dynamic portfolios. *Journal of International Financial Markets, Institutions and Money*, 61, 37-51. Available at: <https://doi.org/10.1016/j.intfin.2019.02.003>.
- Ausloos, M., Ma, Q., Kaur, P., Syed, B., & Dhesi, G. (2019). Duration gap analysis revisited method in order to improve risk management: The case of Chinese commercial bank interest rate risks after interest rate liberalization. *Soft Computing*, 1-19. Available at: <https://doi.org/10.1007/s00500-019-04376-7>.

- Bai, J., & Ng, S. (2013). Principal components estimation and identification of static factors. *Journal of Econometrics*, 176(1), 18-29. Available at: <https://doi.org/10.1016/j.jeconom.2013.03.007>.
- Bañbura, M., Giannone, D., & Reichlin, L. (2010). Large Bayesian vector auto regressions. *Journal of Applied Econometrics*, 25(1), 71-92. Available at: <https://doi.org/10.1002/jae.1137>.
- Baumeister, C., Guérin, P., & Kilian, L. (2015). Do high-frequency financial data help forecast oil prices? The MIDAS touch at work. *International Journal of Forecasting*, 31(2), 238-252. Available at: <https://doi.org/10.1016/j.ijforecast.2014.06.005>.
- Bernanke, B. S., Boivin, J., & Elias, P. (2005). Measuring the effects of monetary policy: A factor-augmented vector autoregressive (FAVAR) approach. *The Quarterly Journal of Economics*, 120(1), 387-422. Available at: <https://doi.org/10.1162/0033553053327452>.
- Bernanke, B. S., Gertler, M., Watson, M., Sims, C. A., & Friedman, B. M. (1997). Systematic monetary policy and the effects of oil price shocks. *Brookings Papers on Economic Activity*, 1997(1), 91-157. Available at: <https://doi.org/10.1016/j.jeconom.2016.04.010>.
- Chen, A., & Groenewold, N. (2019). China's 'New Normal': Is the growth slowdown demand-or supply-driven? *China Economic Review*, 58, 1-22. Available at: <https://doi.org/10.1016/j.chieco.2018.07.009>.
- Chevallier, J. (2011). Macroeconomics, finance, commodities: Interactions with carbon markets in a data-rich model. *Economic Modelling*, 28(1-2), 557-567. Available at: <https://doi.org/10.1016/j.econmod.2010.06.016>.
- Claeys, P., & Vašíček, B. (2014). Measuring bilateral spillover and testing contagion on sovereign bond markets in Europe. *Journal of Banking & Finance*, 46, 151-165. Available at: <https://doi.org/10.1016/j.jbankfin.2014.05.011>.
- Doan, T., Litterman, R., & Sims, C. (1984). Forecasting and conditional projection using realistic prior distributions. *Econometric Reviews*, 3(1), 1-100. Available at: <https://doi.org/10.1080/07474938408800053>.
- Fernald, J. G., Spiegel, M. M., & Swanson, E. T. (2014). Monetary policy effectiveness in China: Evidence from a FAVAR model. *Journal of International Money and Finance*, 49, 83-103. Available at: <https://doi.org/10.1016/j.jimonfin.2014.05.007>.
- Giannone, D., Lenza, M., & Primiceri, G. E. (2015). Prior selection for vector autoregressions. *Review of Economics and Statistics*, 97(2), 436-451. Available at: https://doi.org/10.1162/rest_a_00483.
- Gunter, U., & Önder, I. (2016). Forecasting city arrivals with Google analytics. *Annals of Tourism Research*, 61, 199-212. Available at: <https://doi.org/10.1016/j.annals.2016.10.007>.
- Harvey, A. C. (1990). Forecasting, structural time series models and the Kalman filter (pp. 101-112). Cambridge, UK: Cambridge University Press.
- He, Q., Leung, P.-H., & Chong, T. T.-L. (2013). Factor-augmented VAR analysis of the monetary policy in China. *China Economic Review*, 25, 88-104. Available at: <https://doi.org/10.1016/j.chieco.2013.03.001>.
- James, S. H., & Watson, M. W. (1988). A probability model of the coincident economic indicators. Mass., USA: National Bureau of Economic Research Cambridge.
- Kang, C. (2018). China's monetary policy under the "new normal". *China: An International Journal*, 16(3), 74-96.
- Kuzin, V., Marcellino, M., & Schumacher, C. (2011). MIDAS vs. mixed-frequency VAR: Nowcasting GDP in the euro area. *International Journal of Forecasting*, 27(2), 529-542. Available at: <https://doi.org/10.1016/j.ijforecast.2010.02.006>.
- Litterman, R. B. (1986). Forecasting with Bayesian vector autoregressions—five years of experience. *Journal of Business & Economic Statistics*, 4(1), 25-38. Available at: <https://doi.org/10.1080/07350015.1986.10509491>.
- Liu, C., Song, P., & Huang, B. (2019). The dynamic effectiveness of monetary policy in China: Evidence from a TVP-SV-FAVAR model. *Applied Economics Letters*, 26(17), 1402-1410. Available at: <https://doi.org/10.1080/13504851.2018.1564110>.
- Lütkepohl, H. (2005). New introduction to multiple time series analysis (pp. 222). German: Springer Berlin Heidelberg.
- Marcellino, M., & Sivec, V. (2016). Monetary, fiscal and oil shocks: Evidence based on mixed frequency structural FAVARs. *Journal of Econometrics*, 193(2), 335-348. Available at: <https://doi.org/10.1016/j.jeconom.2016.04.010>.
- Mariano, R. S., & Murasawa, Y. (2003). A new coincident index of business cycles based on monthly and quarterly series. *Journal of Applied Econometrics*, 18(4), 427-443. Available at: <https://doi.org/10.1002/jae.695>.
- Mariano, R. S., & Murasawa, Y. (2010). A coincident index, common factors, and monthly real GDP. *Oxford Bulletin of Economics*

- and Statistics*, 72(1), 27-46. Available at: <https://doi.org/10.1111/j.1468-0084.2009.00567.x>.
- Mi, Z., Meng, J., Guan, D., Shan, Y., Liu, Z., Wang, Y., & Wei, Y. M. (2017). Pattern changes in determinants of Chinese emissions. *Environmental Research Letters*, 12(7), 074003.
- Moench, E., & Ng, S. (2011). A hierarchical factor analysis of US housing market dynamics. Oxford, UK: Oxford University Press.
- Moritz, S., & Bartz-Beielstein, T. (2017). ImputeTS: Time series missing value imputation in R. *The R Journal*, 9(1), 207-218. Available at: <https://doi.org/10.32614/RJ-2017-009>.
- Mumtaz, H., & Surico, P. (2009). The transmission of international shocks: A factor-augmented VAR approach. *Journal of Money, Credit and Banking*, 41, 71-100. Available at: <https://doi.org/10.1111/j.1538-4616.2008.00199.x>.
- Qu, Z., & Perron, P. (2007). Estimating and testing structural changes in multivariate regressions. *Econometrica*, 75(2), 459-502. Available at: <https://doi.org/10.1111/j.1468-0262.2006.00754.x>.
- Schorfheide, F., & Song, D. (2015). Real-time forecasting with a mixed-frequency VAR. *Journal of Business & Economic Statistics*, 33(3), 366-380. Available at: <https://doi.org/10.1080/07350015.2014.954707>.
- Serati, M., & Venegoni, A. (2019). The cross-country impact of ECB policies: Asymmetries in—asymmetries out? *Journal of International Money and Finance*, 90, 118-141. Available at: <https://doi.org/10.1016/j.jimonfin.2018.09.008>.
- Stock, J. H., & Watson, M. W. (1998). Diffusion indexes (No. w6702). National bureau of economic research.
- Stock, J. H., & Watson, M. W. (2002). Macroeconomic forecasting using diffusion indexes. *Journal of Business & Economic Statistics*, 20(2), 147-162. Available at: <https://doi.org/10.1198/073500102317351921>.
- Stock, J. H., & Watson, M. W. (1989). New indexes of coincident and leading economic indicators. *NBER Macroeconomics Annual*, 4, 351-394. Available at: <https://doi.org/10.1086/654119>.
- Tan, Y., Ji, Y., & Huang, Y. (2016). Completing China's interest rate liberalization. *China & World Economy*, 24(2), 1-22. Available at: <https://doi.org/10.1111/cwe.12148>.
- Tung, R. L. (2016). Opportunities and challenges ahead of China's "new normal". *Long Range Planning*, 49(5), 632-640. Available at: <https://doi.org/10.1016/j.lrp.2016.05.001>.
- Zhang, J.-q., Chen, T., Fan, F., & Wang, S. (2018). Empirical research on time-varying characteristics and efficiency of the Chinese economy and monetary policy: Evidence from the MI-TVP-VAR model. *Applied Economics*, 50(33), 3596-3613. Available at: <https://doi.org/10.1080/00036846.2018.1430338>.
- Zhao, X., Wang, Z., & Deng, M. (2019). Interest rate marketization, financing constraints and R&D investments: Evidence from China. *Sustainability*, 11(8), 1-16. Available at: <https://doi.org/10.3390/su11082311>.

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