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Introduction

In this exploratory research, we examine the effect of economic and noneconomic indicators on the creation of Chinese state-owned enterprise policies. Using machine learning time series methods, we find indicators that explain over 97% of monthly state-owned enterprise policy creation variance with a one-month lag, which means that we can predict, to a good extent, the incidence of state-owned enterprise policies. This reduces economic policy uncertainty, thereby having the potential to increase economic activity and reduce costs.

This represents a new area of research that identifies policy incidence and can be applied to a large variety of countries and industries. Understanding when new policies will arise can help the financial sector and firms increase profits, researchers assess when and how to implement development interventions, and governments understand when (interacting) policies from other departments are likely to be implemented. In addition, knowing which factors truly determine policies will bring about a better understanding of how economies develop and function.

In this paper, we discuss the value of predicting policies, then provide a brief literature review. We provide a theoretical basis for Chinese policymaking, then delve into a recent history of Chinese state-owned enterprise reform. We then describe the data, model, and results and discuss the implications of our findings.

Predicting Policies

Why should one predict policies? The scant literature on predicting when policies will occur leads us to believe that few scholars have viewed policy prediction as possible and/or worthwhile. However, we believe it is both. First, regarding the plausibility of policy prediction, we acknowledge that it is exceedingly challenging to find sufficient data and patterns that can predict policy creation, looking at the number of policies created within specific time frames. It is an incredibly time-consuming process, and the research in this area remains exploratory at present. It is also the case that, in uncovering predictive patterns for a certain type of policy in a particular country, one must be resigned to the fact that these patterns are unlikely to hold for other types of policies, especially in other countries with different policymaking processes and macroeconomic environments.

Second, regarding the value of policy prediction, we assert that it is useful in understanding what the political and economic climates will look like in the future. This is a boon for firm and industry actors that operate under these policies, as well as for financial firms that invest in related stocks, government actors, and policy analysts. As the study of policy prediction develops, policy risk can be greatly reduced, and this understanding can bring great reduction in costs related to political and economic uncertainty.

Literature Review

There is truly little research that predicts the creation of policies. One vein of research on Chinese policy uses machine learning. The Policy Change Index, created by the Mercatus Center at George Mason University, uses key words in the People’s Daily to predict major policy changes in China (Chan and

Zhong 2019). The index is analyzed in a journal article, in which policy waves predict the Great Leap Forward and the Cultural Revolution as well as, more recently, supply-side structural reform. The paper uses machine learning techniques, particularly the gated recurrent units (GRU) model developed by Cho et al. (2014), to analyze key phrases. In addition, Lu (2019) uses a neural network and error t-value test to predict monetary policy in China. Six training cases are used to examine the relationship between reserve adjustments and financial markets.

There is also literature on factors that influence public policy. For example, Omer (2004) examines state competition for capital and jobs, finding that state governments compete for capital and jobs and respond to their competitors' tax policy decisions with conforming policy changes. Nay (2017) uses machine learning to understand which bills, out of the tens of thousands that were introduced between 2001 and 2015, were enacted. The author uses a language model that places legislative vocabulary into a semantic-laden vector space.

While there is little research that concretely examines the creation of policies, there is a growing body of research that uses machine learning to predict economic events. These include the prediction of financial crises, in works such as Alessi and Detken (2018), Ward (2017), and Bluwstein et al (2020); prediction of agricultural production, in works including Schwalbert et al (2020), Mann, Warner and Malik (2019), and Palanivel and Surianarayanan (2020); and prediction of stock market behavior, in works such as Gurav and Sidnal (2018), Li et al (2016), and Lee et al (2018).

There is a large literature on the costs imposed by economic policy uncertainty, which makes it more expensive to carry out economic activities. Uncertainty forces economic actors to use precautionary savings or wait and see what policy outcomes will be (Bloom 2009). Monetary policy uncertainty, tax policy uncertainty, and trade policy uncertainty negatively affect they economy (Mumtaz and Zanetti (2013); Fernández-Villaverde et al. (2015); Handley (2014)). Economic policy uncertainty is also applicable to China, and has been found to reduce stock market returns ((Chen et al., 2017) and firm investment (Wang et al., 2014), as well as increase the incidence of mergers and acquisitions (Sha et al 2020).

Theoretical basis

There are several reasons why Chinese policy may be predicted based on financial, economic, and other indicators. Ma and Lin (2012) construct a review of Chinese scholarship on policy making. They divide the Chinese policy-making literature into three strains: one exploring agenda-setting, one on consensus building, and another looking at policy actors.

Chinese scholars have noted that agenda setting is an essential component of policy making. Wang (2006) asserts that agenda setting in China can be classified by the identity of agenda proposers and the extent to which citizens participate. Wang shows that there has been additional influence on policy making since the 1990s, including experts, the media, stakeholders, and the public.

Consensus building has arisen in China as a way to gather support for policy creation. Chen (2006) stated that policy is conducted formally, through the bureaucratic system, and informally, through the negotiation network. In the bureaucratic system, policy is made through consensus, while in the negotiation network, policy is made based on the influence of policy advocates.

Policy making can also be understood through the study of key policy experts, particularly of state related think tanks. Zhu (2006) empirically examined the influence of think tank experts and their role on policy making in China. He found that policy making has changed from a process led by political elites to one led by social elites. He finds three major patterns in policy making, including pretransition, in which policy making is dominated by political elites, preliminary transition, in which social elites begin to influence policymaking, and policymaking diversification, in which there is more interaction between policy advisory and civil society.

According to another theory, policies create a feedback loop that shape how policies are applied and revised. For China, the policy feedback loop continues when state-owned enterprises and local governments respond to central reform directives (Leutert 2021). Successful cases may serve as models or participate in pilot programs for a larger rollout. Government organization may share these successful cases with enterprises, other government bodies, or the public. The central government reviews the advancement of the initial reforms and determines whether additional policies can push forward the initial reforms, or whether the initial reforms should be abandoned.

Specific to state-owned enterprises, the theory of such firms and policies governing them must necessarily change over time. While there is no general theory of state-owned enterprises, Jefferson (1998) puts forward a theory stating that state-owned enterprises can be classified as a type of impure public good with externality and public-policy implications. Jefferson views firms owned by the people with serious agency problems as public. Fiscal and financial subsidies are used to replenish ongoing losses.

During the time in which Jefferson was writing, this theory could easily be applied, but due to years of state-owned enterprise reform, firms have faced harder financial constraints and have been forced to improve management. While firms continue to cope with an agency issue, this problem has been further constrained.

Today, even though state-owned enterprises are no longer public goods per se, they remain agents of the state; otherwise, why has the state gone to such lengths to keep state-owned enterprises in their control? Even though the managerial distance between the state and state-owned enterprises has increased, the policy distance has not. Norris (2016) puts forward five factors that determine if a state can use economic powers to accomplish its strategic goals: the extent to which the state is unified, compatibility between goals of the state and commercial actor, commercial market structure, the reporting relationship between the firm and the state, and the distribution of resources between the state and firm.

In the case of state-owned enterprises, funds in the form of bank loans are made available to the firms to carry out policy directives. Even if there is low compatibility between the goals of the state and the state-owned enterprise, the unified nature of the Chinese state and the power of the Communist party ensure that state-owned firms line up their economic activities with state mandates. In addition, state-owned enterprises have a strong incentive to carry out government directives due to the political advantages such a relationship provides them.

The state has a vested interest in inducing state-owned enterprises to carry out policies. For example, in the wake of the global financial crisis, the Chinese government issued a stimulus package, which initiated large-scale investment in infrastructure. The organizations to carry out infrastructure construction were largely central and local state-owned enterprises. Hence state firms have been deemed vital to the legitimization of the Communist party through economic and social stability.

However, due to the core incompatibility between the policy goals of the state and the profit-oriented goals of state-owned enterprises, future reform policies can be expected to ensure that state firms remain sufficiently capitalized and productive in spite of highly challenging state-imposed requirements. This may require restructuring of firms and their financial resources within policy-executing industries, such as mining, construction, raw materials processing, and technology.

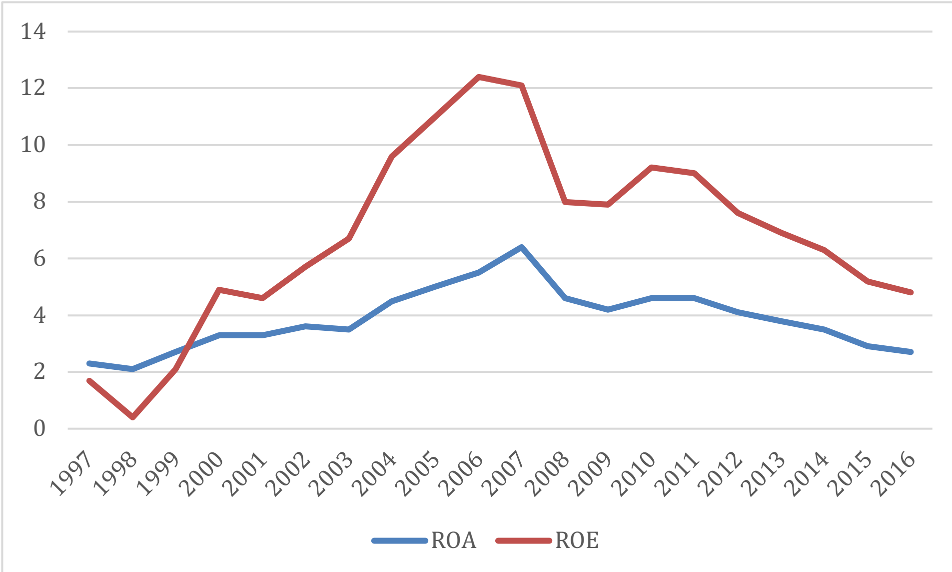
Chinese state-owned enterprise policies

Now, we turn to the changing nature of state-owned enterprise policies. Chinese state-owned enterprise reform and associated policies were important topics for many years after reform and opening-up. State owned enterprises played an important role in the Chinese economy in order to fulfill government policy objectives and maintain strategic operations. However, they were extremely inefficient in many cases, since employment had been guaranteed under the centrally planned economy and SOEs merely had to fulfill government production targets under soft budget constraints. While SOEs played an important role in guaranteeing the livelihoods of workers and providing social welfare services, the separation between owners and managers within SOEs gave rise to the classic principal-agent problem (Song 2018). This is because state firm managers are able to abuse their power for their own gain. State-owned enterprise owners faced difficulties in monitoring the activities of managers as well as low incentives for supervisory agency officials.

Major reforms have attempted to address some of these issues. In the late 1990s, state-owned enterprises experienced a massive shock as the number of such firms was dramatically reduced in order to reduce the role of the state in the economy. The aim was to maintain large SOEs but remove government ownership of small SOEs. By the early 2000s, state-owned enterprise reform was oriented toward restructuring; privatization was carried out through means of employee shareholding, public offerings, enterprise sales, bankruptcy, leasing, and joint ventures. This process greatly improved SOE efficiency but did not bring SOEs up to the performance levels of private firms.

Corporatization and globalization of SOEs occurred between 2003 and 2013. In order to accomplish this, the State-owned Assets Supervision and Administration Commission (SASAC) was created in 2003. Between 2003 and 2006, the number of central SOEs had declined, but state firms that remained were very large corporations due to mergers and acquisitions. Such corporations were concentrated in strategic sectors, such as public utilities, nonrenewable natural resources, and national security. SOEs were provided with preferential loans, and some were permitted to globalize in order to secure critical resources abroad.

Figure 1. ROA and ROE of State-Owned Enterprises



Source: Ministry of Finance

Between 1997 and 2016, the number of SOEs decreased and then increased after 2008, although total assets rose by eleven times over the entire period (Lin et al 2020). SOE total factor productivity and return on assets rose through 2007. However, after 2007, SOE financial performance declined through 2013 because of the global financial crisis. During this time, renewed calls for SOE reform policies rose.

One of the major issues that presented itself was overinvestment. After the global financial crisis, government stimulus was used to increase investment in infrastructure. This led to the construction, in some cases, of "ghost towns," in which no one lived, an example of investment solely for the sake of adding to annual GDP numbers. SOEs and local governments played major roles in this construction. As a result, many SOEs faced high levels of indebtedness, since their projects were insufficiently revenue-generating.

By 2015, SOE reform had become a core goal, particularly with the publication of the "Guiding Opinions on Deepening the Reform of State-owned Enterprises," which put forth the "1 + N" policy system reform based on SOE classification (Lin et al 2020). Under this system, SOEs were classified as commercial SOEs and public service SOEs in order to keep track of their respective performances. Market competition was a main means of judging commercial SOE performance, while political importance was the method of judging public service SOEs. Commercial SOEs were then additionally classified as perfectly competitive sectors and strategic sectors. The main idea of the "1 + N" policy was to strengthen the role of the Communist Party in SOEs and also to reorganize central SOEs. One of the central goals of the reform overall was to promote mixed ownership, in order to attract private capital into SOEs.

Mergers were used to reduce the number of unprofitable SOEs without having to cut jobs, and they had the added benefit of ending price wars among firms. However, the result was the dominance of behemoth firms, creating monopolies with far greater pricing power (Song 2018).

Reforms to corporate governance also took place. A State Council document laid out, in 2017, a means to modernize SOEs by enhancing the role of the Communist Party in corporate governance and requiring that SOEs' boards of directors maintain a slate of mainly external directors. Anticorruption measures were simultaneously applied in order to ensure clean corporate governance.

SOEs continue to play an important role in infrastructure construction as a focus of policy fulfillment. However, Holz (2018) notes that additional SOE reform is necessary to improve good governance that makes profitability an explicit objective. Holz also points out that SOEs carry out functions that are not necessarily part of their official requirements, including maintaining employment for the sake of social stability, creating jobs for party leaders, fulfilling policy needs, and acting as "national champions." These have created conflicting objectives for SOEs. This has been complicated by the fact that the SASAC organization falls short, as it has little authority over appointment of key SOEs and insufficient ability to regulate SOEs.

As noted above, because of the necessary relationship between SOEs and the government, it is likely that inefficiencies and unofficial requirements will continue to plague the sector. China retains SOE for the purposes of carrying out policy objectives and maintaining influence of the Communist party. As SOEs encounter problems associated with excessive debt or insurmountable governance issues, additional policy reforms will likely be implemented. We therefore expect SOE policies to continue to be made, although likely at a slowing rate.

Having discussed the state of SOE reform, we now turn to our model explanation of SOE policy incidence.

Data

First, we describe our data set. We use monthly data taken from January 2005-July 2019 (when the data results for the dependent variable end), with a total of 174 observations.

The dependent variable, monthly number of state-owned enterprise regulations, is taken from the Wanfang China Laws and Regulations Database. We find regulations with the key phrase "state-owned enterprise" in the title. Regulations were issued from different departments, including the Central Government Procurement Center, Central Committee of the Communist Party of China, Ministry of Finance, National Development and Reform Commission, and the State-owned Assets Supervision and Administration Commission.

Other data used for independent variables includes: the number of academic papers in the CNKI database that were funded by the national government with the phrase "state owned enterprise reform" in the title and the number of articles that mention "state-owned enterprise" in the article titles in the People's Daily with the phrase "State Council" within the text. The CNKI (China National Knowledge Infrastructure) database is a national research and information publishing institution. This database contains published journal articles, dissertations, proceedings, books, newspapers, and patents. In this database, we are seeking academic journal-published papers on state-owned enterprises that are government-funded. The People's Daily is the official newspaper of the Communist Party of China. We seek newspaper articles on state-owned enterprise that also mention the State Council, which is the chief administrative authority in China over other administrative bodies, including the State-owned Assets Supervision and Administration Commission of the State Council, which supervises state-owned enterprises but does not create all policies for SOEs.

The number of independent variables is restricted due to the relatively small number of observations for a machine learning model, increasing the robustness of the results.

Other data was excluded due to its insignificant effect in explaining policy variance. Of particular note is the fact that state-owned enterprise financial data, including the industrial value-added of state owned enterprises and number of loss-making firms, had no effect on policy incidence.

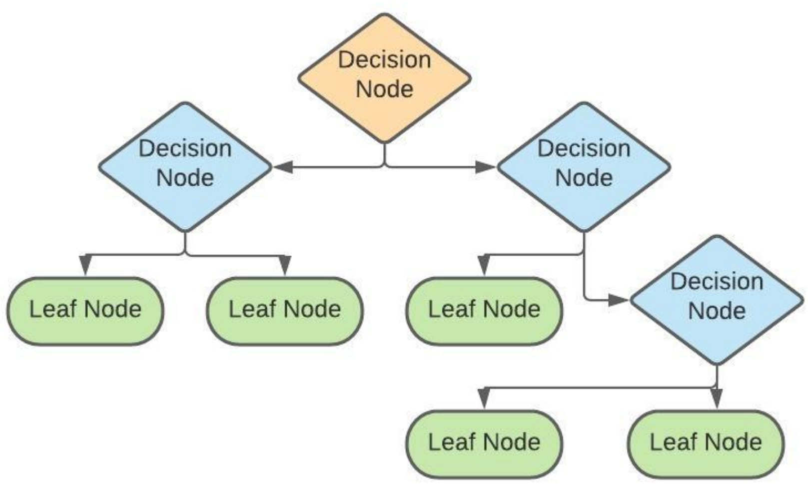
Model

We use machine learning techniques due to the predictive nature of the data; rather than looking at relationships between independent and dependent variables using traditional econometric techniques, we are also determining how well independent variables within a time series can predict policy creation. A set of machine learning techniques was used to measure the impact of various factors on the creation of state-owned enterprise related policies.

The machine learning models were designed and trained using the SKLearn package in Python and Azure Machine Learning. Different models of various types were combined using advanced variants of ensemble learning such as voting, bagging, boosting and stacking (Pedregosa et al 2011).

Stacking is a technique in which output of different ML models are used an input to create a new model (Singh 2018). The output of new model serves as the final result. The Decision Tree Regressor was selected for this problem using k-fold cross validation.

Decision trees represent a breakdown of a given dataset with each decision node noting a test on a particular feature and each leaf node represents a class. This is illustrated by the diagram below.



The Decision tree equation takes the following form, with Y as the target variable and X as regressors.

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

Decision trees are used as the basis of learning in both the random forest and gradient boosting algorithms. 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.

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:

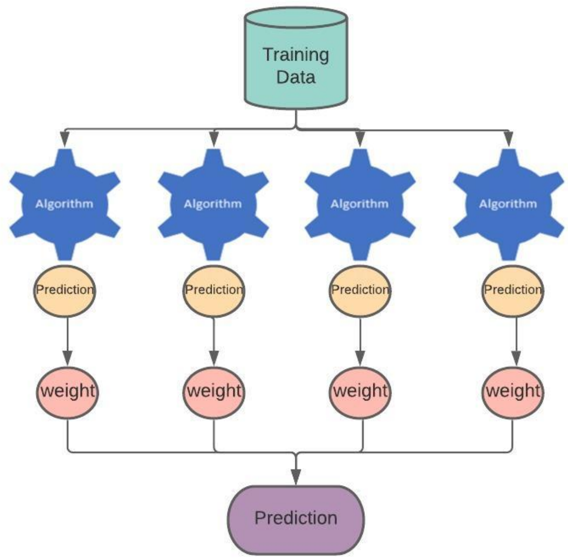
$$\{\beta_m, \boldsymbol{a}_m\}_1^M = \arg\ min_{\{\beta'_m, \boldsymbol{a}'_m\}_1^M} \sum_{i=1}^{N} L\left(y_i, \sum_{m=1}^{M} \beta'_m\, h(\boldsymbol{x}_i \boldsymbol{a}'_m\right)$$

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.

Voting ensemble uses soft-voting, making use of weighted averages. This stacks two layers, in which the first layer has the same models as the voting ensemble, and the second layer model is used to optimally combine models from the first layer. Four Decision Tree regressors were used to predict a value that was averaged to determine the dependent variable. The function is as follows, with predicted probabilities (y_i) as a weighted average (w_j) probability that is predicted by each classifier (p_{ij}).

$$\hat{y_i} = argmax_i \sum_{j=1}^{m} w_j p_{ij}$$

Below, we show how Voting Ensemble functions by combining predictions of multiple classifiers using weighted averages to create a final prediction.

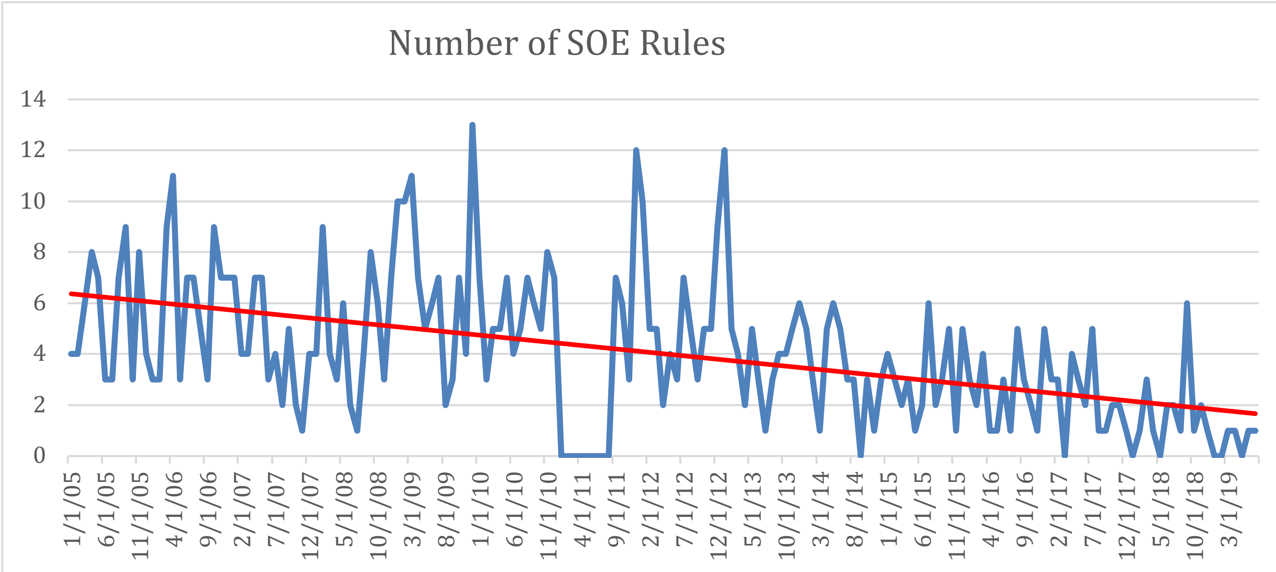


Boosting is a sequential process, where each subsequent model attempts to correct the errors of the previous model. The succeeding models are dependent on the previous model. A variant of boosting algorithm known as adaboost was used for this experiment.

Bagging (or Bootstrap Aggregating) technique uses these 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.

Results

First, we find that there is a strong time trend in SOE policies. We illustrate this below. For the purposes of predicting future SOE policies, this trend is helpful rather than harmful. This type of autocorrelation is often used in share price prediction. Using a separate calculation, we find that the autocorrelation at lag 1 is 48% and 29% at lag 2, which are high.



Source: Wanfang Policies and Laws of China Database

The best performing model among all the experiments was Voting Regressor. The best performing model among all the experiments was Voting Regressor which is a combination of Gradient Boosting Regressor, Random Forests and Decision Trees. A coefficient of determination of 0.974 was obtained which depicts model is able to learn data distribution of 97% of data.

The most important feature is Date, followed by CNKI SOE papers funded by the National government and finally People's Daily mention of SOE, State Council.

The mean absolute error is 0.4822. Compared to the dependent variable's data range, from 0 to 13, this is relatively small.

The feature importance scores that were used in the voting regressor were as follows: People's Daily mention of SOEs and State Council was 0.195. CNKI papers funded by the national government with a mention of SOEs was 0.1075. The date features importance score was 0.6975, underscoring the strong time trend.

This shows the importance and influence of research papers and newspaper articles on reform in the determination of state-owned enterprise policies, as well as the downward time trend. There is strong autocorrelation in the SOE policies, which is similar to the strong autocorrelation trend in stock market returns. The application of autocorrelation in stock market trends can be found in numerous scholarly publications, including Martin (2021), Zhou et al (2017), Jain and Xue (2017). This autocorrelation in asset prices has been used to predict future stock returns, and the same can be applied to SOE policies in this case.

Robustness tests

Given the relatively small size of the data set, we also test the results using a Naïve Bayes method, which is one of the simplest statistical models. We find that the accuracy and precision of the model are both 0.943, with only two false positives and zero false negatives. The F1 score is 0.971. This shows that this model is robust.

We also use more traditional techniques to determine the robustness of our model. We can apply a Vector Autoregressive (VAR) model, as it is possible that variables may be a function of their past lags and other variables' past lags. Using a time series technique by rendering the SOE policy series stationary after taking the first difference and lagging this one period, we perform a Dickey-Fuller test to ensure there is no unit root. The test confirms no unit root with a p-value of 0.00. We perform the same test to ensure stationarity of the other variables.

The VAR model we use with two lags can be expressed as:

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

Where $\overrightarrow{Y_t}$ is a vector of variables SOE Rules 1st Diff, CNKI SOE Mentions, and PD SOE Mentions; $\vec{a}$ is a vector of intercepts; A_t represents coefficient matrices; and $\overrightarrow{\varepsilon_t}$ is the vector of zero mean error terms.

Using a Vector Autoregressive model, we find the following results:

Log Likelihood: -1060.58				
AIC: 12.65				
FPE: 62.59				
	RMSE	R-squared	Chi-squared	P>Chi-squared
SOE Rules 1st Diff	2.59	0.23	50.34	0.00
CNKI SOE Mentions	2.24	0.35	91.64	0.00
PD SOE Mentions	1.31	0.07	12.92	0.04

The results show that CNKI and People's Daily mentions of SOEs as well as SOE rules are linear functions of past lags of themselves and other variables. This underscores the results from the Voting Ensemble machine learning model. The significance of SOE Rules 1st Diff and CNKI SOE Mentions are particularly significant, at the 1% level. PD SOE Mentions are significant at the 5% level.

Discussion

The results show a strong autocorrelation within SOE policy creation. SOE policy creation is likely on a downward trend because China's economy and policy environment are maturing, with less need for further regulations. This does not mean that future SOE policies are not significant; some of the most impactful SOE regulations, such as the SOE mixed ownership policy, were created in more recent years. Due to data limitations, we faced challenges in drilling down further into exploring the factors contributing to specific types of SOE policies made. As more data is collected, under the growing use of big data and machine learning, we expect to have a better ability to predict specific types of SOE policies.

The importance of government-sponsored research paper mentions of state-owned enterprise and government-mouthpiece newspaper People's Daily mentions of "state-owned enterprises" and "State Council" in the article in predicting SOE policies one month later point to the importance of the government in telegraphing its actions through popular and academic channels.

The fact that SOE policies are telegraphed through government-sponsored research papers shows that funding bodies of the government are aware of the need for SOE reform and possibly upcoming SOE legislation. The new formal commanding role of the Communist Party within SOEs as of 2020 increases the likelihood that government bodies will be informed on potential SOE policies.

We also note that there are several caveats to this type of analysis. One is that data trends change over time, and that this type of analysis needs to be applied to time series data regularly to understand how new or different variables may play a role in predicting policies. Another is that not all data is available; if researchers had access to all points of economic, political, and social data, predicting policies would become much easier. One way to overcome this lack of data is to mine existing data such as media resources manually or using natural language processing.

The final caveat is that data may fit that are unrelated to the policy at hand. This can bring about spurious correlations; as a result, only data that can be reasonably hypothesized to be impactful upon the policy prediction should be used. The practice of using a massive number of independent variables to train the model does not make sense in this case. This is made all the more important because policy incidence data, the dependent variable, is limited in number.

Our findings underscore the characteristic of state-owned enterprises as agents of the state, as it is state-funded research and newspaper articles that telegraph new policies. This means that it is beneficial to provide government funds to study potentially viable new policies or other characteristics of SOEs. Discussion is also provided by the People’s Daily, the Communist Party newspaper, which generates awareness of new policies and sets the stage for policies that will be introduced within a short period of time.

The findings also provide some support for two of the three types of Chinese agenda setting. Publishing articles in the People’s Daily can help to ensure agenda setting for the public. Publishing state-funded articles in CNKI on SOEs demonstrates the use of policy experts in policy making.

Interestingly, Chinese SOE policymaking is not dependent on macroeconomic, microeconomic, or other government policy variables, as is Chinese policymaking for other bodies (we have found). This is not something that we would have expected, and policymaking/ SOE theory does not include such indicators as relevant.

Conclusion

We have found that state-owned enterprise policies have a strong time trend (autocorrelation), and are also predicted by government-sponsored research papers and newspapers on the topic of state-owned enterprises. This indicates that China’s government strongly telegraphs its upcoming SOE policies and that SOEs can indeed be considered agents of the state. It also plays into existing Chinese policymaking theory by underscoring elements of agenda setting.

This represents a new area of research that will help to reduce uncertainty. We expect that analysis of China’s policy influences will apply, to some extent, to other countries. It is likely that other countries respond to economic conditions by creating policies. Determining which policies will be implemented in the near future can help companies and governments plan investments and regulations going forward.

China’s policy-making landscape is unique, as regulations are top-down. Even though there are feedback loops between the policy and economy, there is little to no bottom-up policymaking. This means that determinants of Chinese policies are unique to China, and are unlikely to be exactly the same as in other countries.

Chinese SOE policies are not influenced by economic or other government policy variables, only government-funded or run research and journalism. While SOEs have reformed over the past several decades, our research shows that they continue to be closely tied to the government and less influenced by market forces.

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