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Industrial Policy and State Ownership: How Do Commercial Banks Allocate Credit in China?

Prepared by Ying Xu

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Prepared by Ying Xu*

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ABSTRACT: Using a novel data set with bank-sector-level annual loan data from 137 commercial banks in China from 2004 to 2021 and a quantified industrial policy data set based on text analysis, this paper explores the effects of industrial policy on bank credit provision. While the paper finds no conclusive evidence that commercial banks allocate, on average, more credit to sectors promoted by the central government, it does find heterogeneous sensitivities of banks to industrial policy. Rural commercial banks tend to respond most positively to industrial policy compared to other commercial banks. Banks that have lower asset quality, are smaller, have a higher liquidity ratio, and are not listed are more responsive to industrial policy. In addition, sectors dominated by state-owned enterprises (SOEs) benefit more when there is an industrial policy announcement, while policies in SOE-dominated sectors will crowd out credit to other sectors, because SOEs are less risky, both economically and politically. Therefore, banks face a trade-off between political pressure and profitability in response to industrial policy, leading to distortions of financial resource allocation in favor of SOEs.

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WORKING PAPERS

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Executive Summary

Using a novel data set with bank-sector-level annual loan data from 137 commercial banks in China from 2004 to 2021 and a quantified industrial policy data set based on text analysis, this paper explores the effects of industrial policy on bank credit provision. While the paper finds no conclusive evidence that commercial banks allocate, on average, more credit to sectors promoted by the central government, it does find heterogeneous sensitivities of banks to industrial policy. Rural commercial banks tend to respond most positively to industrial policy compared to other commercial banks. Banks that have lower asset quality, are smaller, have a higher liquidity ratio, and are not listed are more responsive to industrial policy. In addition, sectors dominated by state-owned enterprises (SOE) benefit more when there is an industrial policy announcement, while policies in SOE-dominated sectors will crowd out credit to other sectors, because SOEs are less risky, both economically and politically. Therefore, banks face a trade-off between political pressure and profitability in response to industrial policy, leading to distortions of financial resource allocation in favor of SOEs.

Introduction

How powerful is industrial policy in China? Industrial policy has a very long history in practice worldwide, from many East Asian countries at the initial stage of development to developed countries in recent years, especially since the outbreak of Covid. The Chinese government has intensively implemented industrial policy through tariffs, subsidies, and credit convenience offered by development banks in past decades. Although substantial economic growth has been achieved, criticism of distortions and nonmarket competition also followed. Before praising or blaming industrial policy, a key question is to what extent have resources truly been reallocated due to policy interventions when market power exists?

This paper investigates the effectiveness of industrial policy in financial resource allocation in China. Bank credit is one of the most important resources that industrial policy affects. Instead of studying the development banks, which directly execute the country's industrial policy, a study on how government-owned commercial banks respond to industrial policy reveals the trade-off between market and government powers faced by financial institutions.

I first construct a novel data set of quantified industrial policy. Unlike other Chinese industrial policy data sets that focus on specific trade tariff or subsidy policies and only cover limited sectors, such as the manufacturing sector, I collected information on more general industrial policies. These policies cover all sectors of economic activity and different types of policy instruments. Because my main focus is on bank credit allocation, I look at policies from the People's Bank of China (PBoC) and many of them are categorized as "structural" monetary policy in recent years. Based on the logic of text analysis, I quantify these policies according to the topic and the attitude of the raw policy texts collected directly from documents published by the PBoC.

To measure how industrial policies influence financial resources, I test if the distribution of loans across sectors changes pro-cyclically with policy guidance. To test this empirically, I use a unique data set containing annual loan data for 19 sectors from 2004 to 2021. I manually collected this bank-sector-level data set from 137 Chinese commercial banks' annual financial reports and audit reports. The data set is the most exhaustive collection of public information on bank-sector-level loans available so far for Chinese commercial banks. Other commercial or academic databases only contain information from the most recent few years, with many banks and sectors missing.

In the first part of the analysis, I test how the overall credit from all Chinese commercial banks responds to industrial policy. As both industrial policies and financial resources in the sample change across years and sectors, the regression results suggest no strong relationship between the two. The empirical evidence provides the surprising conclusion that there is no conclusive evidence that commercial banks allocate on average more credit to sectors promoted by industrial policy.

One potential explanation for the commercial banks' divergence from industrial policy is their heterogeneous characteristics. I interact industrial policy with different bank characteristics, such as ownership type, size, asset quality, and liquidity ratio, in the model to check which kinds of banks respond most positively to industrial policy. Compared with other ownership types, the study shows that rural commercial banks, which are the least marketized commercial banks, respond most positively. Furthermore, unlisted banks and banks having lower asset quality, are smaller, and having a higher liquidity ratio are more sensitive to industrial policy. Thus, commercial banks that are more competitive in the market and are allowed more discretion by the central government do not necessarily allocate their resources to industrial policy targets. They seem to behave in a more market-oriented way.

Another explanation comes from the different characteristics of the sectors. Banks' sensitivities to industrial policy also depend on the sector to which a credit goes. I categorize sectors into two types, those dominated by SOEs and those not dominated by SOEs. I interact the sector type with industrial policy to examine which type of sector benefits more from industrial policy. The regression results show that compared with other sectors, those that are dominated by SOEs always receive relatively more credit when a preferential industrial policy is announced. Banks' tight connections with SOEs and their risk management can be an explanation for this bias.

The underlying trade-off between political pressure and profitability rationalizes banks' heterogeneous behavior related to bank and sector characteristics. Commercial banks compare their losses between allocating credit to the promoted sectors, which are usually not profitable, and ignoring the policy instruction. Banks with less to lose from disobeying the central government allocate credit in a more market-oriented way, thus becoming less sensitive to industrial policy. Meanwhile, SOEs are always less risky both politically and economically, so for commercial banks, lending to SOE-dominated sectors can be the strategy that both alleviates political pressure and improves asset quality.

This paper builds on the industrial policy and development literature. I use the same definition as Rodrik (2008) for industrial policy, which represents "policies that stimulate specific economic activities and promote structural change." According to this definition, industrial policy includes not only policies in the manufacturing sector and trade promotion policies, but all strategic policies announced by the central government that aim at sectoral reforms and development. Similarly, Cherif et al., (2022) define industrial policy as "targeted sectoral interventions" that raise welfare and address externalities. As Smith (1995) and Rodrik (2004) state, all selective interventions will change the inter-sector resource allocation, either reinforcing or counteracting the existing markets. This paper focuses on the reallocation of financial resources, mainly the bank credit. There has been a long debate on whether governments should utilize industrial policy. Two opposite arguments exist in the literature. People who believe in the power of the market argue that "governments cannot pick winners" (Pack and Saggi, 2006), and industrial policy could only lead to the second-best rather than the optimal choice. They also worry about the potential corruption and rent-seeking behind industrial policy. Criscuolo et al., (2019) give an example of the business support policies in Europe. Their result shows an increase in employment because of the subsidies, but at the same time, they find that large firms appear to accept subsidies without increasing any expected activity. In contrast, supporters of industrial policy argue that there are market failures that require government intervention. The Asian miracle is one piece of the most influential and most frequently mentioned evidence of the success of industrial policy. An early study by Stiglitz and Uy (1996) suggests that public policies that affected the financial market by intervening directly in the allocation of credit contributed to the rapid growth of the economies of East Asia. In particular, a large amount of empirical evidence from emerging markets suggests that the credit market is imperfect and there is a need for government intervention in the financial sector, especially in rural areas (Hoff and Stiglitz, 1990; Besley, 1994). The studies find that government intervention could help alleviate the financial constraints on firms (Banerjee and Duflo, 2014) and improve credit allocation.

Many of the studies mentioned above are case studies and "case studies of success/failure suffer from selection bias and lack of representativeness" (Rodrik, 2004). To overcome this shortage, this paper aims to study the impact of industrial policy more comprehensively, covering almost all the industrial policies related to financial markets in China from 2004 to 2021. Thus, I present a more general and convincing conclusion on the influence of industrial policy. China is always a special but excellent example for studying industrial policy. The Chinese central government has used industrial policy intensively over the past few decades. In recent years, many other developing countries have drawn lessons from the Chinese experience in this area. A general study of Chinese industrial policy could be beneficial since it will not only enhance the understanding of the Chinese economy, but also inspire its followers.

This paper is also related to the literature on government-owned banks because almost all the commercial banks in China are controlled by the central government or local governments. Government ownership of banks is usually associated with slower subsequent financial development (La Porta et al., 2002), lower profitability, and lower efficiency compared to privately-owned banks (Cornett et al., 2010). Two widely accepted theories explain these results. First, as Micco and Panizza (2006) argue, banks with state ownership usually lend to less profitable but socially beneficial projects. Empirical studies support this "social" view by showing that the credit from state-owned banks is less responsive to macroeconomic shocks compared with the credit from private banks (Yeyati et al., 2007; Mihaljek, 2010; Fungáčová et al., 2013; Bertay et al., 2015). Another explanation represents a "political" view, which argues that state-owned banks are influenced by politicians and governments. Empirical evidence supports this view and shows strong effects on state-owned banks' credit during election periods (Sapienza, 2004; Dinç, 2005; Vins, 2008). A study by Ashraf (2016) also proves the existence of political pressure on state-owned banks.

Do the theories in the literature on banks' government ownership and credit behavior correctly predict the behavior of the Chinese banking sector? The answer from this paper is "not really." Using the "social," "political," or both views of interpretation, it is reasonable to believe that the government-owned commercial banks in China would have every reason to reallocate their resources to sectors promoted by the central government. The central government's industrial policies represent the highest political power's long-term socially beneficial development goals. Nevertheless, the empirical results suggest something much more complicated than merely lending to wherever the policy points. Banks have divergent sensitivities to industrial policy and respond differently across sectors. Banks' final behavior is the outcome of a trade-off between political and economic considerations.

The rest of the paper proceeds as follows. Section I presents the background of industrial policy and the banking sector in China, as well as the data sets that I collected for analysis. Section II tests whether Chinese commercial banks indeed lend more to the sectors with preferential industrial policy. Sections III and IV discuss bank characteristics and sector characteristics, respectively, as two explanations for banks' heterogeneous responses to industrial policy. The last section concludes and proposes several policy suggestions.

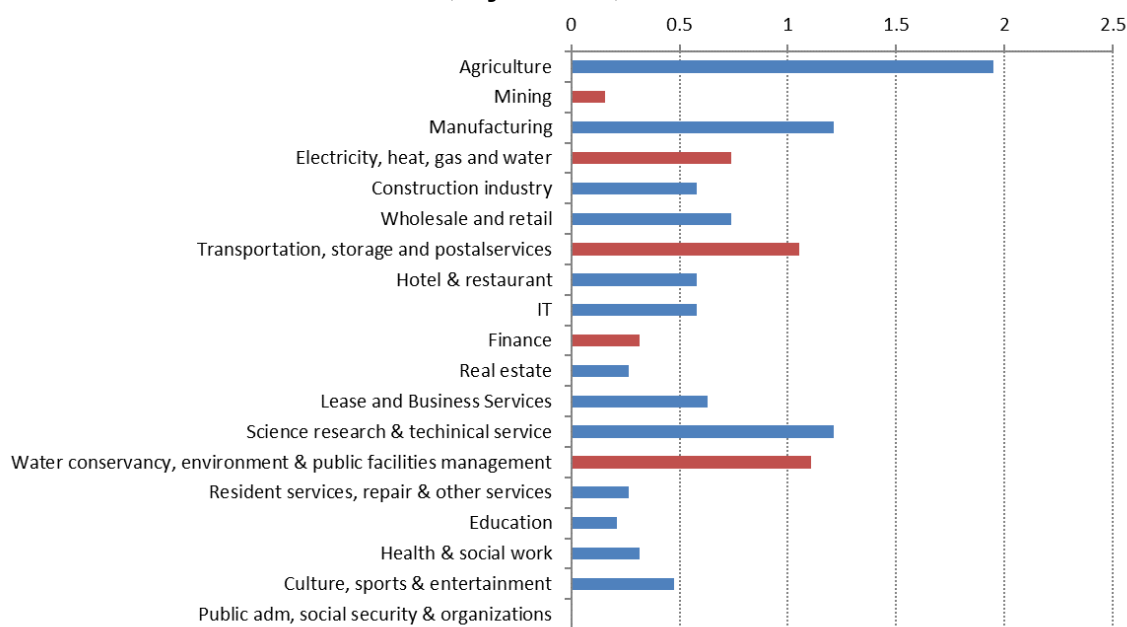
I. Institutional Background and Data

A. Industrial policy and different policy variables

The State Council of the People's Republic of China (the central government) publishes 200–300 official industrial policy documents with titles in red characters every year. The titles usually start with "*Guidance on...*" or "*Announcement on...*" These documents describe the central government's long-term social development goals and cover every aspect of economic activity in the country. The policies are usually strategic and general at the national level. Some of the documents are conceptual and well-rounded without details, thus requiring further interpretations by local governments and institutions before implementation.

Based on the State Council's guidance each ministry individually or jointly issues official policies to the public. These ministerial-level policies summarize several official documents into one or directly forward official documents from the central government. The policies the ministries choose to issue usually depend on the congruence between their own mission and the focus of a specific document from the State Council. Thus, the ministerial-level policies provide detailed guidance to the institutions under the supervision of that specific ministry. To implement these policies, different measures are applicable, such as direct government investments, tax benefits and investment incentives, tight control and fines, and direct or indirect financial sector interventions. The institutions choose instruments based on direct indications from policy texts or their internal interpretations.

Average Number of Policies Announced per Year by the People's Bank of China, by Sector, 2003–2021



NOTE: sectors in red are SOE-dominated sectors, and sectors in blue are not SOE-dominated sectors.

Industrial policies announced by the PBoC have a direct and strong influence on financial markets and, therefore, bank credit. The PBoC is the central bank of China. However, different from central banks in other

countries, the PBoC is less independent and partially acts more like a ministry to follow the instructions from the central government. When the State Council announces official documents, the PBoC follows up with related policies in the financial markets. These follow-up policies are the main interests of this study. Figure 1 shows the average number of policies announced and jointly announced by the PBoC, by sector, from 2003 to 2021. It is a representative summary of the central government's industrial policies. The figure shows that the central government values the agriculture sector the most, with almost two policies per year announced in the recent 20 years. Sectors with significant externalities, such as transportation, storage, and postal services; water conservancy, environment, and public facilities management; and science research and technical service, together with the manufacturing sector, are also frequently mentioned in policy documents, and there is more than one policy announced every year in each of these sectors on average.

Based on this background, for the critical explanatory variable *IP*, I collected the texts of the official policies announced by the PBoC or jointly announced by the PBoC, China Banking Regulatory Commission (CBRC) and other ministries. There are two primary sources of these policy documents. The first one is the *Summary of Chinese Monetary Policy*, published annually by the Monetary Policy Department of the PBoC. This summary includes not only monetary policies announced by the PBoC, but also all the key industrial policies during the entire year. To ensure that I obtained the full text of each policy, I also checked each web page listed in the section "Credit Policy > Policy and Law" on the official website of the Financial Market Department of the PBoC. From these two sources, I collected the texts of 83 industrial policies that were announced between 2003 and 2021. My sample excludes policies related to personal credit, specific supervision regulations over financial markets, and those that only targeted financial institutions other than banks (such as insurance companies, security companies, investment funds, and other institutions). In addition, I also exclude policies specifically targeting small and micro enterprises (SMEs) because the loan data on SME lending is not commonly available at the bank level in my sample. In 2020 and 2021, there were several Covid-related policies announced by the PBoC. Because these policies do not match the definition of industrial policy in this study, I exclude them from my analysis too.

To quantify the policy documents, I apply the underlying logic of text analysis. I first identify the topic of each policy document and classify it into one or several sectors. After the topics are categorized, I put weights on each sector. I assume a value of 1 for each policy, and then divide it into one or several sectors according to their importance in the document. Further, I assume the greater is the length of a policy document on a specific sector, the more important the sector is within the policy document. For example, if a policy document mentions two sectors, A and B, and one-third of the document is on sector A while the rest is on sector B, then for this policy, it equals 1/3 unit for A and 2/3 unit for B. The second step is to discern the attitude of the policy document. A policy could promote or discourage the (over) development in a sector. The second case is rare, but it happens when there is an irrational boom or harmful social externalities in a sector. In the former case, the policy documents usually have words such as encourage, promote, improve, support, and so on. In the latter case, the documents have words such as: excess, overheating, limit, reduce, exit, and so on. Using the previous simple example, if in the text of the policy document the attitude toward sector B is negative, while the attitude toward sector A is positive, then the values of this policy will be +1/3 for sector A and -2/3 for sector B. Here I exclude the situation where the attitude is neutral. If a policy document mentions these sectors, it implies attention from the central government, which can be interpreted as either a positive or negative policy shock to the public and financial institutions.

In addition to topics and attitudes, another crucial factor for consideration is the potential time lag of the policy's influence. In my quantification, I assume that each policy's influence lasts 12 months. I divide its influence into year t (the year the policy is announced) and year $t+1$ (one year after the policy is announced). The rules of dividing the influence of one policy into two years are as follows: assume the policy is announced on D/M/Y. If $D \leq 15$, then the value of the policy in year t will be $(13-M)/12$ and the value of the policy in year $t+1$ will be $(M-1)/12$; if $D > 15$, then the value of the policy in year t will be $(12-M)/12$ and the value of the policy in year $t+1$ will be $M/12$. Multiplying the value of the policy for a specific year and the value of the policy for a specific sector yields the final value of that policy in a specific year for a specific sector. The following is an example to help clarify the quantification of a policy document.

On July 18, 2015, the PBoC announced a policy titled *Guidance on Promoting the Healthy Development of Internet Finance*. In the text of this policy document, the information technology sector (I) and the financial sector (J) are equally positively mentioned, so the policy values are +1/2 unit for each sector. Considering the date of the policy announcement, $D=18>15$, the final value of this policy in sector I (or sector J) for 2015 is $(12-7)/12 \times 1/2 = 5/24$; the final value of this policy in sector I (or sector J) for 2016 is $7/12 \times 1/2 = 7/24$.

The sum of the values of all the policies related to sector s for year t provides the quantified annual sector-level data for the variable IP_{ts} . The classification of sectors follows the National Standard of the People's Republic of China. According to the Industrial Classification for National Economic Activities, there are 19 major sectors labeled A to S. The official national standard document lists the detailed economic activities for each sector, and most banks report their loans by sector based on the same categorization. Thus, I adopted this method of classification.

Furthermore, I divide the sectors into two groups: those dominated by SOEs and those not dominated by SOEs. The SOE-dominated sectors include mining (B); electricity, heat, gas, and water (D); transportation, storage, and postal services (G); finance (J); and water conservancy, environment, and public facilities management (N). These sectors are mainly controlled by SOEs (oligopolies), while the others are relatively more competitive markets or pure public sectors. On average, the SOE-dominated sectors accounted for 18 percent of gross domestic product between 2004 and 2021. According to Zhao (2012), the national capital shares of sectors B, D, G, J, and N were 71 percent, 83 percent, 85 percent, 77 percent, and 56 percent, respectively, in 2004. Thus, they were the top sectors with overwhelming state ownership. In 2010, the national capital shares of sectors B, D, and G were still very high, at 72 percent, 79 percent, and 56 percent, respectively. The capital shares of sectors J and N decreased to less than 50 percent, but the sectors were dominated mainly by SOEs with large shares of public ownership (national capital and collective capital).

Based on the quantified IP , the other policy variables, IP_Oth , can be obtained by computing the weighted average of other related sectors in each year. The policy variable IP_{ts} is the number of industrial policies in sector s in year t ; IP_Oth_{ts} is the number of industrial policies in all sectors except sector s in year t ; $IP_Oth_SOE_{ts}$ is the number of industrial policies in all SOE-dominated sectors in year t , except sector s if sector s itself is also an SOE-dominated sector; and $IP_Oth_NSOE_{ts}$ is the number of industrial policies in all sectors that are not dominated by SOEs in year t , except sector s if sector s itself is not an SOE-dominated sector. As defined above, IP_{ts} is the number of policies for one sector (sector s itself), and all other policy variables are the weighted average (by sectoral value added) number of policies in related sectors. All the policy variables vary across time. IP_{ts} and IP_Oth_{ts} vary across all sectors. $IP_Oth_SOE_{ts}$ varies across SOE sectors, and $IP_Oth_NSOE_{ts}$ varies across non-SOE sectors. The following are the formulas for calculating IP_Oth_{ts} :

$$IP_Oth_{ts} = \sum_{j \neq s} w_{tj} IP_{tj}, \quad (1)$$

$$IP_Oth_SOE_{ts} = \sum_{j \in SOE \text{ sectors}, j \neq s} w_{tj} IP_{tj}, \quad (2)$$

$$IP_Oth_NSOE_{ts} = \sum_{j \in NSOE \text{ sectors}, j \neq s} w_{tj} IP_{tj}, \quad (3)$$

Where $w_{tj} = \frac{\text{value-added}_{tj}}{\sum \text{value-added}_{tj}}$, $j = A, B, \dots, S$.

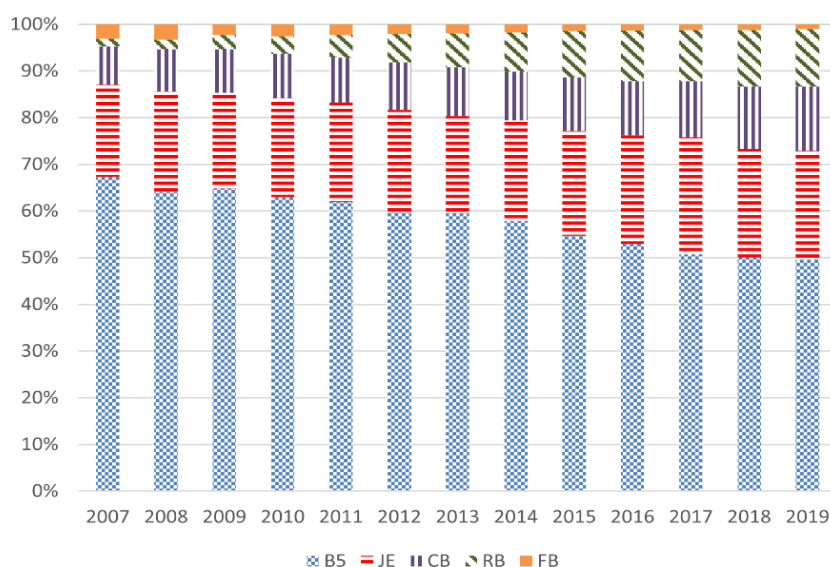
Besides industrial policy, standard monetary policies implemented by the PBoC could also affect bank credit allocation. Following Chen et al., (2017), I consider three standard instruments the PBoC use: the required reserve ratio, the benchmark lending rate, and the benchmark deposit rate. The three instruments usually go in

the same direction. If there was a tightening/no change/easing in the policy stance, the corresponding monetary policy variable MP will be equal to $-1/0/+1$. In the following empirical analyses, I include the monetary policy variable whenever possible to exclude confounding effects from standard monetary policy to banking credit.

B. Banking sector and sample construction

There is a high level of government ownership in the Chinese banking sector. There are three pure policy banks and one postal bank, and almost all the commercial banks in China are also public banks. This means they are controlled by the central government, local governments, and/or SOEs. Private banks have been allowed to enter the market only since 2015, and the market share of private banks was still negligible in 2023. There are four main types of commercial banks in China, officially set by the CBRC, namely “Big Five” banks, joint-equity banks, city commercial banks, and rural commercial banks, in descending order of average scale. The Big Five banks, as the name entails, are five giant banks directly owned by the central government, and their biggest shareholders are the Ministry of Finance and Central Huijin Investment Company Limited, a state-owned financial management company. Joint-equity banks are mainly controlled by large SOEs and/or the local governments of major cities and provinces (such as Shanghai and Shenzhen) but with relatively more private and foreign capital investment than other commercial banks. There are 12 joint-equity banks in total, which operate nationwide. City commercial banks are usually controlled by local city governments and/or local SOEs. There are more than 130 city banks in China whose business is usually regional, that is, they operate in the local city and nearby cities. Due to geographical limitations and their relatively small size, city banks face intense competition with their counterparts, which are local branches of the Big Five and joint-equity banks. Because of this competition, several joint-equity banks and city banks have been able to establish a market-oriented business model (Dong et al., 2016). For example, city banks and joint-equity banks tend to conduct more nontraditional business than other banks, to increase revenues (Dong et al., 2014). Lastly, rural commercial banks are usually established by local rural governments and/or rural SOEs, and there were almost 1,500 rural commercial banks in the rural areas in China in 2019. They have a relatively small scale and a highly concentrated local business compared with other commercial banks.

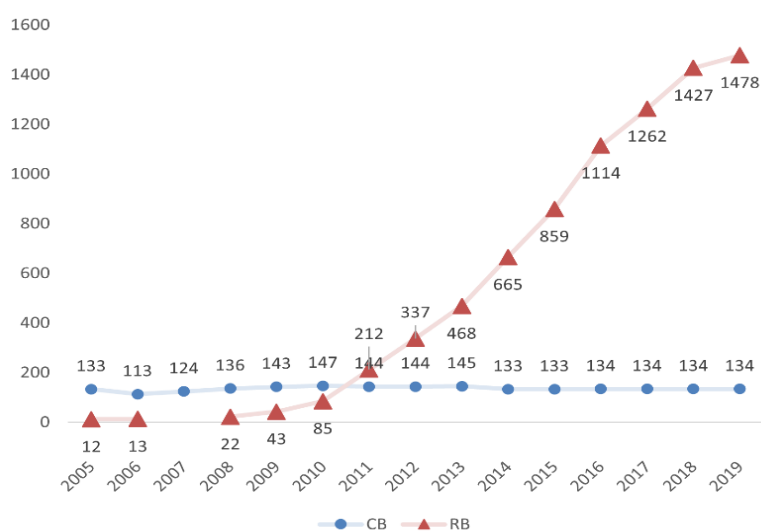
Figure 2. Share of Loans by Different Types of Banks, 2007–2019



NOTE: B5 = Big Five; CB = city banks; FB = foreign banks; JE = joint-equity banks; RB = rural banks.

Figure 2 shows the changing market shares of loans from these four types of banks and foreign banks in the Chinese credit market from 2007 to 2019. Rural banks' share increased over time from less than 2 percent to 12 percent, which was due to the dramatic increase in the number of rural banks. As Figure 3 suggests, there were 12 rural banks in 2005 but 1,478 in 2019, an increase of more than 100 times. The reason behind this phenomenon was that the CBRC started to promote the transformation of all rural financial institutions in 2011, such as rural credit cooperatives and rural cooperative banks, to rural commercial banks. In the meantime, the share of the Big Five decreased from more than 67 percent to around 49 percent of total credit over the 12 years. Medium-size commercial banks are increasingly taking market share from the state-owned giants. However, the overwhelming public ownership in the banking sector remains.

Figure 3. Numbers of City Commercial Banks and Rural Commercial Banks in China



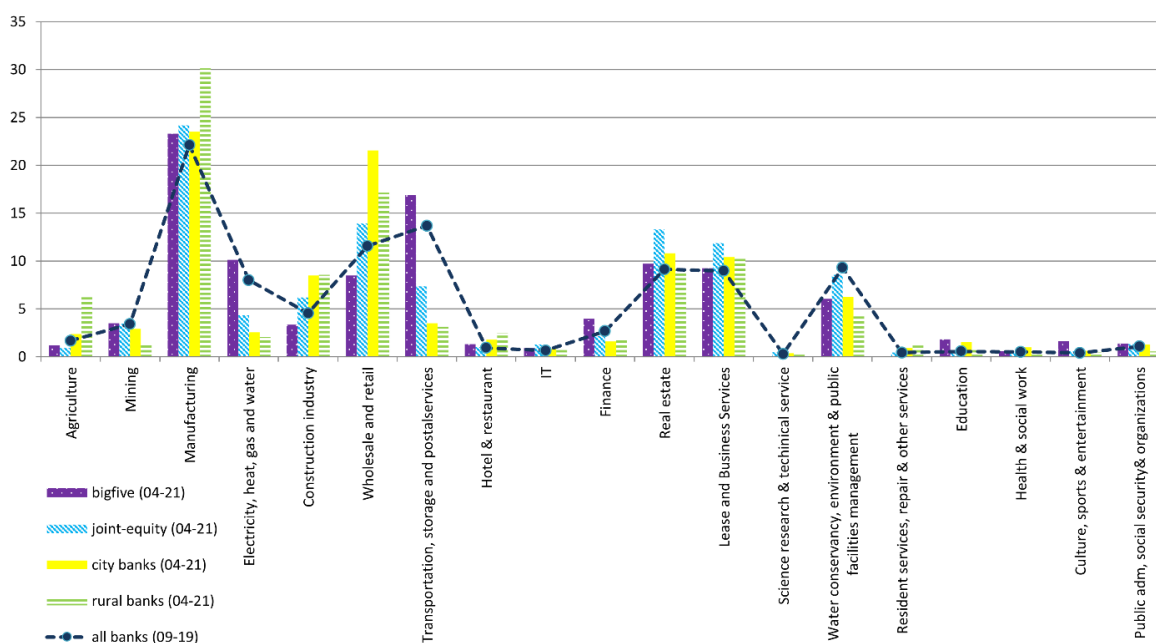
Note: CB = city banks; RB = rural banks. The number of rural banks in 2007 is not available.

Different bank ownership types imply potentially different lending preferences. Figure 4 shows this difference clearly. I take the average share of loans in each sector from different types of banks in the sample during the period between 2004 and 2021. Rural banks (green bars) have a much higher ratio of credit to the agriculture sector compared with the other banks. City banks (yellow bars) have an average of more than 20 percent of their credit to the wholesale and retail sector, which is much higher than the shares from the other banks. The Big Five banks (purple bars) provide higher shares of credit in sectors that are usually highly controlled by the central government, such as electricity, heat, gas and water, transportation, storage and postal services, and finance.

The differences lie not only in the diverse types of bank ownership, but also in different sectors. In Figure 4 I also plot loan distribution across sectors by all commercial banks in China (dashed line). The manufacturing sector has the most bank credit, with all types of commercial banks allocating more than a quarter of their credit to this sector. Sectors like science, education, health, culture, and social security usually have larger portions of direct government investments and financial appropriations. Hence, they have relatively lower shares of bank credit compared to the others. Compared with Figure 1, which pictures sectors promoted by industrial policy, there are similarities and differences between bank credit and industrial policy. This leads to the following question: are government-owned commercial banks trying their best to follow the State Council, or do they prioritize their own considerations while allocating credit among sectors?

Based on this background, I constructed two data sets for loan variables: one at the industry level and the other at the bank level. The industry-level data set includes annual loan data in each sector for all the commercial banks in China from 2009 to 2019. These data are calculated based on the information reported by the CBRC Annual Reports (before 2018) and data published by the China Banking and Insurance Regulatory Commission (CBIRC, since 2018). The bank-level data set includes annual loan data for 137 commercial banks from 2004 to 2021. I manually collected these data from the banks' financial reports and audit reports since there is currently no existing high-quality alternative database providing loan data in each sector at the bank level in China.

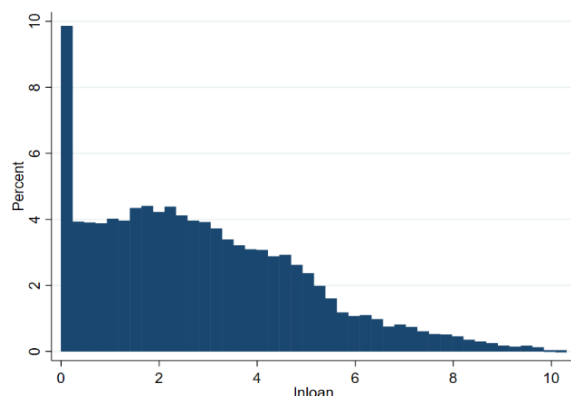
Figure 4. Bank Credit Share by Sector (Average, percent)



This novel bank-level data set covers the Big Five banks, 12 joint-equity banks, 82 city commercial banks, and 38 rural commercial banks. Banks, especially the listed ones, publish their annual financial reports on their own websites, which contain their annual loans to each sector. However, this method does not always work because many of the banks are not listed, and some only have financial reports online for the most recent years. I then turn to two databases owned by the China Foreign Exchange Trading System and National Interbank Funding Center and the China Central Depository and Clearing Co., Ltd. These two websites (as far as I know) have the most exhaustive documents on all types of banks, with free access for the public. The available documents include financial reports, audit reports, credit rating reports, official documents for initial public offerings, and official documents for bond issuance. I used both websites to double-check and obtained information that is as complete as possible. Using these sources, I maximize the number of banks analyzed in my study to the greatest extent possible. Meanwhile, each bank in the sample has at least nine successive years of data for the purpose of comparison. The last period in the series is the year 2021, so all the banks in the sample were established or transformed at least before 2013.

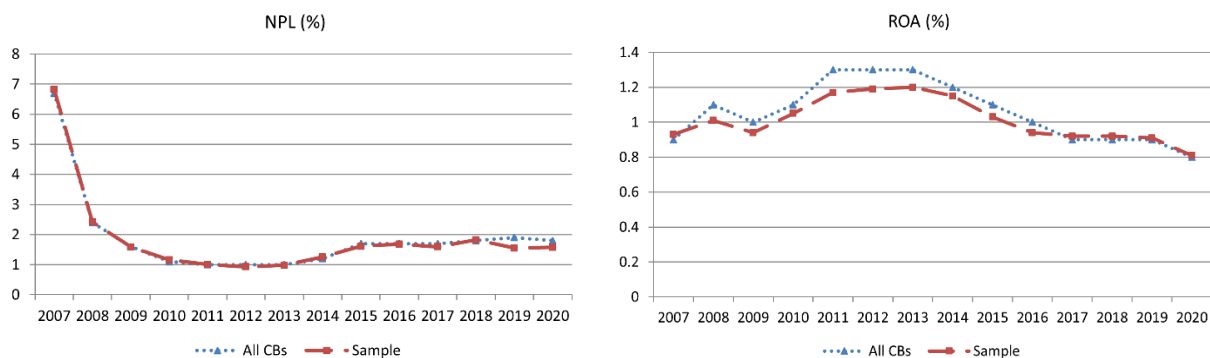
Figure 5 presents the distribution of the size of the *loan* variable in the sample. There are 26,048 bank-level observations, and around 10 percent of the observations are loans of less than 0.28 billion RMB, including more than 4 percent of which are 0s. In my analyses, I use the log value of the loan plus one as the dependent variable to deal with potential situations of banks providing no credit to specific sectors in some years.

Figure 5. Distribution of Loans (Bank-Level Sample)



Although the data collection process was exhaustive, the sample may still be limited. Not all government-owned commercial banks report their loan data to the public. Some banks have time series available for a shorter period, for which reason they are excluded from my sample. This is especially the case for many smaller city and rural commercial banks. They only report complete data to supervisors, from which it is nearly impossible to gather information at the individual bank level as an external researcher. Despite being restricted by this limitation, it is still meaningful to utilize this data set to test some interesting hypotheses. The results drawn from the data set are valuable since the sample accounts for 96.9 percent of Chinese commercial banks' total assets. Figure 6 compares the average asset quality and profitability of the banks in the sample with industry-level data from all commercial banks in China. Both the nonperforming loan (NPL) rates and the return to asset (ROA) ratios of the banks in the sample share similar trends as those at the industry level. The asset quality of the banks in the sample was extremely close to the industrial level and was slightly better than the industrial average in most recent years, while their profitability was slightly below the industrial average in early years but caught up in recent years.

Figure 6. Representativeness of the Bank-Level Sample: Compared with Industry-Level Data

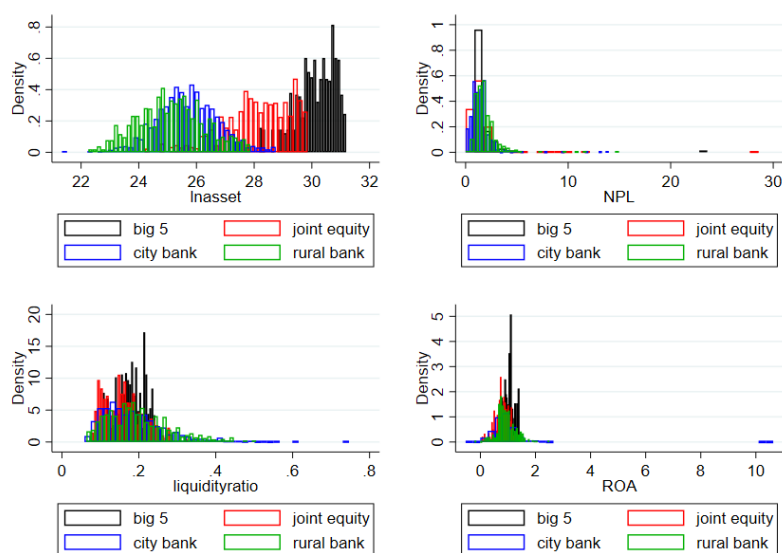


NOTE: All CBs = All commercial banks, industry-level; NPL = nonperforming loans ratio; ROA = return to asset ratio.

Bank characteristics are important independent variables in my analysis besides policy variables. For consistency, I used the same source as for the loan data to collect information on bank characteristics. *Security_invest* is the ratio of a bank's security investment over the total assets of the bank; *NPL* is the ratio of NPLs over the total loans of the bank; *ROA* is the total net income over the assets of the bank; *Log(asset)* is the log of the total assets of the bank; *listed* is a dummy variable that equals 1 if the bank was listed before the last quarter of year t and 0 otherwise; and *liquidityratio* is the ratio of liquid assets, which is defined as the sum of cash and balances with the central bank, loans and advances to other financial institutions, and precious metal over the total assets of the bank. Figure 7 shows the distributions of several bank characteristics for

different types of commercial banks. The figure illustrates the diversity of the sizes of the banks in the sample across different types of ownership. Rural and city commercial banks are relatively small, compared with joint-equity banks, and the Big Five banks are much larger. Rural commercial banks generally have the highest NPL rates, and city commercial banks have the lowest. There are no apparent differences in liquidity ratios or ROA ratios among the four types of banks.

Figure 7. Bank Characteristics (Bank-Level Sample)



Note: NPL = nonperforming loans rate; ROA = return to asset ratio.

Table 1 presents summary statistics for all the variables in the analyses. In addition to the log value of loans (plus 1), I use other loan variables for robustness tests. The variable $share_{ts}$ is the percentage of loans in sector s among all sectors from all commercial banks in year t , and $growthrate_{ts}$ is the growth rate of loans in sector s from all commercial banks in year t . In the table, SOE_s is a dummy variable that equals 1 if sector s is an SOE-dominated sectors and 0 otherwise. The sectoral control variable $value-added_{ts}$ is the share of value added in sector s among all sectors in year t .

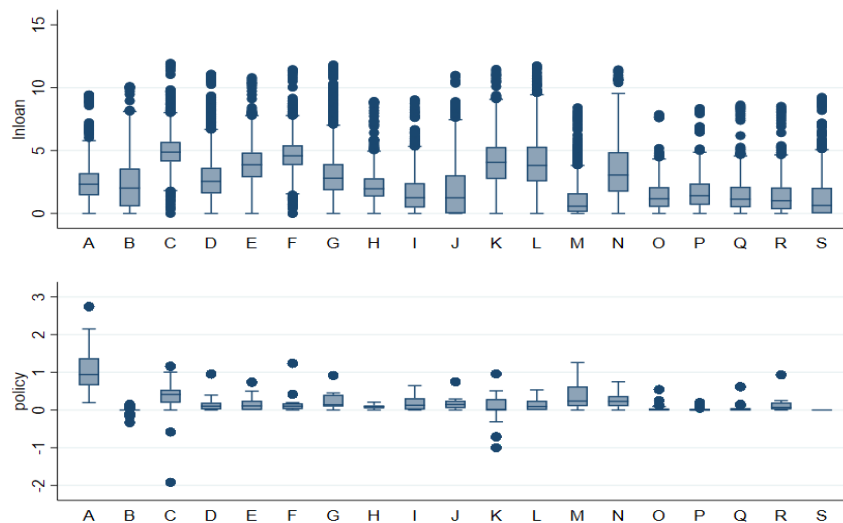
Table 1. Summary Statistics

Variable	Units	N	Mean	Sd	Min	Median	Max
$\log(\text{loan})_{ts}(\text{all CBs})$	-	209	9.44	1.51	6.18	9.41	11.94
$share_{ts}(\text{all CBs})$	percent	209	5.26	5.98	0.19	2.1	26.01
$gowthrate_{ts}(\text{all CBs})$	percent	190	0.12	0.16	-0.42	0.11	0.87
$\log(\text{loan})_{its}(\text{sample})$	-	26,048	2.83	2.09	0	2.52	10.31
IP_{ts}	-	26,048	0.2	0.33	-1.92	0.1	2.74
IP_Oth_{ts}	-	26,048	0.3	0.14	-0.74	0.27	0.66
$IP_Oth_SOE_{ts}$	-	26,048	0.17	0.12	-0.13	0.13	0.64

Variable	Units	N	Mean	Sd	Min	Median	Max
IP_Oth_NSOE _{ts}	-	26,048	0.34	0.17	-0.91	0.29	0.77
MP _t	-1/0/1	26,048	0.52	0.73	-1	1	1
Value-added _{ts}	-	26,048	0.06	0.07	0	0.04	0.33
SOE _s	0/1	26,048	0.28	0.45	0	0	1
NPL _{it}	percent	26,048	1.6	1.42	0	1.42	28.58
ROA _{it}	percent	26,048	0.89	0.48	-0.54	0.86	10.63
log(asset) _{it}	-	26,048	25.92	1.55	21.34	25.73	31.19
listed _{it}	0/1	26,048	0.22	0.41	0	0	1
liquidityratio _{it}	percent	26,048	0.19	0.08	0.06	0.17	0.75
security_invest _{it}	percent	26,048	0.28	0.12	0	0.29	0.72

As comparison, Figure 8 presents the distributions of two key variables: loans and quantified industrial policy shocks in the sample for 19 sectors. There are large heterogeneities across sectors for both variables. The policy shocks are mainly positive, with a few observations of negative values. The distributions of the two variables are very different and there is no strong correlation between the two (see Appendix B for the correlation matrix).

Figure 8. Distributions of Loans (Bank-Level Sample) and Industrial Policies, by Sector



Note: the top panel shows the distribution of the log(loan) variable across sectors, and the bottom panel shows the distribution of the IP (Industrial Policy) variable across sectors.

II. Does Credit Go to Sectors Promoted by Industrial Policy?

This section answers the following question: do banks respond to industrial policy by providing more credit to the promoted sectors? Based on the "political/social" views in the literature discussed in the Introduction Section, commercial banks should allocate more credit to sectors promoted by industrial policy. China has only one party in power, which means the central government should be the only source of political influence on banks' behavior. Meanwhile, almost all industrial policies discussed in this paper are aimed at social development. By design, achieving social development is a duty of government-owned banks. Thus, both "political" and "social" views support the hypothesis that commercial banks in China, more than 99 percent of which are government-owned, should tightly follow the industrial policies announced by the central government.

To verify my hypothesis, I estimate changes in commercial banks' overall loans in the sectors in which the central government announced industrial policies. I use the model below (equation 4). Quantified industrial policy is the key explanatory variable for the allocation of loans in this model. Subscript t represents year and s represents sector, and the model includes year and sector fixed effects. $Policies_{ts}$ include different measures of industrial policy as well as the measure of monetary policy. If $\beta_{1,IP} > 0$, there is an allocation effect among sectors on bank credit from the introduction of industrial policy.

$$loan_{ts} = \beta_1 Policies_{ts} + \alpha_t + \delta_s + \epsilon_{its} \quad (4)$$

Table 2 reports the estimated coefficients based on this baseline model and shows that there is no conclusive evidence that commercial banks lend on average more to the sectors promoted by industrial policy. Model (1) is a simple ordinary least squares (OLS) regression without any fixed effects. Model (2) adds year fixed effects and Model (3) adds sector fixed effects to Model (1). Model (4) has both year and sector fixed effects. As expected, an easing of monetary policy increases overall bank credits. But the estimated coefficients suggest no consistent result on the effect of industrial policy on bank credit allocation. The coefficient for IP is positive in Column 4, but the result is not robust when adding other control variables or using other definitions of the dependent variable as presented in the following columns. In Model (5) I add value added by sector to control other sector-year biases that year and sector fixed effects may not explain. The estimated coefficient for the policy variable is no longer statistically significant in Column (5). Since the loan data in the data set are stock values, they may be largely influenced by the values in the previous year. In Model (6), I introduce lagged values of the dependent variable. The estimated coefficient for IP becomes negative and not statistically significant. When I quantify industrial policies, I assume that the influence only lasts for a period of one year, but it may be the case that the policies have longer-term effects. Therefore, in Model (7), I run the same regression as Model (4) but with a one-year-lagged policy variable. Column (7) shows that there is still no effect of industrial policies in the longer term. For robustness checks, I use two different loan variables: the share and growth rate of loans, in Models (8) and (9). The estimated coefficients from these two models suggest no and negative effect of industrial policy on bank credit allocation. The last model in Table 2 uses the first difference to exclude potential bias due to time. Again, the estimated coefficient from Model (10) does not suggest a significant effect of industrial policy. To summarize, Table 2 suggests that different from what might have been expected, there is no conclusive evidence that the commercial banks in China allocate, on average, their financial resources to sectors promoted by the industrial policies announced by the central government.

**Table 2. Regression Results: Industrial Policy and Bank Credit
(All Commercial Banks)**

	Log(loan) (1)	Log(loan) (2)	Log(loan) (3)	Log(loan) (4)	Log(loan) (5)	Log(loan) (6)	Log(loan) (7)	Share (8)	Growth rate (9)	Δ Log(loan) (10)
IP	0.227 (0.81)	0.360 (1.38)	-0.106 (-0.98)	0.143* (1.68)	0.096 (1.48)	-0.054 (-1.13)		-0.172 (-0.48)	-0.053* (-1.77)	
MP	0.355*** (2.71)		0.342*** (8.47)							
Log(loan _{t-1})						0.813*** (11.37)				
Δ IP										0.025 (0.71)
IP _{t-1}							0.104 (1.35)			
Value-added					21.65*** (4.50)					
cons	9.265*** (69.90)	9.365*** (80.52)	9.342*** (184.42)	9.412*** (292.80)	8.283*** (32.11)	1.920*** (2.83)	9.419*** (298.39)	5.300*** (40.40)	0.132*** (12.36)	0.153*** (9.74)
N	209	209	209	209	209	190	209	209	190	190
Year	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: t-statistics are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

I further examine the spill-over effects of industrial policy on bank credit to non-targeted sectors in Table 3, and the regression results suggest that policies targeting SOE-dominated sectors have a crowding-out effect on credit allocation. Some recent studies analyze industrial policy from the perspective of input-output linkages (Lane, 2022; Liu, 2019) and show the potential transmission of industrial policy among sectors. The study by Lane (2022) on South Korea's manufacturing revolution suggests that industrial policies positively impacted forward-linked (downstream) industry but negatively impacted backward-linked (upstream) industry. To test potential spill-overs of targeted industrial policy in financial resource allocation, I use the quantified industrial policies in other sectors as explanatory variables. Models (1) and (2) in Table 3 show that bank credit allocation to a specific sector is not affected by the overall number of industrial policies announced in other sectors. However, in Models (3) and (4), when I divide industrial policies in other sectors into two types: those in other SOE-dominated sectors and those in other sectors not dominated by SOEs, the regression results show that industrial policy announced in other SOE-dominated sectors have a crowding-out effect because the credit to its own sector decreases (the estimated coefficient for IP_Oth_SOE is negative and statistically significant).

**Table 3. Regression Results: Industrial Policy Spill-over Effects on Bank Credit
(All Commercial Banks)**

Model	Dependent variable: Log(loan)			
	(1)	(2)	(3)	(4)
IP		0.240* (1.80)		0.113 (0.93)
IP_Oth	-0.242 (-0.39)	1.046 (1.35)		
IP_Oth_SOE			-8.539*** (-3.40)	-8.223*** (-3.25)
IP_Oth_NSOE			0.349 (0.85)	0.792 (1.53)
N	209	209	209	209
Year	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes

Note: t-statistics are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Thus, from the discussion above, there is no strong evidence that commercial banks in China allocate credit to sectors promoted by industrial policy. But the industry-level evidence shows potential heterogeneity across sectors. Another potential explanation is that each individual bank may respond to industrial policy in a divergent way, which in the end leads to no consistent reaction at the industry level. In the next two sections, I use also bank-level data to unveil banks' divergent behavior masked at the aggregate level.

III. Heterogeneous Responses I: Bank Characteristics

In this section, I explore the heterogeneous responses caused by bank characteristics to understand why commercial banks as a whole do not respond to industrial policies. The empirical evidence shows that rural commercial banks respond most positively to industrial policy. Looking at the characteristics of individual banks, the banks that are relatively more compliant with the industrial policies announced by the Chinese government usually have lower competitiveness and a higher liquidity ratio. Lower competitiveness implies that a bank has a higher NPL rate, is smaller, or is not listed. A higher liquidity ratio implies the potential inefficient use of financial resources.

Interpreting the data at the industry level neglects the heterogeneity among banks' behaviors. Different banks' sizes, business operation modes, ownership types, and geographical coverage are so diverse that it is reasonable to believe there will not be a uniform response to industrial policy, as proved in the previous section. The following model is thus used to estimate the potentially different sensitivities of individual banks to industrial policy:

$$\begin{aligned} loan_{its} = & \beta_1 IP_{ts} + \beta_2 IP_{ts} \times bankcharacteristics_{it} \\ & + \beta_3 bankcharacteristics_{it} + \beta_4 MP_t \times bankcharacteristics_{it} + \alpha_t + \delta_s + \vartheta_i + \epsilon_{its} \quad (5) \end{aligned}$$

Different from the previous section, which looked at industry-level bank credit (all commercial banks), this section introduces the bank-level data set into the model. Here, i represents bank, and $bankcharacteristics_{it}$ is a set of variables that includes the type of bank ownership, the ratio of security investment over total assets, NPL, ROA, log of assets, liquidity ratio, and a dummy variable for whether the bank is listed or not. In this model, besides year (α_t) and sector (δ_s) fixed effects, I also consider bank fixed effects (ϑ_i). I interact the policy variable IP with these different bank characteristics. The estimated coefficients of the interactions are the main outcomes of interest. If for a specific bank characteristic the estimated coefficient is positive ($\beta_2 > 0$), then banks with this characteristic will respond more positively to industrial policy. In addition, to control for the effects from standard monetary policy, I also interact bank characteristics with MP .

The type of bank ownership is a reason for the heterogeneity, and the evidence provided in Table 4 supports this argument. For Models (1) to (4), I use the subsamples of Big Five banks, joint-equity banks, city commercial banks, and rural commercial banks, respectively, in each regression. The estimated coefficients of the policy variables for Big Five banks and rural commercial banks are positive although not statistically significant. For city commercial banks, industrial policy seems to have a negative effect on credit allocation. Models (5) and (6) use the full sample, and I introduce interaction terms between bank ownership type and policy. Variables $b5$, je , cb , and rb are dummy variables that equal 1 if the bank belongs to Big Five, joint-equity, city, and rural commercial banks, respectively, and 0 otherwise. In Model (5), I use rb as the base, and in Model (6), I use cb as the base, but they are the same model written in different ways. To estimate the coefficients of the ownership dummy variables presented in the final results, I drop the bank fixed effects in the last two columns. However, the coefficients for the interaction terms do not change significantly when bank fixed effects are included.

Table 4. Regression Results: Industrial Policy, Bank Credit, and Different Government Ownership (Bank-Level Sample)

Model	Dependent variable: Log(loan)					Full Sample (6)
	B5 (1)	JE (2)	CB (3)	RB (4)	(5)	
IP	0.017 (0.44)	-0.005 (-0.11)	-0.183*** (-7.44)	0.061 (1.38)	0.275*** (7.21)	-0.196*** (-8.23)
IP × b5					-0.438*** (-5.27)	0.033 (0.42)
IP × je					-0.600*** (-10.10)	-0.129** (-2.53)
IP × cb					-0.471*** (-11.58)	
IP × rb						0.471*** (11.58)
b5					0.983*** (19.58)	0.820*** (17.65)
je					0.412*** (11.92)	0.249*** (8.32)
cb					0.163*** (8.27)	
rb						-0.163*** (-8.27)
cons	12.83 (0.89)	-12.15*** (-4.64)	-10.72*** (-12.16)	-11.31*** (-5.88)	-19.12*** (-108.13)	-18.95*** (-105.32)
N	860	2382	16190	6615	26,048	26,048
Year	Yes	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes	Yes
Bank	Yes	Yes	Yes	Yes		
MP × Bank characteristics					Yes	Yes

Note: t-statistics are in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01. rb: rural commercial banks, b5: "big-five" banks, je: joint equity banks, cb: city commercial banks.

There are three main takeaways from Table 4. First, rural commercial banks respond most positively to industrial policy. Compared with all the other types of commercial banks, rural commercial banks are the most immature financial institutions, with weak corporate governance. To some extent, also because of historical reasons, many rural commercial banks act as local policy banks in rural areas to provide financing and support development rather than exclusively pursue business profits. Thus, it is not surprising that rural commercial banks are the most responsive to industrial policy. Second, city commercial banks and joint-equity banks are less responsive to industrial policy. Compared with the other two types, joint-equity banks and city commercial banks have absorbed more private and foreign capital, therefore, less direct state ownership. Under the control of the local city or provincial government, joint-equity banks and city commercial banks face less direct intervention from the central government. There are also potentially different targets between local governments and the central government. These factors imply that city commercial banks and joint-equity banks potentially have more discretion in their lending policies. Third, by contrast to other commercial banks, the Big Five banks have direct state ownership and less discretion, making them more likely to respond to industrial policy. Nevertheless, the Big Five are all listed companies and they also care about profitability. As mentioned by Yao et al., (2008), these state-owned banks have improved their lending strategies and tried to reduce the influence of government interventions. Thus, fully behaving as policy banks is not their preference either.

In addition to the type of government ownership, I examine six other bank characteristics in Table 5. Even with the same type of ownership, the operation of individual commercial banks varies from bank to bank. The regression results confirm this by showing that banks with a higher NPL rate, smaller size, and not listed respond relatively more positively to industrial policy. In Table 5, I introduce interaction terms of each bank characteristic with industrial policy and test whether banks with specific characteristics respond more positively to industrial policy. In Models (1) to (6), I test the role of security investment, NPL rate, ROA ratio, asset size, listing, and liquidity ratio, respectively. On the one hand, the regression results from Models (1), (3), and (6) suggest that there is no influence from banks' security investment, ROA, and liquidity ratio on their sensitivities to industrial policy. Using ROE, an alternative measure of bank profitability, as a robustness check, does not change the results. On the other hand, the coefficient for $IP \times NPL$ from Model (2) is positive, and the coefficient for $IP \times \text{Log}(\text{asset})$ is negative from Model (4), which suggest that banks with a higher NPL rate and a smaller size will be more sensitive to industrial policy. The estimated coefficient for the interaction term $IP \times \text{Listed}$ in Model (5) is negative, which means that holding all other variables the same, compared with non-listed commercial banks, listed banks are less likely to respond to industrial policy. For non-listed banks, there will be fewer constraints from external private investors. Thus, non-listed banks could relatively freely move their financial resources among sectors based on policy instructions.

Table 5. Regression Results: Industrial Policy, Bank Credit, and Bank Characteristics (Bank-Level Sample)

Dependent variable: Log(loan)						
Model	(1)	(2)	(3)	(4)	(5)	(6)
IP	-0.0593 (-1.27)	-0.184*** (-6.22)	-0.100*** (-2.78)	1.177*** (4.30)	-0.075*** (-3.29)	-0.076* (-1.71)
Security_invest	-0.855*** (-7.60)	-0.846*** (-8.55)	-0.842*** (-8.55)	-0.830*** (-8.43)	-0.846*** (-8.59)	- 0.867*** (-8.76)
IP×Security_invest	-0.168 (-1.08)					
NPL	0.017*** (4.01)	0.008 (1.63)	0.017*** (4.01)	0.017*** (4.01)	0.017*** (3.94)	0.016*** (3.80)
IP×NPL		0.054*** (3.48)				
ROA	-0.001 (-0.10)	-0.001 (-0.05)	-0.002 (-0.10)	-0.004 (-0.28)	-0.002 (-0.15)	-0.005 (-0.32)
IP×ROA			0.002 (0.06)			
Log(asset)	0.573*** (21.00)	0.572*** (20.94)	0.573*** (20.95)	0.593*** (21.32)	0.579*** (21.04)	0.582*** (21.27)
IP×Log(asset)				-0.050*** (-4.69)		
Listed	0.082*** (3.32)	0.084*** (3.42)	0.084*** (3.41)	0.078*** (3.16)	0.074*** (2.58)	0.082*** (3.34)
IP×Listed					-0.096** (-2.48)	
Liquidity ratio	-0.042 (-0.35)	-0.046 (-0.38)	-0.041 (-0.34)	-0.076 (-0.63)	-0.051 (-0.43)	0.051 (0.39)

IP×Liquidity ratio						-0.153 (-0.70)
	6.111*** (9.05)	6.166*** (9.21)	6.144*** (9.18)	5.908*** (8.85)	6.062*** (9.10)	6.289*** (9.37)
cons	-11.83*** (-16.88)	-11.77*** (-16.77)	-11.81*** (-16.83)	-12.53*** (-17.30)	-11.95*** (-16.94)	- 12.02*** (-17.15)
<i>N</i>	26,048	26,048	26,048	26,048	26,048	26,048
Year	Yes	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes	Yes
Bank	Yes	Yes	Yes	Yes	Yes	Yes
MP × Bank characteristics	Yes	Yes	Yes	Yes	Yes	Yes

Note: t-statistics are in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01.

Demand-side factors can strongly influence banks' credit allocation. Table 6 shows that the above results are robust when excluding this bias by taking *Year*×*Sector* fixed effects. Similar to Models (2), (4), and (5) in Table 5, Models (1) to (3) in Table 6 test the role of NPL, asset size, and listing in banks' sensitivity to industrial policy, while controlling demand-side bias. The estimations of the interaction terms in Table 6 are very similar to those in Table 5; thus, the same conclusions still hold. In addition, Model (4) in Table 6 tests the role of liquidity ratios. Different from the result in Table 5, here the estimated coefficient for the interaction term *IP*×*Liquidity* ratio is positive, which means that holding all other variables the same, banks with a higher liquidity ratio are more responsive to industrial policy. Intuitively, banks with a higher liquidity ratio are more likely to have extra financial resources to allocate to sectors promoted by industrial policy.

Table 6. Regression Results: Industrial Policy, Bank Credit, and Bank Characteristics (Bank-Level Sample, Year × sector fixed effects)

Model	Dependent variable: Log(loan)			
	(1)	(2)	(3)	(4)
IP × NPL	0.054*** (3.65)			
IP × Log(asset)		-0.082*** (-7.18)		
IP × Listed			-0.124*** (-3.28)	
IP × Liquidity ratio				0.642** (2.31)
Security_invest	-0.862*** (-8.99)	-0.848*** (-8.87)	-0.863*** (-9.03)	-0.888*** (-9.26)
NPL	0.009* (1.94)	0.018*** (4.44)	0.018*** (4.40)	0.017*** (4.24)
ROA	-0.005 (-0.39)	-0.008 (-0.61)	-0.006 (-0.47)	-0.010 (-0.69)
Log(asset)	0.604*** (23.23)	0.630*** (23.71)	0.608*** (23.27)	0.614*** (23.60)

Listed	0.073*** (3.13)	0.067*** (2.90)	0.078*** (2.89)	0.070*** (3.03)
Liquidity ratio	-0.096 (-0.82)	-0.124 (-1.07)	-0.099 (-0.86)	-0.168 (-1.27)
cons	-12.60*** (-18.89)	-12.99*** (-18.93)	-12.72*** (-18.97)	-12.83*** (-19.26)
N	25,963	25,963	25,963	25,963
Year × Sector	Yes	Yes	Yes	Yes
Bank	Yes	Yes	Yes	Yes
MP × Bank characteristics	Yes	Yes	Yes	Yes

Note: t-statistics are in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01.

Are all banks with lower asset quality more likely to take industrial policy into consideration in their lending, or are the regression results in Model (2) of Table 5 mainly driven by rural banks in the sample? High NPL rates imply low asset quality, which often (but not always) happens with small banks. In Figure 8, we have seen that rural commercial banks match both characteristics — high NPL rates and small bank sizes — in general. Table 7 reveals the answer to this question. Models (1) to (4) in Table 7 are estimated with subsamples of only rural commercial banks, the Big Five banks, joint-equity banks, and city commercial banks to run the same regression as Model (2) in Table 5. Model (5) uses a subsample with all banks, excluding rural commercial banks. Coefficients of the interaction term $IP \times NPL$ are positive for all columns and statistically significant for the subsample of rural banks and joint-equity banks, as well as the subsample of all non-rural banks. To summarize, the estimates in Table 7 show that the coefficient of the interaction between industrial policy and NPL rate is positive and significant not only because of rural commercial banks in the sample. For all types of commercial banks with a higher NPL rate, they respond more positively to industrial policy. A similar test for asset size also suggests that the results are not driven by rural commercial banks only.

**Table 7. Regression Results: Industrial Policy, Bank Credit, and NPL
(Bank-Level Sample)**

	Dependent variable: Log(loan)				
	RB	B5	JE	CB	-RB
Model	(1)	(2)	(3)	(4)	(5)
IP	-0.030 (-0.45)	0.010 (0.15)	-0.065 (-1.40)	-0.225*** (-5.43)	-0.187*** (-6.29)
NPL	0.007 (0.63)	0.011 (0.22)	0.012 (1.19)	-0.005 (-0.58)	0.008 (1.47)
IP × NPL	0.048* (1.78)	0.004 (0.15)	0.039*** (2.86)	0.030 (1.21)	0.028* (1.94)
Security_invest	-0.673*** (-3.15)	1.390* (1.83)	-0.841*** (-2.70)	-0.807*** (-6.57)	-0.787*** (-7.08)
ROA	0.027 (0.52)	-0.221 (-0.84)	-0.055 (-0.47)	-0.011 (-0.66)	-0.003 (-0.16)
Log(asset)	0.539*** (6.92)	-0.192 (-0.40)	0.620*** (6.50)	0.525*** (15.15)	0.527*** (17.24)
Listed	0.240*** (4.86)	0.170 (1.26)	0.109* (1.68)	0.026 (0.83)	0.042 (1.49)

Liquidity ratio	0.283	-1.106	0.275	-0.217	-0.149
	(1.22)	(-0.93)	(0.44)	(-1.48)	(-1.05)
cons	-11.43***	13.55	-12.12***	-10.63***	-10.45***
	(-5.90)	(0.93)	(-4.62)	(-12.00)	(-13.17)
<i>N</i>	6,615	860	2,382	16,190	19,433
Year	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes
Bank	Yes	Yes	Yes	Yes	Yes
MP × Bank characteristics	Yes	Yes	Yes	Yes	Yes

Note: t-statistics are in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01.

IV. Heterogeneous Responses II: Sector Characteristics

In addition to banks' characteristics, another explanation for the heterogeneous responses to industrial policy is commercial banks' bias toward specific sectors. In this section, the empirical evidence shows that sectors that are mainly dominated by SOEs benefit more from industrial policy compared with sectors that are not dominated by SOEs.

When the announced industrial policies target different sectors, banks' responses can differ based on which sectors receive preferential policies. Banks may find some sectors more attractive, so they would tightly follow the policy instructions when lending is encouraged by the central government. In contrast, banks may be reluctant to change their positions to some other sectors, even with preferential policies. A series of studies focusing on public banks' behavior in China find that SOE-dominated sectors might be the biggest winners of the implementation of industrial policy. These studies show that Chinese state-owned banks are biased in favor of SOEs for bank lending (Wei and Wang, 1997; Firth et al., 2008; Yeung, 2009; Gao et al., 2019; Ho et al., 2017; Cong et al., 2019). Moreover, the government tends to allocate capital systematically toward SOEs (Boyreau-Debray and Wei, 2005). Thus, to test whether sectors with higher state ownership receive more credit following the industrial policy announcements, I estimate the following model:

$$loan_{ts} = \beta_1 Policies_{ts} + \beta_2 Policies_{ts} \times SOE_s + \beta_3 MP_t \times SOE_s + \alpha_t + \delta_s + \epsilon_{ts} \quad (6)$$

The coefficient of the interaction between policy and the dummy variable SOE_s reveals how banks' responses diverge in the two types of sectors. $Policies$ is a set of industrial policy variables, including those targeting at its own sector and at other sectors. If $\beta_2 > 0$, it suggests that, compared to other sectors, SOE-dominated sectors can benefit more credit resources from industrial policy. In this model, I consider both sector and time fixed effects. To control for the effects of monetary policy, I also add the interaction term between MP_t and SOE_s . For tests using the bank-level sample, I add bank fixed effects with bank characteristics controlled.

Table 8 shows that SOE-dominated sectors benefit more from industrial policy and policy targeting SOE-dominated sectors has a crowding-out effect on other sectors. In Table 8, Model (1) uses a subsample of observations in SOE-dominated sectors, and Model (2) uses observations in sectors not dominated by SOEs (NSOE sectors). The estimated coefficient of policy variable for SOE sectors in Column (1) is positive and statistically significant, implying that banks may respond more positively when industrial policy targets SOE-dominated sectors. In Models (3) to (5), I introduce interaction terms between the industrial policy variables and the dummy variable indicating whether the sector is SOE-dominated or not. I use observations from all sectors in these regressions. The coefficients for $IP \times SOE$ are always positive, which means that banks respond more to industrial policy when it targets SOE-dominated sectors than other sectors. Model (5) presents the large crowding-out effect from policies in other SOE-dominated sectors to its own sector. The coefficient of $IP \times SOE$ is still positive though no longer statistically significant. Because the magnitudes of the different policy variables differ, to make the estimations comparable in the same regression, I use standardized policy variables in Models (6) and (7) by running the same regressions as Models (4) and (5). The absolute values of estimations change but the main message remains consistent.

**Table 8. Regression Results: Industrial Policy, Bank Credit, and State Ownership
(All Commercial Banks)**

	Dependent variable: Log(loan)						
	SOE	NSOE	All Sectors		All Sectors (STD)		
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IP	1.702***	0.018	0.008	0.015	0.053	0.005	0.018
	(3.09)	(-0.20)	(0.09)	(0.12)	(0.43)	(0.12)	(0.43)
IP_Oth				0.061		0.009	
				(0.08)		(0.08)	
IP_Oth_SOE					-8.020**		-0.975**
					(-2.40)		(-2.40)
IP_Oth_NSOE					0.548		0.095
					(1.09)		(1.09)
IP × SOE			1.467***	1.465***	0.284	0.489***	0.095
			(2.90)	(2.87)	(0.59)	(2.87)	(0.59)
IP_Oth × SOE				0.039		0.006	
				(0.06)		(0.06)	
IP_Oth_SOE × SOE					0.135		0.016
					(0.11)		(0.11)
IP_Oth_NSOE × SOE					-0.282		-0.049
					(-0.56)		(-0.56)
<i>N</i>	55	154	209	209	209	209	209
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MP × SOE			Yes	Yes	Yes	Yes	Yes

Note: t-statistics are in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01.

The same conclusions hold when I use bank-level data: when there is an industrial policy announcement, SOE-dominated sectors can benefit relatively more compared with other sectors. Table 9 replicates the first three columns in Table 8 using bank-level data. The first two columns in Table 9 use observations from only SOE-dominated sectors and only NSOE sectors, respectively. The coefficient of policy variable for SOE sectors is still positive but not statistically significant while the coefficient for NSOE sectors is negative. For the full-sample tests, Model (3) in Table 9 reinforces that SOE-dominated sectors benefit more compared with other sectors when there is an industrial policy announcement. In the last two columns in Table 9, I use the Tobit model and the Hurdle model, respectively, for robustness checks, because more than 4 percent of the observations are 0s. The estimations from Model (4) using the Tobit model are very similar to those from Model (3). Meanwhile,

the Hurdle model also considers the following situation: industrial policy influences banks' decisions very differently on (i) lending more to sectors to which they have lent in the past, and (ii) lending to sectors to which they have not lent in the past. Thus, I run the regression in two stages with the Hurdle model. The first stage tests how industrial policy influences banks' decisions on whether to lend to a sector or not. The second stage tests how industrial policy influences banks' decisions on how much to lend when they have decided to lend to the sector. In Model (5) of Table 9, I report the combined effect from the two stages of the Hurdle regression. The values of the coefficients are much larger than those from the simple OLS and Tobit models, but the signs of the coefficients do not change.

**Table 9. Regression Results: Industrial Policy, Bank Credit, and State Ownership
(Bank-Level Sample)**

Sectors	Dependent variable: Log(loan)				
	SOE OLS	NSOE OLS	OLS	All Sectors Tobit	Hurdle
Model	(1)	(2)	(3)	(4)	(5)
IP	0.004 (0.07)	-0.138*** (-6.43)	-0.127*** (-5.79)	-0.127*** (-5.70)	-0.300*** (-4.56)
IP×SOE			0.183*** (3.08)	0.205*** (3.39)	0.881*** (5.42)
<i>N</i>	7,258	18,790	26,048	26,048	26,048
Year	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes
Bank	Yes	Yes	Yes	Yes	Yes
Bank characteristics	Yes	Yes	Yes	Yes	Yes
MP × SOE			Yes	Yes	Yes

Note: t-statistics are in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01.

V. Conclusions and Policy Implications

Banks' heterogeneous responses to industrial policy relating to bank characteristics and sector characteristics are outcomes of the underlying trade-off between losses from going against political pressure and profits from market-oriented behavior. Each bank chooses the best allocation for its credit resources based on its individual situation. Meanwhile, interventions from local authorities could also direct financial resources to deviate from what is encouraged by the central government.

Using industry-level and bank-sector-level loan data sets and based on quantified policy shocks, I tested whether Chinese commercial banks respond to industrial policy and reallocate their credit accordingly among sectors. There is no conclusive evidence that Chinese state-owned commercial banks, in general, allocate their resources to sectors promoted by industrial policy, or the so-called "structural" monetary policy in recent years. The banks' sensitivities to industrial policy vary based on their type of government ownership and balance sheet status. Banks that are allowed more discretion by the central government and that have more constraints from private investors — listed for trading — implying fewer losses from going against policy but higher losses from ignoring the market, do not respond much to industrial policy. By contrast, banks that have a higher level of public ownership or are more vulnerable — have lower asset quality and smaller sizes — with a potential possibility to ask for assistance from the central government, which implies higher losses from deviation, respond more positively to industrial policy to prove their loyalty.

There is an underlying political logic for this mismatch between central government policy and banks' behavior. First, the central government's policies are often high-level refined and lack details, so it is unclear how institutions should implement them. The interpretations of local governments or financial institutions may be totally on the wrong track, although their initial purpose may be to follow what the policy documents suggest. A severer problem is the excessive discretion of administrative departments and other related institutions due to this lack of clarification in the policy documents. Different institutions with different interest groups have divergent utility functions, which do not necessarily align with the central government's targets. As one PBoC official said, "selective law enforcement" is prevalent. For many commercial banks, the final allocation of financial resources results from a bargain among the local government, central government, SOEs, bank managers, and other potential interest groups. Thus, the banks cannot solely act as a financing tool for industrial policy.

Banks' trade-off between policy and market power can also explain the banks' bias toward SOE-dominated sectors when there is an industrial policy announcement.

"In real practice, there are some misunderstandings and biases. For example, some bankers believe that providing credit to SOEs is safe while offering credit to private enterprises is politically risky, so they would rather do nothing than make political mistakes."

LIU He, former Vice Premier of the People's Republic of China

SOEs are both politically and economically safer. Politically, there are frequent movements among managers of SOEs, managers of government-owned commercial banks, and central government officials. They are almost always the same group of people, and providing support to SOEs in some cases equals providing support to the central government. Commercial banks may not lend to the promoted sectors, but they lend more to SOEs, to balance out the political risks. Economically, SOEs may have lower margins for banks, but SOEs have inherent underlying guarantees from the local or central government, which would bail out all potential defaults in the future. No bank will say no to holding an asset that has a much lower default rate compared with its non-SOE counterparties. They run after it. Indeed, private firms are active players in the Chinese economy, but they are also highly risky. After the Global Financial Crisis as well as the Covid pandemic, many banks suffered from higher NPL rates, mainly due to their previous loans to private firms. Commercial banks must perform portfolio management and risk assessment. When there is pressure from industrial policy to lend to sectors that are less profitable and riskier, the solution to balance political pressure and profitability is to lend more to SOEs. Therefore, we see strong crowding-out effects from SOE sectors to other sectors in credit allocation.

What policy suggestions can be drawn from this study? One extreme suggestion would be leaving what belongs to the market to the market and leaving what belongs to the government to the government. That is, only pure policy banks should be used as a tool for industrial policy, and government-owned commercial banks should be true commercial banks. However, it seems to be too early to achieve this at the current stage of financial development in China. Especially for credit to small and medium-sized enterprises and the least developed areas, such as rural areas, pure commercial banks will neglect these credit demands while pure policy banks do not have enough resources. Thus, policy guidance and enforcement on local financial institutions in these areas will still be essential as pure policy banks cannot fulfill all the needs. A central government that wishes to promote its industrial policy and push forward structural change should offer better incentives and implement stronger supervision. Then government-owned banks' utility functions will not deviate too much from the central government's objectives and the banks will allocate financial resources to where the industrial policy aims.

Another suggestion is to deepen SOE reforms and make SOEs' funding costs priced based on its true risks. SOEs in China have unique and crucial roles in supporting economic development and achieving long-term social benefits. Nevertheless, this study shows that industrial policy has furthered banks' credit bias more toward SOEs than private firms, distorting financial resource allocation. If the central government wants to avoid or reduce this distortion, it should push further well-coordinated SOE reforms with focus on sound corporate governance or implement sunset clauses for SOEs that achieved their objectives. To make the funding costs of SOEs reflecting its true market risks, it would be helpful to limit connections among governments, SOEs, and government-owned banks and reduce implicit guarantees from the government to SOEs. Only in this case would commercial banks be motivated to adjust their portfolios and reallocate their resources to more efficient and profitable firms.

There are some limitations of this study. As discussed earlier, the sample size is limited by data availability especially for rural and city banks because many of them do not report publicly. A wider coverage of small banks might provide more insights into policy effects. Another limitation of this study is that the sectors discussed in my analysis are 19 broad sectors of basic economic activity without more detailed subsector, company-level, or transaction-level data. Some financial resource reallocation following industrial policy happens at the subsector level, especially within the manufacturing sector, while other reallocations happen across different types of firms from several sectors. For example, according to the official data, at the end of 2023, credits to inclusive SMEs increased by 23.5%, credits to technology-driven SMEs increased by 21.9%, credits to high-tech enterprises increased by 15.3%, and credits for green transition increased by 36.5% compared with one year ago. Some of these policy effects may not be identified due to the data limitation in this study. Last but not least, this study only used data from the supply side (data from banks). In the future, it would be worthwhile to use data from the demand side (data from firms) to check whether the conclusions still hold.

References

- Badar Nadeem Ashraf, 2016, "Political Institutions, Political Pressure And State-Owned Banks Lending And Performance: Evidence From Developing Countries."
- Abhijit V Banerjee and Esther Duflo, 2014, "Do Firms Want To Borrow More? Testing Credit Constraints Using a Directed Lending Program," *Review of Economic Studies* Volume 81, No. 2, pp. 572–607.
- Ata Can Bertay, Asli Demirgüç-Kunt, and Harry Huizinga, 2015, "Bank ownership and credit over the business cycle: Is lending by state banks less procyclical?" *Elsevier*, Volume 50.
- Timothy Besley. 1994. "How do market failures justify interventions in rural credit markets?" *The World Bank Research Observer*, Volume 9, No.1, pp. 27–47.
- Genevieve Boyreau-Debray and Shang-Jin Wei. 2005. "Pitfalls of a state-dominated financial system: The case of China," Technical report, *National Bureau of Economic Research*.
- Hongyi Chen, Kenneth Chow, and Peter Tillmann. 2017. "The effectiveness of monetary policy in China: Evidence from a qual var." *China Economic Review* 43:216–231.
- Reda Cherif, Fuad Hasanov, Nikola Spatafora, Rahul Giri, Dimitre Milkov, Saad N Quayyum, Gonzalo Salinas, and Andrew M Warner, 2022, "Industrial policy for growth and diversification: A conceptual framework," *IMF Departmental Papers*, 2022/017.
- Lin William Cong, Haoyu Gao, Jacopo Ponticelli, and Xiaoguang Yang, 2019, "Credit allocation under economic stimulus: Evidence from China," *The Review of Financial Studies* Volume 32, No.9, pp. 3,412–3,460.
- Marcia Millon Cornett, Lin Guo, Shahriar Khaksari, and Hassan Tehranian, 2010, "The impact of state ownership on performance differences in privately-owned versus state-owned banks: An international comparison," *Journal of Financial Intermediation*, Volume 19, No. 1, pp.74–94.
- Chiara Criscuolo, Ralf Martin, Henry G Overman, and John Van Reenen. 2019. "Some causal effects of an industrial policy," *American Economic Review*, Volume 109, No.1, pp. 48–85.
- I Serdar Dinç, 2005, "Politicians and banks: Political influences on government-owned banks in emerging markets," *Journal of Financial Economics*, Volume 77 No.2, pp. 453–479.
- Yizhe Dong, Chao Meng, Michael Firth, and Wenxuan Hou, 2014, "Ownership structure and risk-taking: Comparative evidence from private and state-controlled banks in China," *International Review of Financial Analysis* Volume 36, pp. 120–130.
- Yizhe Dong, Michael Firth, Wenxuan Hou, and Weiwei Yang, 2016, "Evaluating the performance of Chinese commercial banks: A comparative analysis of different types of banks," *European Journal of Operational Research* Volume 252, No.1, pp. 280–295.
- Michael Firth, Chen Lin, and Sonia ML Wong, 2008, "Leverage and investment under a state-owned bank lending environment: Evidence from China," *Journal of Corporate Finance* Volume 14, No. 5, pp. 642–653.
- Zuzana Fungáčová, Risto Herrala, and Laurent Weill, 2013, "The influence of bank ownership on credit supply: Evidence from the recent financial crisis," *Emerging Markets Review*, Volume 15, pp. 136–147.

- Haoyu Gao, Hong Ru, Robert Townsend, and Xiaoguang Yang, 2019, "Rise of bank competition: Evidence from banking deregulation in China," Technical report, *National Bureau of Economic Research*.
- Chun-Yu Ho, Dan Li, Suhua Tian, and Xiaodong Zhu, 2017, "Policy distortion in credit market: Evidence from a fiscal stimulus program," Mimeo.
- Karla Ho and Joseph E. Stiglitz, 1990, "Introduction: Imperfect information and rural credit markets-puzzles and policy perspectives," *The World Bank Economic Review* Volume 4, No.3, pp. 235–250.
- Gabriel Jiménez, Steven Ongena, José-Luis Peydró, and Jesús Saurina, 2012, "Credit supply and monetary policy: Identifying the bank balance-sheet channel with loan applications," *American Economic Review* Volume 102, No. 5, pp. 2,301–26.
- Rafael La Porta, Florencio Lopez-de Silanes, and Andrei Shleifer, 2002, "Government ownership of banks," *The Journal of Finance* Volume 57, No.1, pp. 265–301.
- Nathan Lane, 2022, "Manufacturing revolutions-industrial policy and industrialization in South Korea," *Monash University Paper*.
- Ernest Liu, 2019, "Industrial policies in production networks," *The Quarterly Journal of Economics*, Volume 134, No.4, pp. 1,883–1,948.
- Alejandro Micco and Ugo Panizza, 2006, "Bank ownership and lending behavior," *Economics Letters* Volume 93, No. 2, pp. 248–254.
- Dubravko Mihaljek, 2010, "Domestic bank intermediation in emerging market economies during the crisis: locally owned versus foreign-owned banks," *BIS papers*, Volume 54, pp. 31–48.
- Howard Pack and Kamal Saggi, 2004, "The case for industrial policy: a critical survey," *The World Bank*
- Dani Rodrik, 2006, "Industrial policy for the twenty-first century."
2008. "Normalizing industrial policy."
- Paola Sapienza. 2004. "The effects of government ownership on bank lending". *Journal of Financial Economics* Volume 72, No. 2, pp. 357–384.
- Heather Smith, 1995, "Industry policy in East Asia," *Asian-Pacific Economic Literature* Volume 9 No.1, pp. 17–39.
- Joseph E Stiglitz and Marilou Uy, 1996, "Financial markets, public policy, and the east Asian miracle," *The World Bank Research Observer* Volume 11, No. 2, pp.249–276.
- Oliver Vins, 2008, "How politics influence state-owned banks: the case of German savings banks," Technical report, *Working Paper Series: Finance & Accounting*.
- Shang-Jin Wei and Tao Wang. 1997. "The Siamese twins: Do state-owned banks favor state-owned enterprises in China?" *China Economic Review* Volume 8, No.1, pp. 19–29.
- Shujie Yao, Zhongwei Han, and Genfu Feng, 2008, "Ownership reform, foreign competition and efficiency of Chinese commercial banks: A non-parametric approach," *World Economy*, Volume 31, No. 10, pp. 1,310–1,326.
- Godfrey Yeung, 2009, "How banks in China make lending decisions," *Journal of Contemporary China*, 18(59): pp. 285–302.

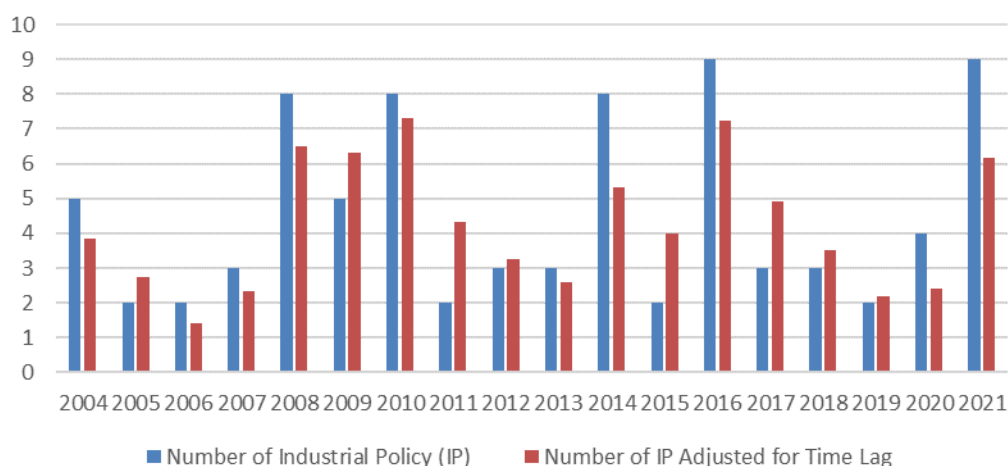
Eduardo Levy Yeyati, Alejandro Micco, Ugo Panizza, Enrica Detragiache, and Andrea Repetto, 2007, “A reappraisal of state-owned banks [with comments],” *Economía*, Volume 7, No. 2, pp. 209–259.

Huaquan Zhao, 2012, “A quantitative analysis and evaluation of the status of public ownership as the mainstay (in Chinese).” *Contemporary Economic Research* (in Chinese), pp. 3.

Appendix

A. Industrial Policy over Time

Figure A.1. Number of Industrial Policy over Time



B. Correlation Matrix

Table A.1. Correlation Matrix

	log(loan)	IP	IP_Oth	MP	Value-added	security_invest	NPL	ROA	log(asset)	listed	Liquidity ratio
log(loan)	1.00										
IP	0.029	1.00									
IP_Oth	-0.027	-0.071	1.00								
MP	0.051	0.047	-0.035	1.00							
Value-added	0.356	0.249	-0.091	0.005	1.00						
security_invest	0.097	0.032	-0.020	0.361	-0.006	1.00					
NPL	0.005	0.029	-0.007	0.086	0.004	-0.018	1.00				
ROA	-0.077	0.024	0.039	0.147	0.000	-0.227	0.263	1.00			
log(asset)	0.734	0.016	-0.047	0.140	0.049	0.293	0.037	0.145	1.00		

listed	0.511	- 0.010	-0.029	0.062	0.037	0.117	- 0.046	- 0.043	0.668	1.00	
Liquidity ratio	-0.203	0.049	0.043	- 0.306	-0.010	-0.597	- 0.141	0.334	-0.348	- 0.235	1.00

Note: the correlation between $\log(\text{loan})$ and $\log(\text{asset})$ is higher than 0.7, but the VIF of $\log(\text{asset})$ is between 1 to 3, so there is no issue of multicollinearity to include this variable in my regressions.

C. Robustness Test Results

Table A.2. Robustness Test Results: Excluding Real Estate Sector (All Commercial Banks)

Model	Dependent variable: Log(loan)		
	(1)	(2)	(3)
IP	0.149 (1.64)	0.073 (1.12)	0.006 (0.06)
IP×SOE			1.468*** (2.89)
Value-added		22.66*** (4.47)	
cons	9.333*** (275.69)	8.169*** (30.58)	9.278*** (213.35)
N	198	198	198
Year	Yes	Yes	Yes
Sector	Yes	Yes	Yes
MP×SOE			Yes

Note: t-statistics are in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A.3. Robustness Test Results: Excluding Real Estate Sector (Bank-Level Sample)

Model	Dependent variable: Log(loan)				
	(1)	(2)	(3)	(4)	(5)
IP	-0.169*** (-6.31)	-0.182*** (-5.46)	1.135*** (3.71)	-0.059** (-2.33)	-0.121*** (-4.87)
IP × rb	0.438*** (10.27)				
IP × b5	-0.092 (-0.99)				
IP × je	-0.156*** (-2.74)				
rb	-0.157*** (-7.72)				
B5	0.944*** (18.43)				
je	0.273*** (8.51)				
IP×NPL		0.060*** (3.53)			
IP×Log(asset)			-0.0473***		

			(-4.03)		
IP×Listed				-0.133*** (-3.14)	
IP×SOE					0.171*** (2.84)
Security_invest	-1.602*** (-21.89)	-0.804*** (-7.84)	-0.787*** (-7.70)	-0.804*** (-7.88)	-0.803*** (-7.86)
NPL	0.028*** (6.64)	0.005 (0.89)	0.0156*** (3.48)	0.0153*** (3.39)	0.0155*** (3.45)
ROA	0.0224 (1.53)	-0.00125 (-0.08)	-0.00458 (-0.28)	-0.00250 (-0.16)	-0.000752 (-0.05)
Log(asset)	0.832*** (113.94)	0.544*** (19.28)	0.566*** (19.71)	0.552*** (19.43)	0.544*** (19.28)
Listed	0.178*** (9.26)	0.102*** (3.95)	0.0941*** (3.65)	0.0938*** (3.09)	0.101*** (3.93)
Liquidity ratio	-0.0554 (-0.53)	0.000671 (0.01)	-0.0289 (-0.23)	-0.00515 (-0.04)	0.00584 (0.05)
cons	-18.47*** (-98.93)	-11.15*** (-15.38)	-11.97*** (-16.00)	-11.37*** (-15.61)	-11.17*** (-15.42)
N	24,398	24,398	24,398	24,398	24,398
Year	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes
Bank		Yes	Yes	Yes	Yes
MP × Bank	Yes	Yes	Yes	Yes	
characteristics					
MP×SOE					Yes

Note: t-statistics are in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01. rb: rural commercial banks, b5: "big-five" banks, je: joint equity banks.

Table A.4. Robustness Test Results: Adding Time-varying Sectoral Control

Model	Dependent variable: Log(loan)				
	(1)	(2)	(3)	(4)	(5)
IP	-0.213*** (-8.91)	-0.202*** (-6.55)	0.987*** (3.53)	-0.094*** (-4.07)	-0.136*** (-6.14)
IP × rb	0.483*** (11.87)				
IP × b5	0.020 (0.26)				
IP × je	-0.140*** (-2.70)				
rb	-0.166*** (-8.44)				
b5	0.818*** (17.75)				
je	0.247*** (8.29)				
IP×NPL		0.056*** (3.52)			
IP×Log(asset)			-0.042*** (-3.98)		
IP×Listed				-0.082** (-2.09)	
IP×SOE					0.141** (2.38)

Security_invest	-1.586*** (-22.37)	-0.845*** (-8.56)	-0.830*** (-8.44)	-0.846*** (-8.60)	-0.845*** (-8.59)
NPL	0.0291*** (7.30)	0.007 (1.55)	0.017*** (4.01)	0.017*** (3.93)	0.0167*** (3.98)
ROA	0.0191 (1.38)	-0.001 (-0.04)	-0.004 (-0.27)	-0.002 (-0.13)	-0.000557 (-0.04)
Log(asset)	0.855*** (121.39)	0.571*** (20.90)	0.591*** (21.26)	0.577*** (21.01)	0.571*** (20.90)
Listed	0.149*** (8.13)	0.084*** (3.41)	0.077*** (3.14)	0.069** (2.42)	0.0833*** (3.41)
Liquidity_ratio	-0.0656 (-0.65)	-0.045 (-0.37)	-0.075 (-0.63)	-0.051 (-0.43)	-0.0412 (-0.34)
Value-added	6.274*** (9.26)	6.166*** (9.21)	5.908*** (8.85)	6.062*** (9.10)	5.910*** (8.88)
cons	-19.31*** (-104.45)	-12.09*** (-17.18)	-12.80*** (-17.66)	-12.26*** (-17.34)	-12.08*** (-17.19)
<i>N</i>	26,048	26,048	26,048	26,048	26,048
Year	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes
Bank		Yes	Yes	Yes	Yes
MP × Bank	Yes	Yes	Yes	Yes	
characteristics					
MP × SOE					Yes

Note: t-statistics are in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01. rb: rural commercial banks, b5: "big-five" banks, je: joint equity banks.



PUBLICATIONS

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