Predicting Chinese Banking Policy Incidence

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August 2021
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In this exploratory research, we examine the effect of economic and noneconomic indicators on the creation of Chinese Banking and Insurance Regulatory Commission policies. We find indicators that explain 94% of the policy creation with a one-month lag, which means that we can predict, to some extent, the incidence of CBIRC policies.

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 machine learning has been used to predict policy. For example, Lu (2019) uses a neural network and error t-value test to predict monetary policy. In this paper, Lu incorporates six training cases to examine the relationship between reserve adjustments and financial markets.

There is also research that uses machine learning to predict financial trends. Gan, Wang, and Yang (2020) propose a machine learning method to solve the challenge of accurately pricing arithmetic and geometric average options. Zhu et al (2017) apply various machine learning methods to predict SMEs credit risk in supply chain finance. The authors find that the best performing method is the RS–boosting model. Boughaci and Alkhawaldeh (2020) evaluate the performance of machine learning models using several datasets issued from banks and financial institutions. They find, for example, that the LogitBoost method works for both the Polish and Australian datasets, while the AdaBoost method functions best for the Japanese dataset.

Machine learning has been applied specifically to the banking industry as well. Abdou et al (2017) use machine learning techniques to predict Capital Intelligence banks’ financial strength ratings (FSRs) group membership for Middle Eastern commercial banks. The authors find that CART and discriminant analysis perform better than other techniques in predicting bank financial strength ratings. 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.

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 “extra” regulation that would not be necessarily 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 January 2005-January 2018 (when the data results for the dependent variable end), with a total of 158 observations. This monthly number of CBIRC policies is taken from the Wanfang China Laws and Regulations Database. The general trend of the data can be seen below. Spikes in regulation occurred in July 2015 and April 2010 as some financial risks rose.

![CBIRC Regulations Chart]

Independent variables include change in open market operations by month and the first difference of regulations from the State Administration of Foreign Exchange. The change in open market operations is a reflection of monetary policy. Data is taken from the People’s Bank of China and aggregated by month to find the net sum of open market operations, including central bank bill sales and purchases, implementation of repurchase and reverse repurchase agreements, and MLF/TMLF/PSL operations. 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
under the State Council 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.

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. Incidence of central bank regulations also did not impact CBIRC regulations.

**Model and Result**

We use the first difference and first lag of the CBIRC policies as the dependent variable. Independent variables include the monthly change in open market operations and the first difference of SAFE policies.

A set of machine learning techniques were used to measure the impact of various factors on the Chinese Banking and Insurance Regulatory Commission policies. This was chosen as the main method of analysis in order to use a prediction process rather than an explanatory process for the data. The method also permits the machine learning algorithm to obtain its own pattern directly from the data, allowing for complex variable interactions. This was done using a variety of techniques.

Pre-processing was performed on the data using MinMax Scaling to convert it to a normal form. Minmax scaler will transform all features into the range $[0,1]$ meaning that the minimum and maximum value of a feature/variable is going to be 0 and 1, respectively. The MinMax Scaler does this by subtracting the respective minimum value from every feature and scales it using the maximum value. This helps to avoid creating a bias caused due to feature values in different range.

The machine learning models were designed and trained using Sklearn package of python programming language. Different models of various types were combined using advanced variants of ensemble learning such as voting, bagging, boosting and stacking.

Stacking is a technique in which output of different ML models are used an input to create a new model. The output of new model serves as the final result. It uses a meta-learning algorithm to learn how to best combine the predictions from two or more base machine learning algorithms.

Two variants of stacked regressor were selected for this problem. The first variant used Ridge Regressor with Cross Validation, Decision Tree Regressor and KNN Regressor as initial estimator while Random Forest Regressor as the final estimator. The second variant used Cross Validation and Decision Tree Regressor as initial estimator while Gradient Boosting Regressor as final estimator.

A voting ensemble (or a “majority voting ensemble”) is an ensemble machine learning model that combines the predictions from multiple other models. A voting ensemble works by combining the predictions from multiple models. It can be used for classification or regression. In the case of regression, this involves calculating the average of the predictions from the models. Gradient boosting regressor, Decision Tree regressor and Random forest regressor predicted a value that was averaged to determine the dependent variable.
The Gradient boosting regressor was proposed by Friedman (1999). In a scenario with finite data, this nonparametric approach can be used to estimate mapping $x$ to $y$—$F^* (x)$—at $x$ values outside of the training sample points. A parameter optimization can be applied to minimize the data-based estimate of expected loss:

$$\{\beta_m, a_m\}_1^M = \arg\min_{(\beta'_m, a'_m)} \sum_{i=1}^{N} L \left( y_i, \sum_{m=1}^{M} \beta'_m h(x; a'_m) \right)$$

Where $a$ are parameters, $y$ are output variables, and $x$ are input variables and $h(x, a)$ is a parameterized function of input variables $x$.

Decision trees are made up of many decision nodes that test a particular feature, with each leaf node representing a class. The Decision tree equation is as follows, with $Y$ as the target variable and $X$ as regressors.

$$\hat{Y}(x) = \sum_{i=1}^{n} Y_i \times I_i(X)$$

The Random Forest algorithm uses the mean squared error (MSE) in order to branch data from each node, calculating the distance of each node from the actual value. The equation applied to each node is:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (f_i - y_i)^2$$

Where $N$ is the number of data points, $f_i$ is the value returned by the model, and $y_i$ is the actual value for data point $i$.

Voting ensemble uses soft-voting, incorporating weighted averages. Within a two-layered model, the first layer includes well-performing models, and the second layer model is used to optimally combine models from the first layer. The Gradient boosting regressor, Decision Tree regressor and Random forest regressor were used to predict a value that was averaged to determine the dependent variable. The function is as follows, with predicted probabilities ($y$) as a weighted average ($w_i$) probability that is predicted by each classifier ($p_{ij}$).

$$\bar{y}_i = \arg\max x_i \sum_{j=1}^{m} w_j p_{ij}$$

Voting Ensemble therefore combines predictions of multiple classifiers using weighted averages to create a final prediction.

‘Boosting’ refers to a family of algorithms which converts weak learner to strong learners. Boosting is an ensemble method for improving the model predictions of any given learning algorithm. The idea of boosting is to train weak learners sequentially, each trying to correct its predecessor. A variant of boosting algorithm known as adaboost was used for this experiment. It fits a sequence of weak learners on different weighted training data. It starts by predicting original data set and gives equal weight to each observation. If prediction is incorrect using the first learner, then it gives higher weight to observation which have been predicted incorrectly. Being an iterative process, it continues to add learner(s) until a limit is reached in the number of models or accuracy.
Bagging in ensemble machine learning takes several weak models, aggregating the predictions to select the best prediction. The weak models specialize in distinct sections of the feature space, which enables bagging leverage predictions to come from every model to reach the utmost purpose. It works by creating subsets (bags) to get a fair idea of the distribution (complete set). The size of subsets created for bagging may be less than the original set. Independent models are trained on each dataset and results all models are combined to give final prediction. Random forest, a variant of bagging which uses decision trees as base models was used for this experiment.

The best performing model among all the experiments was Voting Regressor. A coefficient of determination of 0.936 was obtained which depicts model is able to learn data distribution of 93% of data. The mean absolute error was 0.76 and mean squared error was 1.33.

The most important feature is 'OMOchange', followed by 'SAFE1stdiff'. The feature importance scores that were used in the voting regressor were as follows: change in open market operations was 0.75. SAFE first difference was 0.25. These are nondirectional scores.

Robustness test

As a robustness test, we use a vector error correction model (VECM). We first apply the Dickey Fuller test for unit root to all three variables: CBIRC first difference, first lag; change in OMO, and SAFE policies first difference. We find that all variables are significant and can reject the null hypothesis of nonstationarity.

We then test for cointegration. After saving the residuals from a linear regression, we perform an auxiliary regression as in:

$$\Delta \hat{\epsilon}_t = \phi \hat{\epsilon}_{t-1} + \nu_t$$

The t-ratio is equal to –20.75, and the p-value is highly significant at the < 0.1% level. The null hypothesis of no cointegration is rejected, which means that the CBIRC1stdiff1lag, OMOchange, and SAFE1stdiff are cointegrated.

This is verified by the Johansen test for cointegration, which finds no significance across 154 in a maximum of two lags.

<table>
<thead>
<tr>
<th>Max Rank</th>
<th>Parms</th>
<th>Eigenvalue</th>
<th>Trace Statistic</th>
<th>5% critical value</th>
<th>1% critical value</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>12</td>
<td>357.7653</td>
<td>29.68</td>
<td>35.65</td>
<td></td>
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<tr>
<td>1</td>
<td>17</td>
<td>0.64862</td>
<td>196.6983</td>
<td>15.41</td>
<td>20.04</td>
</tr>
<tr>
<td>2</td>
<td>20</td>
<td>0.57463</td>
<td>65.0580</td>
<td>3.76</td>
<td>6.65</td>
</tr>
<tr>
<td>3</td>
<td>21</td>
<td>0.34456</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Using a vector error correction model with up to 2 lags, we find the following results.

<table>
<thead>
<tr>
<th>Log Likelihood</th>
<th>AIC</th>
<th>Det(Sigma_ml)</th>
<th>HQIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>-1258.997</td>
<td>16.5714</td>
<td>2532.558</td>
<td>16.70757</td>
</tr>
</tbody>
</table>
All of the variables are significant and the AIC is low relative to that of other models. In addition, the p-statistic of the cointegration equation is significant at the .1% level.

<table>
<thead>
<tr>
<th>Equation</th>
<th>Parms</th>
<th>RMSE</th>
<th>r-sq</th>
<th>Chi2</th>
<th>P&gt;chi2</th>
</tr>
</thead>
<tbody>
<tr>
<td>D_OMOchange</td>
<td>5</td>
<td>3.38766</td>
<td>0.2974</td>
<td>63.07877</td>
<td>0.0000</td>
</tr>
<tr>
<td>D_SAFE1stdiff</td>
<td>5</td>
<td>4.04395</td>
<td>0.6415</td>
<td>266.6279</td>
<td>0.0000</td>
</tr>
<tr>
<td>D_CBIRC1stdiff</td>
<td>5</td>
<td>4.40245</td>
<td>0.6381</td>
<td>262.6791</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Our results confirm the significance of the relationship between change in open market operations, SAFE policies (1st difference), and CBIRC policies (1st difference, 1st lag).

**Discussion**

It is interesting that CBIRC policies are not sensitive to financial and real variables, but are sensitive to monetary and foreign exchange policy. The cointegration test reveals that the relationship between the three variables is positive. The fact that CBIRC policies are not sensitive to other policies means that, to some extent, monetary policy leads banking regulations, since it heavily impacts financial conditions. In turn, financial conditions may be exacerbated by a tight or loose monetary policy. When monetary policy is constricted, financial risks are more prone to become apparent. Foreign exchange policy reflects both China’s currency liberalization efforts as well as perceived risks with regard to the international monetary regime. Since Chinese banks deal in both domestic and foreign exchange, they are sensitive to SAFE policies.

The reason that banking policy is responsive to open market operations may be that monetary policy changes bank reserves and, potentially, marginal costs (Adams and Amel 2005). There is a positive relationship between open market operations and the lagged first difference of the CBIRC policies, which means that an increase in liquidity actually boosts the number of CBIRC policies created one month later. This is probably because increased liquidity in the financial system has resulted in growth of risky areas of finance that require regulation. It is also potentially because open market operations are carried out during periods of low growth, and low growth tends to reveal risks within the real and financial economies. This, in turn, increases the need for banking regulation.

The relationship between SAFE policies- first difference and the lagged first difference of the CBIRC policies is not entirely clear, since all variables are positively cointegrated, but the direct correlation between the two variables negative. Simply looking at the correlation, the negative relationship means that as foreign exchange policies increase, banking and insurance policies decrease. China’s exchange rate regime is a managed float, as the currency tracks a basket of currencies. Our hypothesis 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 monetary policy and SAFE policies, and not on financial or real indicators, tells us that CBIRC policies are very much reliant on the government’s stance toward inward-facing and outward-facing currency factors. It is the government’s position (and therefore policies) on the currency climate that governs its response to banking risks. In other words, the overall monetary and foreign exchange regulatory environment strongly influence how financial risks are dealt with. One can also say that CBIRC regulators are watching the central bank and SAFE regulators for cues on how to interpret financial risks.

**Conclusion**

We provide an analysis of CBIRC policies and indicators which precede them using a machine learning framework. We find that CBIRC policies are predicted by open market operations 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 key money-related 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.

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