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Predicting Chinese Banking Policy Incidence Using a VAR Model

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Abstract

In this exploratory research, we examine the effect of economic and noneconomic indicators on the creation of Chinese Banking and Insurance Regulatory Commission policies using a VAR model. We find that CBIRC policies are predicted by State Council construction policies and policies set by the State Administration of Foreign Exchange. This indicates that the CBIRC is inward-looking, observing what other regulators are doing rather than responding to changes in the real and financial economy. This may be a product of market distortions due to China's unique blend of state-oriented and market-based institutions.

Introduction

In this exploratory research, we examine the effect of economic and noneconomic indicators on the creation of Chinese Banking and Insurance Regulatory Commission (CBIRC) policies using a VAR model. We find that CBIRC policies are predicted by State Council construction policies and policies set by the State Administration of Foreign Exchange. This indicates that the CBIRC is inward-looking, observing what other regulators are doing rather than responding to changes in the real and financial economy. This may be a product of market distortions due to China's unique blend of state-oriented and market-based institutions.

This paper is unique in predicting economic policy incidence. We test various indicators to discover which variables might influence the number of policies created on a monthly basis by China's banking and insurance regulators, and find two that have a strong impact on CBIRC policy creation. This type of study that attempts to explain how banking regulations are made is scarcely found in the literature, and represents a new way of understanding the policy making process, particularly in a regulatory regime that is frequently less transparent than in Western nations.

The importance of this type of study is substantial, since it can help policy watchers and investors understand which direction Chinese policies are likely to take and why. This can help to reduce policy uncertainty and increase investor and business confidence, creating a more stable economic environment. Next, we turn to the literature review of this topic.

Literature Review

There is very little research that predicts policy incidence. One strain of Chinese policy prediction that uses machine learning incorporates key words found in the People's Daily to predict major policy changes in China. This is developed within the Policy Change Index, created by the Mercatus Center at George Mason University (Chan and Zhong 2019). In an article that incorporates this index, policy waves predict the Great Leap Forward, the Cultural Revolution, and the more recent supply-side structural reform. This paper uses the gated recurrent units (GRU) model developed by Cho et al. (2014), to analyze key phrases. Chinese monetary policy is another area in which policy has been predicted. For example, Lu (2019) uses machine learning, in particular a neural network and error t-value test, to predict monetary policy. In this paper, Lu examines the relationship between reserve adjustments and financial markets.

There is also research that predicts financial distress. Behn et al (2017) construct an early-warning model predict banking-sector vulnerabilities, finding that global credit growth in particular is a strong predictor of domestic banking vulnerabilities. Petropoulos et al (2021) use various machine learning techniques to predict bank insolvencies on US-based financial institutions, showing that the Random Forests model is the best performing. Duca and Peltonen (2013) use multivariate discrete choice models that combine domestic and global indicators of macro-financial vulnerabilities across 28 countries to predict systemic financial crises. Betz et al (2014) use a new dataset that incorporates bankruptcies, defaults, state interventions, and mergers in distress in order to predict bank distress in European banks.

A related body of research forecasts monetary policy. Vasnev, Skirtun, and Pauwels (2013) employ a triple-choice probit method to forecast monetary policy decisions of the Reserve Bank of Australia, finding that combined forecasts outperform multivariable models. Qiu, Li, and Qiu (2020) predict monetary policy made by the People's Bank of China using a random forest algorithm model with 16 macroeconomic indicators. The model has a predictive accuracy of 79% in predicting monetary policy direction.

As we can see, the literature on this topic is scarce. Therefore, we provide a backdrop against which our study is made, providing an overview of China’s banking and insurance systems, as well as the regulatory environment surrounding them.

China’s banking and insurance system and regulation

China’s financial system is dominated by banks, especially by the largest state-owned institutions. These include the Industrial and Commercial Bank of China (ICBC), China Construction Bank (CCB), Bank of China (BOC), Agricultural Bank of China (ABC) and the Bank of Communications (BCOM). These banks receive about one-half of the banking systems’ assets and deposits. These banks are listed on the stock exchange and majority-owned by the government. The rest of the banking system contains twelve smaller listed commercial banks, three ‘policy’ banks, a postal savings bank, over one hundred city commercial banks, and three thousand credit cooperatives and rural finance organizations (Turner, Tan and Sadeghian 2012).

The financial system has expanded over time with the growth of the shadow banking sector. Shadow banking includes wealth management products, many of which are sold by banks, as well as trust products sold by trust companies and asset management products sold by asset management companies, and entrusted loans between enterprises. Many of these products and institutions have been brought out of the shadows through regulation and are now counted as part of total social finance, along with traditional bank loans.

The insurance industry includes life insurance and property–liability insurance. The life insurance sector contains private health insurance and short-term casualty insurance. Social insurance provided by the government are part of China’s social protection regime.

The China Banking and Insurance Regulatory Commission (CBIRC) is the central government regulator for the banking and insurance industries. This body resulted from the merger of the China Banking

Regulatory Commission and the China Insurance Regulatory Commission in early 2018. The mandate of the CBIRC is to supervise the banking and insurance sectors, as well as to ensure fair competition and protect the rights of stakeholders (CBIRC 2021). This body is responsible for legislation just above the most basic levels of legislation, which were enacted by the National People's Congress. These basic levels of legislation include the Banking Regulation Law (2006), the People's Bank of China Law (2003) and the Commercial bank Law (2015). The CBIRC is responsible for prudential regulation in the medium term and fair competition in the long term. Much of the CBIRC’s regulation is comprised of guidance, notice, and rules (Wang and Tan 2021).

The China Banking Regulatory Commission, which preceded the CBIRC, was set up in order to take action against risks and destabilizing forces generated by the banks (Yazar 2015). This represented delegation by the state in order to increase efficiency. This body was set up in 2003 as China prepared to open up to foreign bank competition. The need to regulate foreign banks, as well as the occurrence of banking scandals during this time resulted in the creation of the CBRC.

The CBRC assisted the process of banking reform. After the modernization of the banking system, the initial wave of banking reform was implemented in the late 1990s, in order to reduce non-performing loans at the major state-owned banks (Sun 2020). Asset management companies were created in order to take on such non-performing assets and the banks received capital injections. In the second wave of reform, starting in 2003, banks were required to improve corporate governance. Banks were financially restructured and publicly listed.

The CBIRC issues prescriptive rules that cover a wide range of topics. Banks as well as their products and services are covered by prudential regulation, and information disclosure is a key part of these rules (He 2012). As China’s banking system has developed, the CBIRC has taken the role of encouraging strong banking practices in order to improve the direction of growth. In addition, the CBIRC controls the appointment of banks’ directors and senior executives, who must be specific requirements in order to hold office.

The global financial crisis had a significant impact on regulatory bodies around the world, as it revealed shortcomings of principles-based regulation in the UK and rules-based regulation in the US. In response, Chinese regulators further increased regulatory control, moving in the direction of command-control regulation. The CBIRC then reformed the regulatory framework in 2015 and set up the Prudential Regulation Bureau in order to unify rules of Prudential Management within the banking industry.

In 2018, the CBIRC introduced the Measures for the Liquidity Risk Management of Commercial Banks, which implemented new indicators in conformance to Basel III liquidity risk requirements. These include the net stable funding ratio, the liquidity matching ratio, and the adequacy ratio of high-quality liquid assets, in addition to the traditional indicators, liquidity coverage ratio and liquidity ratio.

The CBIRC opened up further to foreign participation in the banking and insurance industries in 2018. Restrictions on the foreign ownership cap in life insurance companies were eased from 50% to 51%, foreign ownership limits in Chinese banks were removed, and allowing foreign-owned insurance brokerages were permitted to operate at the same scope as domestic insurance brokerages (Chen and Huang 2020). Foreign banks fall under rules similar to those of domestic banks in terms of establishment or articles of association approval. However, foreign banks also require approval to engage in foreign currency and RMB business such as taking deposits and issuing loans, providing letters of credit, and engaging in interbank business.

The insurance industry became more focused on risks after the revision of the Insurance Law in 2009, which improved information disclosure and consumer rights protection and standardized contracts and procedures (Chen et al 2013). Greater focus was brought to ensure supervision of solvency and market conduct. Chinese insurance regulators make use of on-site and off-site inspections to ensure compliance and monitor risks.

Improvements in the insurance industry came as China's domestic insurance market developed and as the industry opened to foreign competition. Currently, there are several regulations that insurance companies must comply with. Life insurance companies must be in compliance with the CBIRC rules that include the Provisions on Basic Services for Life Insurance Business, the Administrative Provisions on Authenticity Management of Personal Insurance Customer Information, and the Administrative Provisions on Insurance Terms and Insurance Rates of Life Insurance Companies, among others. Property and casualty insurers must meet rules including the Administrative Provisions on Insurance Terms and Insurance Rates of Property Insurance Companies and the Guidelines on Development of Insurance Products by Property Insurance Companies. Foreign insurance companies must follow the requirements laid out by the Administrative Regulations of the People's Republic of China on Foreign-funded Insurance Companies, which ensure a minimum total capital, and the Implementing Rules for the Administrative Regulations on Foreign invested Insurance Companies.

Regulations have kept pace with changes in the industry, catching up to international standards. Rules introduced in 2020 attempted to improve supervision of insurance asset and liability management and implement constraint-based asset and liability management (Ernst and Young 2020).

CBIRC leadership

The CBIRC leadership has had an impact on regulations implemented over the years. The first chairman of the CBRC was Liu Mingkang, who served until 2011. Liu had served as Chairman of Bank of China, Chairman of China Everbright Group, and Deputy Governor of the People's Bank of China. Liu had been sent in to China Everbright after the previous chairman was arrested for corruption, and later into the Bank of China in the wake of another corruption scandal, this time at the US branch. Liu pushed the Bank of China forward into financial reform, listing the Hong Kong operations of the bank successfully on the Hong Kong Stock Exchange (Naughton 2003).

As chairman of the CBRC, Liu helped to orient bank from serving state-owned enterprises to providing retail banking services and serving the market economy. Liu also made the case for providing banks with a permanent outlet for removing non-performing loans from their balance sheets (Reuters 2007). Liu also ushered the banking system through the global financial crisis by investing a large amount of credit to stabilize the financial economy (Xinhua 2010). During this time, the CBRC attempted to regulate further the real estate industry and ensure funding availability to small and medium sized enterprises.

The next chairman was Shang Fulin. Shang had previously acted as Chairman of the China Securities Regulatory Commission, President of the Agricultural Bank of China, and Vice-Governor of the People's Bank of China. Shang aided the development of some private banks, first under pilot programs, then under the supervision of local regulatory authorities. Shang aimed to steer the financial system toward serving the needs of the real economy and increase the coverage of financial services (Liujiazui Forum 2012).

The first chairman of the China Insurance Regulatory Commission (CIRC, which was merged with the CBIRC in 2018) was Ma Yongwei, whose tenure was from 1998 to 2002, at the initial establishment of the CIRC. Ma had acted as president of the Agricultural Bank of China and chairman of the Chinese People's Insurance Company. Ma set up insurance regulatory bureaus in 11 regions across China. Ma established an insurance market framework with Chinese characteristics.

Wu Dingfu was chairman from 2002 to 2011. He had previously been Secretary-General of the Central Commission for Discipline Inspection and Vice Chairman of the China Insurance Regulatory Commission. As chairman of the CIRC, Wu helped to guide China's insurance industry away from risks. Supervision of senior executives was strengthened, and requirements for insurance companies to reduce fraud were tightened (21st Century Business Herald 2010).

Xiang Junbo was chairman from 2011 to 2017. Xiang was formerly president and then chairman of the Agricultural Bank of China as well as deputy governor of the People's Bank of China. Xiang was investigated in 2017 for serious violations of discipline and removed from office, then expelled from office.

The CIRC was merged with the CBRC in 2018 to improve its leadership. Guo Shuqing was appointed in 2017. In 2018, Guo was also named party secretary of the People's Bank of China Party Committee in order to improve communication between the two bodies. Guo held many high-profile state posts, including director of the State Administration of Foreign Exchange, chairman of the China Securities Regulatory Commission, and chairman of the China Securities Regulatory Commission.

Guo brought much-needed regulation to the CBIRC. He pointed out some of the pitfalls of products that suffered from high risks due to a lack of transparency and aimed to fill regulatory gaps and update regulations that had become outdated (China News Network 2017). Immediately in 2017, Guo implemented 26 projects to make up for regulatory shortcomings. Shadow banking and cross-financing among financial institutions became his focus.

Theoretical basis

Application of bank regulation can be viewed from several perspectives. The general theories of microprudential and macroprudential regulation describe different methods of managing the financial system. Microprudential regulation is based on the concept moral hazard deterrence; that is, bank deposits are insured by the government and provide an incentive for managers to engage in risky behavior (Hanson, Kashyap and Stein 2011). Therefore, microprudential regulation forces banks to internalize losses. Macroprudential regulation controls for systemic risk. Such measures reduce the social costs associated with a sudden shock to banks' balance sheets.

China uses both microprudential and macroprudential regulation. The CBIRC has focused somewhat more on microprudential regulation, with a more recent system of macroprudential regulations introduced through Basel III regulations beginning in 2011 (Chance 2011). In addition, a Macro Prudential Assessment (MPA) framework supervised by the People's Bank of China was implemented on January 1, 2016 in order to address pro-cyclicality, regulatory arbitrage, and enhance market-based reforms (Zheng 2018).

While theories about microprudential and macroprudential regulation can be applied to China, theories such as regulatory capture are not relevant. The regulatory capture theory states that it is inevitable for the state's regulatory function to be captured by those being regulated, since banks are able to lobby the government. The Chinese government is closely connected to banks but has more control over banks' objectives than in Western economies.

Therefore, a separate theory for Chinese bank regulation holds more explanatory power. Cousin (2012) asserts that Chinese supervision can be taken as core to its financial system, with Western regulatory instruments used as add-ons. This is underscored by the fact that the state remains the banking safety net, with the CBIRC possessing the power to take over failed institutions. Another way to state this is that, even though the Chinese government created a separate regulatory body for banks and insurance companies, this does not end collusion between the state and regulatory agencies. As a result, China continues to demonstrate features of interventionist developmental state (Yazar 2015).

What is interesting and unique about China's financial system is that, even though regulations following Basel III regulatory theory were applied, including the principle of sound liquidity supervision, China's financial system remains, to some extent, financially repressed. Despite the fact that Chinese experts have called for additional financial liberalization over the years, the process has been slow due to the close relationship between state-owned banks and the government. In the wake of the global financial crisis in particular, bank lending was used as a key channel of government fiscal stimulus, with much lending provided to state-owned enterprises. This effectively acted as a tax on private firms, who are at a disadvantage in obtaining bank loans under these circumstances. Although the government called on banks to lend to small and medium sized enterprises, banks often failed to do so, given the alternative of lending to state-owned enterprises whose ultimate backstop was the government.

Market distortions due to financial repression in the banking system have resulted in moral hazard, in which banks take undue risks in the expectation that the government will step in if banks experience financial deterioration. This has led to the need for constant regulatory action in order to make up for a smoothly functioning market-based system. For example, as the shadow banking system arose in the wake of the global financial crisis, banks took part by selling wealth management products, which often contained excessively risky underlying assets. There was an expectation that the government would bail out failed products. As a result, banking regulators had to create specific regulations to crack down on the worst practices, such as bank-trust cooperation, in which banks raised funds through wealth management products that were channeled to shadowy trust companies.

This means that China's financially repressive system has given rise to distortions that have resulted in a need to implement "extra" regulation that would not be necessary in a well-functioning, risk-controlling banking system. Not only are microprudential and macroprudential regulations necessary, but due to the close relationship between banks and the government, the government has been forced to carry out some of the basic duties of risk management, which in a market-based system should normally fall to individual banks, through regulation. This goes beyond enforcement of microprudential regulation, such as enforcing Basel III standards. We call China's style of regulation as it applies to unique risks arising from moral hazard a market-distortion correction type of regulation.

China's unique style of regulation has given rise to a special pattern of banking regulation, with spikes during time of excessive risks. We next turn to an exploration of the data.

Data

First, we describe our data set. We use monthly data taken from February 2005-December 2017 (when the data results for the dependent variable end). This monthly number of CBIRC policies is taken from the Wanfang China Laws and Regulations Database. Spikes in regulation occurred in July 2015 and April 2010 as some financial risks rose.

Independent variables include the first difference of monthly State Administration of Foreign Exchange policies and the first difference of construction-related State Council policies. Regulations from the State Administration of Foreign Exchange (SAFE) are taken from the Wanfang China Laws and Regulations Database and include the number of monthly regulations. SAFE is an agency that is responsible for regulating foreign exchange and to gradually promote the convertibility of the RMB under the capital account and further develop the foreign exchange market. Construction-related State Council regulations are also taken from the Wanfang China Laws and Regulations Database.

Interestingly, we find that other variables that could impact CBIRC regulations per month did not do so. These include financial and monetary indicators, such as interbank interest rates, M2, seven day repo rate, and one year deposit benchmark rate, and real economic indicators, such as real estate investment, producer price index, consumer price index, and economic policy uncertainty. News articles did not impact CBIRC regulations. These include the mention of economic reform and, separately, financial risk in the People's Daily.

Model

In order to capture the dynamic relationship between CBIRC policy incidence (CBIRC), State Administration of Foreign Exchange policies (SAFE) and the number of "Construction" mentions in State Council regulations (CSC). We can apply a simple VAR model, which is often used in macroeconomic analysis. The simple VAR model can be written as follows:

$$\overrightarrow{Y_t} = \vec{a} + A_1\vec{Y}_{t-1} + A_2\vec{Y}_{t-2} + \cdots + A_p\vec{Y}_{t-p} + \overrightarrow{\varepsilon_t}$$

Where $\overrightarrow{Y_t}$ is the vector of all variables and $\vec{Y}_{t-p}$ is the p^{th} lag of these variables, while $\overrightarrow{\varepsilon_t}$ is the error term. In the VAR model, all variables are treated as endogenous variables, which means that each of them can be determined by of function of its own lags and the lags of other variables. For example, the incidence of CBIRC can be influenced by its lags and the lags of SAFE and CSC. The lag period is chosen by the information criteria.

Empirical Results

Before we analyze the relationship between these variables, we first divide the sample period into two discrete parts. The first period is from 2005m2 to 2017m6, which is used to build the VAR model; this is the training sample. The second period is from 2017m7 to 2017m12, which is used as the test sample, and we can use the VAR model training estimation to forecast the incidence of CBIRC policy in the test sample. In order to correctly build the VAR model, we first take difference of all variables to make sure that all the time series are stationary, and the Augmented Dickey-Fuller (ADF) test of all three variables reject the null hypothesis that these time series have a unit root, which means we can use them to estimate the VAR model.

As shown in Figure 1, all the time series are stationary. There are also some other unique characteristics in the time series. First, the volatility of CBIRC policies is much bigger than other two variables. Second, all the three variables fluctuate more in the end of 2009 and 2015 to 2016, which may be related to the subprime crisis and the reform in the exchange rate regime in China. Lastly, all the variables show similar fluctuations, which may be driven by the business or policy making cycle.

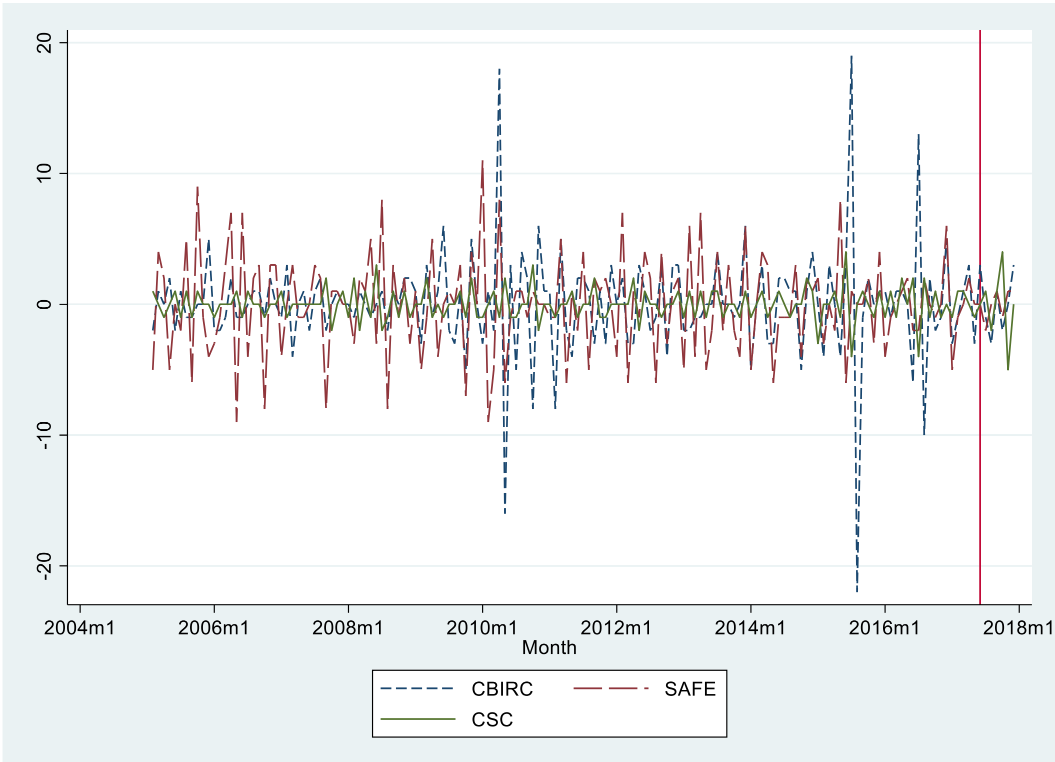

Figure1 Time series of different variables

Before we build the VAR model, we should choose the optimal lags of the VAR model, and this determined by different information criteria, e.g., FPE, AIC, HQIC, SBIC. As shown in Table 1, most information criteria reveal that 5 is the optimal lag period. So, in our next analysis, we use VAR (5) as the baseline model. The HIQC and SBIC tests show that 4 and 3 are optimal lag periods. Therefore, in the robustness test, we consider different lags and the main conclusions still hold.

Table1 The optimal lags of the VAR model

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1000.07				372.032	14.4326	14.4583	14.4959
1	-928.416	143.3	9	0.000	151.047	13.5312	13.6341	13.7845
2	-906.696	43.442	9	0.000	125.809	13.3481	13.5283	13.7915
3	-883.55	46.291	9	0.000	102.691	13.1446	13.402	13.7779*
4	-867.888	31.324	9	0.000	93.3881	13.0488	13.3833*	13.8721
5	-857.881	20.014	9	0.018	92.1762*	13.0343*	13.4461	14.0476
6	-852.904	9.9534	9	0.354	97.8741	13.0921	13.5812	14.2955
7	-849.558	6.6934	9	0.669	106.475	13.1735	13.7397	14.5668
8	-838.756	21.603	9	0.010	104.147	13.1476	13.791	14.7309
9	-834.208	9.0966	9	0.428	111.581	13.2116	13.9323	14.985
10	-825.487	17.442*	9	0.042	112.717	13.2156	14.0135	15.179

Basic VAR model. Table 2 shows the estimation results of the VAR model. The R-squared of all the three equations are significant, varying from 49% to 55%. The R-squared of the CBIRC equation is 55%, which means that its own lags as well as the other two variables can explain over a half the change in CBIRC monthly policy incidence. The estimation results of the coefficients are shown in Table 3. Focusing on the coefficients of the CBIRC equation, we can see that the lags of CBIRC itself have strong positive predictability. For the CSC, the first three lags are positive and significant. While when we turn to the SAFE, only the first lag is negative and significant. To this extant, we can say that when predicting the incidence of CBIRC policy, the number of "Construction" mentions in State Council regulations (CSC) seems to matter more than the State Administration of Foreign Exchange policies (SAFE). Furthermore, the influence of SAFE and CSC on the incidence of CBIRC policy is quite different because the sign of their coefficients is just the opposite.

Table2 The estimation results of VAR model

Equation	Parameters	RMSE	R-sq	chi2	P>chi2
CBIRC	16	3.06877	0.5458	173.0173	0.0000
SAFE	16	2.94146	0.4887	137.6296	0.0000
CSC	16	.894172	0.5080	148.667	0.0000

Table3 The regression results of VAR model (CBIRC)

		Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
CBIRC							
CBIRC	L1.	-.7637145	.0827709	-9.23	0.000	-.9259424	-.6014866
	L2.	-.7184406	.1014389	-7.08	0.000	-.9172572	-.519624
	L3.	-.5077614	.1097958	-4.62	0.000	-.7229573	-.2925655
	L4.	-.2854951	.1021419	-2.80	0.005	-.4856894	-.0853007
	L5.	-.0874662	.0776041	-1.13	0.260	-.2395675	.0646351
SAFE	L1.	-.2364482	.0863198	-2.74	0.006	-.4056319	-.0672645
	L2.	-.0946199	.1136863	-0.83	0.405	-.317441	.1282013
	L3.	.0174279	.1185658	0.15	0.883	-.2149568	.2498125
	L4.	.0546062	.1107783	0.49	0.622	-.1625153	.2717277
	L5.	.1324762	.0853905	1.55	0.121	-.0348861	.2998386
CSC	L1.	1.16483	.2726465	4.27	0.000	.6304522	1.699207
	L2.	.7287298	.3489892	2.09	0.037	.0447236	1.412736
	L3.	.9189278	.3503567	2.62	0.009	.2322413	1.605614
	L4.	.5771516	.3544996	1.63	0.104	-.1176549	1.271958
	L5.	.2575376	.29313	0.88	0.380	-.3169866	.8320618
	_cons	.0705955	.2417656	0.29	0.770	-.4032563	.5444474

Tests for the VAR model. After the VAR model is estimated, several tests should be conducted to make sure the model is built correctly. First, we'd like to use the Wald test to confirm the joint significance of all lags. If all the lags are significant, then the chosen lag period tends to be correct. As shown in Table 4, all the joint significance of coefficients are smaller than 1%, which means that the lag period is chosen correctly. Second, if the model is built appropriately, then the residuals should follow a white noise process and there is no self-correlation in the time series. Table 5 shows the results of LM test of residuals, and we can not reject the null hypothesis that the series is not self-correlated, which means the model is specified in a right way. Third, in order to make sure the VAR system is stable, we have to calculate the eigenvalues of the variables. As shown in Figure 2, all the eigenvalues are smaller than 1, indicating a stable VAR system. All these tests show that, the VAR model in our paper is set correctly and can be used to do further analysis.

Table4 Wald test for the joint significance of all coefficients in VAR model

Equation	lag	P> chi2	lag	P> chi2	lag	P> chi2	lag	P > chi2	lag	P> chi2
CBIRC	1	0.000	2	0.000	3	0.000	4	0.013	5	0.194
SAFE	1	0.000	2	0.000	3	0.000	4	0.043	5	0.519
CSC	1	0.000	2	0.000	3	0.000	4	0.000	5	0.001
All	1	0.000	2	0.000	3	0.000	4	0.000	5	0.009

Table5 LM test for self-correlation of the residuals

lag	chi2	df	Prob > chi2
1	9.9431	9	0.35511
2	7.0110	9	0.63597

Forecasting. The results of basic VAR model show that State Administration of Foreign Exchange policies (SAFE) and the number of “Construction” mentions in State Council regulations (CSC) have some predictability power in the in-sample test. While, whether they can predict the incidence of CBIRC policy in the out-of-sample is still not clear. So, we use the VAR model to predict the incidence of CBIRC policy from 2017m7 to 2017m12, the results are shown in Figure 3. As we can see from Figure 3, the 95% confidential interval covers the true value of the CBIRC, and the predicted value is close to the true value as well, which means these two variables, SAFE and CSC, can also predict the incidence of the CBIRC policy both in-sample and out-of-sample.

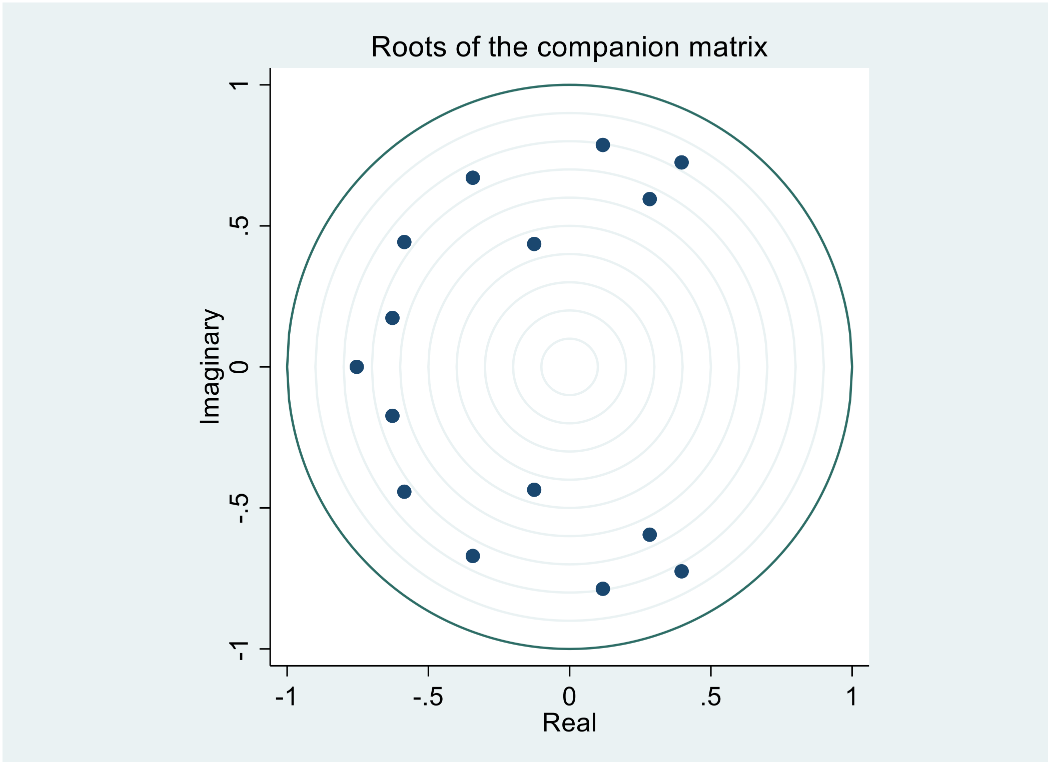

Figure2 Unit root test for the VAR model

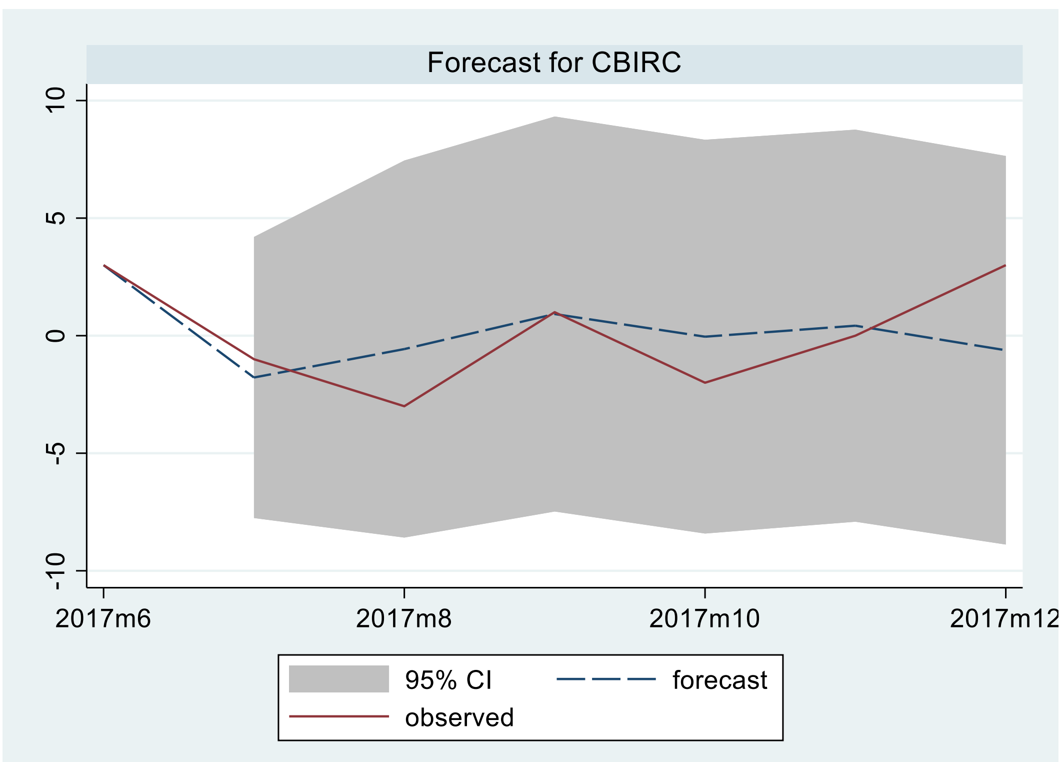

Figure3 Forecasting with the VAR model

Granger Causality Test. After exploring the in-sample and out-of-sample predictability of SAFE and CSC. We further want to know whether there is causal relationship among these variables. Or, in other words, whether SAFE and CSC can add new information when predicting the incidence of CBIRC model. The results are shown in Table 6. According to the results, both SAFE and CSC can be the Granger causality of the incidence of CBIRC policy.

Table6 Granger causality test of VAR model

Equation	Excluded	chi2	df	Prob > chi2
CBIRC	SAFE	13.552	5	0.019
CBIRC	CSC	22.191	5	0.000
CBIRC	ALL	36.182	10	0.000
SAFE	CBIRC	8.1119	5	0.150
SAFE	CSC	4.1472	5	0.528
SAFE	ALL	11.65	10	0.309
CSC	CBIRC	4.4637	5	0.485
CSC	SAFE	2.4739	5	0.780
CSC	ALL	7.5115	10	0.676

Impulse Response. In order to capture the dynamic relationship between these variables, we further do impulse response analysis. The basic concept of impulse response is that when the error term of one specific variable change and with other conditions unchanged, what other variables will response in the following periods. To be more specific, when the error term (or exogenous shocks) of the SAFE or CSC changes, what will the CBIRC change. Figure 4 shows the results of the impulse response, and subfigure 1 to 3 show the response of CBIRC to the impulse of CBIRC, CSC and SAFE. We can see that CBIRC response positively to its own shocks in period 0, then reverse in period 1 and then decrease to 0 in period 3 and after that. So, the impact of the CBIRC shock is quite small on itself, which means when there is an exogenous shock of CBIRC, the policy may increase immediately but then decrease and have no impact after that. Similarly, the impact of CSC on the incidence of CBIRC policy is significantly positive in period 1 and then significantly negative in period 2 and then decrease to 0 after that. However, the impulse response of the SAFE is different from them. CBIRC responses negatively to the impulse of SAFE in period 1 and then become positive in period 2 and become zero after that. So, we can conclude that, both the change of SAFE and CSC can affect the CBIRC incidence, however, their impacts are just the opposite and rather short and seems not to have long impacts on CBIRC incidence.

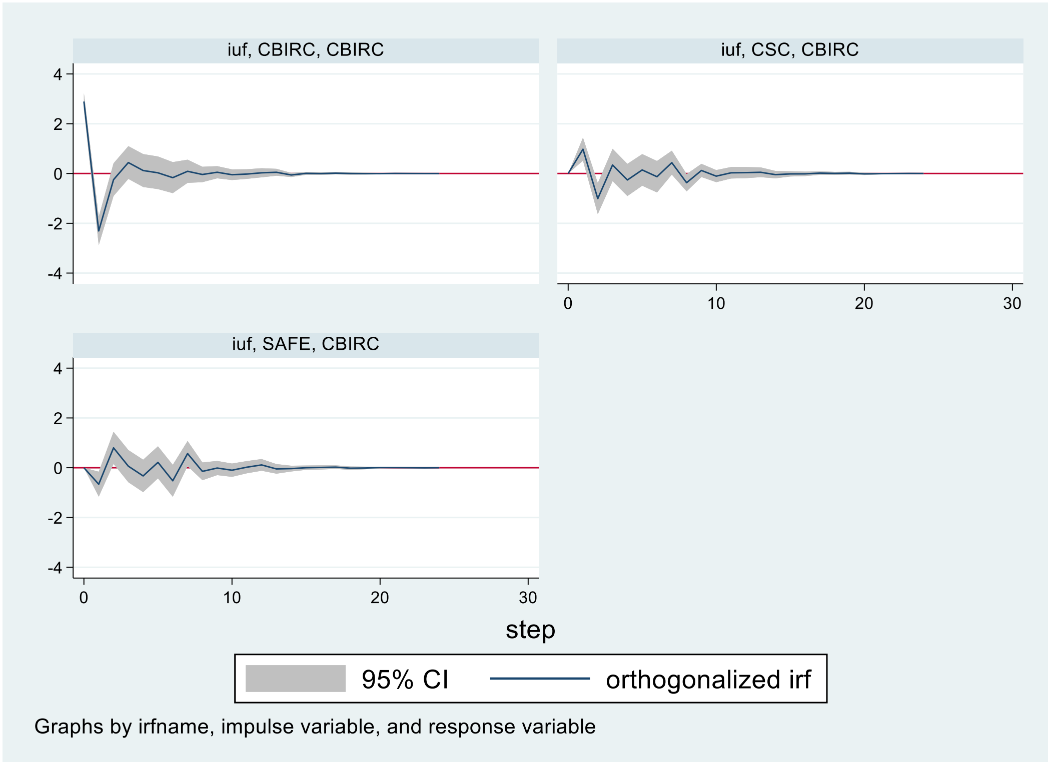

Figure4 The impulse response of CBIRC policy

Variance Decomposition. We the use the variance decomposition method to investigate the explanatory power of different variables on one variable. To be more specific, how can the SAFE and CSC explain the variance of the incidence of CBIRC in the short period and long period. The results are reported in Figure 5 and Table 7. We can see that, both variables can explain the variance of CBIRC, and the explanatory power increases as the period becomes longer and finally become stable at a certain level. For the CBIRC itself, after 24 period (i.e., 2 years) the variance explained by itself falls to 76%. And for the CSC and SAFE, they can explain the variance of CBIRC by 14% and 10% in the long run, which indicates that they are important factors that affect the incidence of CBIRC policy. Meanwhile, the CSC seems to matter more than the SAFE in the long run. And combined with the above analysis, we can say that the CSC is a more important predictor for the incidence of the CBIRC policy both in the short-run and long-run.

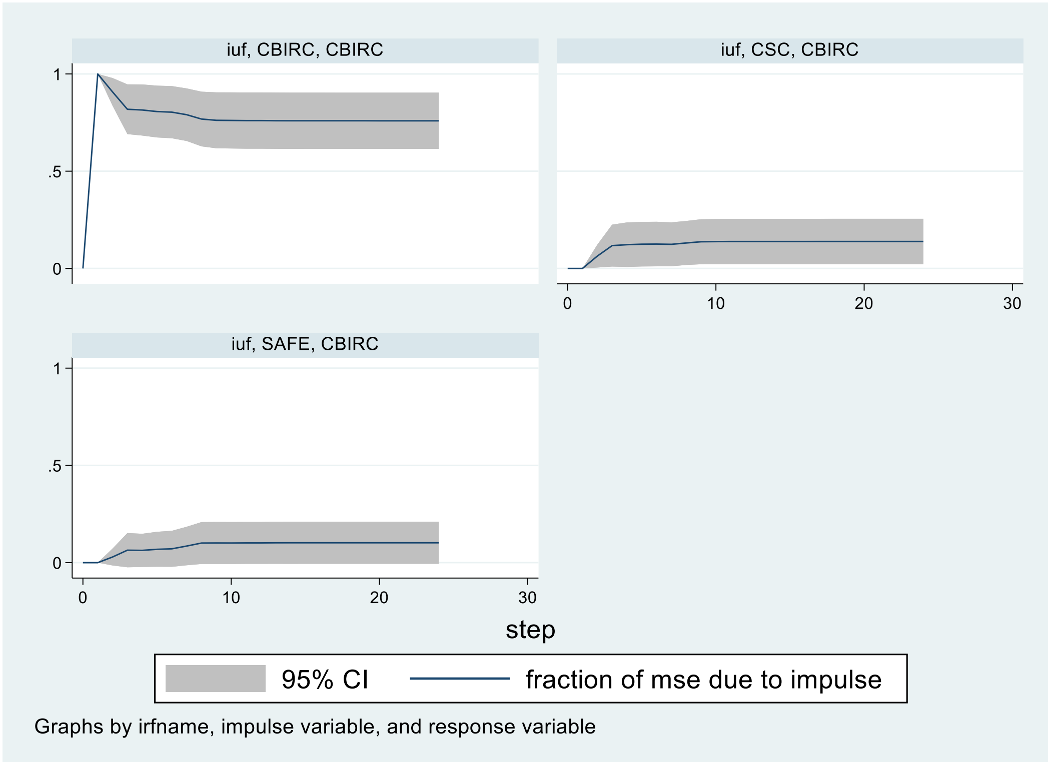

Figure5 The variance decomposition of VAR model

Table7 Variance decomposition of VAR model

Step	Fevd: CBIRC	Fevd: SAFE	Fevd: CSC
0	0	0	0
1	1	0	0
2	.907498	.029088	.063414
3	.818506	.064094	.1174
4	.81472	.063138	.122142
5	.806616	.068702	.124682
6	.803481	.071136	.125383
7	.790466	.085494	.12404
8	.768205	.100851	.130944
9	.761608	.101137	.137255
10	.761002	.101047	.137951
11	.760168	.101456	.138377
12	.76012	.10147	.13841
13	.759549	.102085	.138366
14	.759386	.102165	.138449
15	.759297	.102196	.138507
16	.759288	.102195	.138517
17	.759275	.1022	.138524
18	.75924	.102227	.138533
19	.759226	.102242	.138532
20	.759213	.102246	.13854
21	.759204	.102247	.138548
22	.759202	.102248	.13855
23	.759202	.102248	.13855
24	.759201	.102249	.138551

Robustness test

We do several tests to make sure the results in our paper are robust. First, as mentioned before, the HIQC and SBIC test show that 4 and 3 are optimal lag periods. So, we construct the VAR (3) and VAR (4) model, and then test the relationship among these variables. Our main findings remain the same. Second, the former papers argue that the order of the variables, thus affect the results of impulse response and variance decomposition. So, we change the order of CBIRC, SAFE and CSC, and test whether the results remain similar, and we find that the order do not affect the main results. Thus, the results in our paper are robust.

Discussion

In this paper, we use VAR model to study the relationship between CBIRC policy incidence (CBIRC), State Administration of Foreign Exchange policies (SAFE) and the number of “Construction” mentions in State Council regulations (CSC), and test whether SAFE and CSC can predict the incidence of CBIRC policy. We find that both SAFE and CSC are powerful predictors of the incidence of CBIRC. Meanwhile, the CSC can positively and the SAFE can negatively predict the CBIRC incidence. The impulse response and variance analysis reveals that State Council construction policies are a more important indicator to predict the CBIRC incidence than the SAFE both in short-run and long-run.

It is interesting that CBIRC policies are not sensitive to financial and real variables, but are sensitive to domestic construction and foreign exchange policy. State Council construction policies likely positively influence CBIRC policies because banks have acted as major lenders to the construction sector. Under China’s fiscal policies in the period under study, infrastructure has been frequently targeted as a means to boost GDP during economic downturns. Construction is encouraged, and banks are frequently expected to lend to firms that are engaged in new building. Thus it does not seem unnatural that these policies are linked. With increased usage of construction and bank lending, it is likely that new policies must be generated to reduce risks in each area.

Foreign exchange policy reflects both China’s currency liberalization efforts as well as perceived risks with regard to the international monetary regime. Banking regulators are sensitive to SAFE policies, and tend to refrain from making additional policies in the immediate aftermath of more SAFE policies. This may be due to the shift in focus from the domestic economy to the international economy in the very short run. Another plausible explanation for this relationship is that additional SAFE policies attempt to control a very gradually liberalizing area in order to reduce exchange rate risk. As exchange rate risk come increasingly under further control, the potential for exchange rate risk to migrate into the banking sector is likely reduced, also reducing the need for new banking policies. The nuances for this hypothesis have not been tested, and may be the subject of future research.

Based on the fact that CBIRC policies are influenced by State Council construction and SAFE policies, and not on financial or real indicators, this tells us that CBIRC policies are very much reliant on the government’s stance toward its own regulatory regime. It is the government’s position on foreign exchange and domestic construction (major means of fiscal policy and source of risk) that governs its response to banking risks. In other words, the overall industrial and foreign exchange regulatory environment strongly influence how financial risks are dealt with. One can also say that CBIRC regulators are watching the State Council and SAFE regulators for cues on how to interpret financial risks.

Conclusion

We provide an analysis of banking policies and indicators which precede them using a VAR framework. We find that CBIRC policies are predicted by State Council construction policies and policies set by the State Administration of Foreign Exchange, and not by financial and real variables. This indicates that the CBIRC is inward-looking, observing what other regulators are doing rather than responding to changes in the real and financial economy. This may be a product of market distortions due to China's unique blend of state-oriented and market-based institutions.

Data Availability

The data used are from a private sources, the Wanfang Database.

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