5-12-2024

THREE ESSAYS ON THE POLICY PROCESS OF SUBNATIONAL INDUSTRIAL POLICYMAKING IN CHINA

Shiyang Xiao
Syracuse University

Abstract

This dissertation consists of four chapters that focus on the policy process of provincial industrial policymaking targeting the manufacturing sector in China. In the first chapter, I introduce an original dataset called the "Chinese Industrial Policy Attention Dataset" (CIPAD). CIPAD contains 612 central-level and 1907 provincial-level Chinese industrial policies issued between 2001 and 2019. A novel design of CIPAD is that the full text of each industrial policy is transformed into a distribution-of-attention vector which records the attention allocation of each policy among 155 finely segmented industrial categories in the manufacturing sector. By transforming industrial policies into distribution-of-attention vectors, CIPAD allows researchers to quickly identify the industry categories that receive the most attention from governments and to quickly compare similarities between different industrial policies.

In Chapter 2, I examine the phenomenon of industrial policy convergence among 30 provincial governments in China. Policy convergence is common both within and across countries. However, the concept has not received as much attention as some related concepts such as policy diffusion and policy learning. In this chapter, I study policy convergence from the perspective of policy similarity networks which provide a rigorous and straightforward way to measure, visualize, and study the phenomenon. By analyzing industrial policy data from CIPAD, I find a dramatic convergence of industrial policies in 30 provinces in mainland China between 2015 and 2019. Applying the additive and multiplicative effects network models (AMEN models), I find that provincial governments tend to adopt very similar industrial policies when 1) they have similar local industrial structures or 2) they are both highly susceptible to central industrial policies. Moreover, I find strong evidence that the dramatic industrial policy convergence across Chinese provinces is mainly caused by the overall increasing susceptibility of provincial governments to

central industrial policies issued by the State Council (i.e., the chief administrative authority of China) after 2015.

In Chapter 3, I go one step further and discuss why Chinese provincial governments are becoming increasingly susceptible to central industrial policy. Here, I argue that top-down inspection as a central political control instrument reduces provincial governments' preference for using discretion in industrial policymaking. As a result, provincial governments become more likely to simply follow what the central government has done, thus showing increasing susceptibility to central industrial policies. I test this claim by examining the effect of central disciplinary inspections on provincial industrial policymaking in China. Using data from CIPAD, I find that provincial governments significantly decrease their preference for using discretion in industrial policymaking during inspection-active periods. This is evidenced by a reduced willingness of provincial governments to target those industrial categories that were not previously targeted by central industrial policy. Moreover, I find that central disciplinary inspections have a stronger impact on uninspected provinces that observe their peers being inspected than on provinces that are themselves being inspected. Additional analysis suggests that central disciplinary inspections, by dampening bureaucrats' preference for discretion in policymaking, lead to increasing policy homogeneity across provinces in China.

In Chapter 4, I examine the underlying motives of provincial governments to selectively support certain industry categories in the manufacturing sector after controlling for the impact of central industrial policies. I develop several hypotheses based on two conflicting assumptions about government behavior. The first assumption is that the government behaves as a benevolent and omniscient policymaker and selectively supports industry categories to address market failures. The second assumption is that the government behaves as a self-interested agent who is driven by two main motives: 1) to obtain private benefits by engaging in rent-seeking activities with special interest groups and 2) to pursue job promotion or re-election in government. Based on data from CIPAD, I find that provincial leaders in China who are driven by the motive of job promotion adopt an "output-oriented strategy" which supports industry categories that have already created large value-added output either within the jurisdiction or in other jurisdictions. I also find that provincial governments have some ability to identify and support industry categories that have revealed comparative advantage locally. Moreover, there is evidence that after 2008 Chinese provincial governments have begun to support industry categories that are dominated by high-income countries. This shows the intention of Chinese provincial governments to cultivate their competence in industry categories with imperfect competition and high rents.

THREE ESSAYS ON THE POLICY PROCESS OF SUBNATIONAL INDUSTRIAL POLICYMAKING IN CHINA

by

Shiyang Xiao

M.A., Tsinghua University, 2017

B.A., Peking University, 2015

DISSERTATION

Submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy in Social Science.

Syracuse University

June 2024

Acknowledgements

I would like to take this opportunity to express my sincere gratitude to my mentors, family members, and friends, without whom this dissertation would not be possible.

At the forefront of my gratitude is my advisor, Yilin Hou. I cannot thank him enough for the extraordinary amount of time and effort he has spent and invested in me. He shares with me his own experience of pursuing a Ph.D. and encourages me to keep going when I face difficulties during my Ph.D. journey. He teaches me what good research is and always shows his confidence in my potential to do good research. Indeed, Yilin has been a professional and personal role model for me all these years.

I would also like to express my sincere gratitude to Mary Lovely, whose enthusiasm, passion, and kindness are inspiring. I still remember all the days I spent with her to discuss my research project. Mary offered me her insights and suggestions to help me take the research to a higher level. She also generously supported me financially by spending her own research funds to hire me as an RA. Her guidance and support means a lot to me.

My sincere thanks also go to Alfonso Flores-Lagunes, Saba Siddiki, and Junyan Jiang who spent their precious time and effort to read my research and provide me with constructive comments and feedback. I would like to thank Xufeng Zhu, who introduced me to the academic world and helped me complete and publish my first research paper in public administration. My appreciation extends to Yingyi Ma, who provided me with summer RA funding and with whom I had the privilege of publishing a joint paper. I would also like to thank Hugo Jales, Renée de Nevers, Tammy Salisbury, Xueyi Chen, Can Chen, Hongtao Yi, Fan Zhang, Jin Xie for their help throughout my Ph.D. journey.

Many thanks to Dongmei Zuo, Poonam Argade, Yao Wang, Wenzhen Lin, Ziqiao Chen, and all my dear friends with whom I share my joys and pains. I cannot express how grateful I am to have met all these sweet people in my life.

Finally, I would like to express my sincere gratitude to my parents. Their unconditional love and support for me is the reason why I have the chance to get a Ph.D. today. Thank you and I love you!

Table of Contents

List of Figures

List of Tables

Chapter 1: Construction of Chinese Industrial Policy Attention Dataset (CIPAD)

1. Background and Motivation of the Study

Choosing industrial policy-making in China as the focus of my dissertation is driven by a profound interest in generic theory building about the role of government in national development, particularly through the lens of dynamic interactions between central and subnational governments. Previous literature on "developmental states" emphasizes the critical role of government in planning and boosting national economic development. However, such literature often treats central and subnational governments as one single actor without discussing their different or even contradictory roles in national development. In real-world situations, however, subnational governments may have both de jure and de facto power to stipulate their own developmental policies, which may or may not follow the baseline policies proposed by the central government. My dissertation attempts to address this gap by examining the industrial policymaking process of subnational governments and how it is impacted by the central government in the context of China.

China's remarkable journey from a poor country to the world's second-largest economy and the complex central-local relations inside its multilevel governmental system makes the country a great example to study. In 1952, China's GDP was only 30.55 billion dollars (current price, National Bureau of Statistics). In 2022, this number became 17.89 trillion dollars (current price), which is over 500 times that of 1952. During the same period, the relationship between Chinese central and subnational governments experienced multiple large changes which greatly influenced economic development in China.

The first phase is between 1949 and 1978, during which the Chinese central-local relationship was characterized by highly centralized political control and a planned economy.

Subnational governments had little autonomy and were largely dependent on central allocations for resources and directives.

The second phase is between 1979 and 1993, during which Chinese de facto top leader Deng Xiaoping initiated reform and opening-up policies, which shifted the country from a centrally planned economy to a more market-oriented one. During this period, local governments were granted greater autonomy to experiment with economic policies and attract foreign investment. This was particularly evident in Special Economic Zones (SEZs) like Shenzhen.

The third phase is between 1994 and 2012, during which China had relatively balanced central-local relations. On the one hand, the Chinese central government implemented a tax reform in 1994 which re-centralized significant revenue streams, such as the value-added tax, to the central government, reducing fiscal autonomy of subnational governments. On the other hand, Chinese subnational governments still possessed a lot of decision-making freedom in attracting investment and boosting regional economic development. The entry into the WTO during this period enhanced the integration of Chinese firms with the world market, which further stimulated China’s rapid economic growth.

The fourth phase is from 2013 until now, during which China has witnessed a significant shift towards greater centralization and consolidation of power. The Chinese central government strengthen its control over subnational governments through large-scale anti-corruption campaigns and various kinds of oversight. At the same time, central directives have outweighed local initiatives in their role of directing social and economic development. Some major national policies, such as the poverty alleviation campaigns, mixed-ownership reforms, and the Belt and Road initiatives, are widely believed to have created a great impact on Chinese national development.

In my dissertation, I try to explore the dynamic interactions between the central and subnational governments and their role in national development through the lens of industrial policy-making in China. Industrial policies are one of the most common tools for governments to influence the economy. Industrial policies are also highly controversial in terms of whether or not governments have the capacity as well as the motives to stipulate the right industrial policies that enhance social welfare. Industrial policies have become a hot topic worldwide, particularly after the fierce trade war between China and the United States. Nowadays, not only China but also countries all over the world have increasingly resorted to industrial policies to boost the economy. This trend further increases the necessity of deepening our understanding of industrial policy-making and its potential impact on national development. My dissertation is an initial attempt to address this research gap.

2. Dataset Introduction

The "Chinese Industrial Policy Attention Dataset" (CIPAD) is an original dataset that contains 612 central-level and 1907 provincial-level Chinese industrial policies from 2001 to 2019 along with their allocation of attention across 155 finely segmented manufacturing industry categories.

A novel design of the CIPAD is that by using computational text analysis techniques, the full text of each industrial policy is transformed into a distribution-of-attention vector. A distribution-of-attention vector can be written as $(x_1, x_2, \ldots, x_{155})$, with $x_i \in [0,1]$ and $\sum_1^{155} x_i = 1$. Each vector describes the attention allocation of an industrial policy to the 155 industry categories in the manufacturing sector and xi equals the proportion of attention paid to the *i*th industry category. The 155 industry categories are based on the three-digit codes in the Chinese Industrial Classification for National Economic Activities (GB/T 4754-2002). To the best of our knowledge, this dataset stands out as one of the first to identify industry categories as granular as three-digit levels in the full texts of industrial policies.

By transforming each policy full text into a distribution-of-attention vector, the CIPAD allows researchers to accomplish the following tasks: 1) Quickly identify the most frequently mentioned industry categories in each policy; 2) compare the similarities of targeted industry categories between policies; 3) track changes in government's attention to different industry categories over time; 4) compare similarities of policy attention between different governments. In the following sections, I will explain in detail how I constructed the dataset, and I will demonstrate with examples how CIPAD helps researchers to achieve the above tasks.

3. Criteria for Selecting the Industrial Policies Included in the Dataset

The first challenge to construct CIPAD is to decide what kinds of industrial policies are included in the dataset. Table 1 below shows the detailed criteria based on which industrial policies were selected to be added to CIPAD. I collected all the industrial policies from pkulaw.com, a comprehensive database for searching laws, regulations, and policies issued by Chinese central and subnational governments since 1949. I first found all the policies that contain keywords "industry (chanye & gongye)," "firm (qiye)," or "manufacturing (zhizaoye)" in their title or content that were issued by provincial governments (and their offices) or by the five central agencies between 2001 and 2019. Then I manually checked the title and the content of each policy and finally selected 612 central-level and 1907 provincial-level Chinese industrial policies to be included in the dataset.

Table 1: Criteria for Selecting Industrial Policies

No.	Criteria
1	An industrial policy should target particular industry categories in the manufacturing sector.

2	An industrial policy should express a clear intention to intervene in the production of particular industry categories by altering the output, productivity, product quality, or level of innovation of the previous industry categories.
3	The main content of an industrial policy should be related to industry intervention and development rather than other topics such as environmental protection, food safety, etc.
4	An industrial policy should be issued between 2001 and 2019.
5	An industrial policy is either issued by 30 provincial governments or their offices (except Tibet due to low level of industrialization) in mainland China or by at least one of the following five Chinese central agencies: a) State Council b) Ministry of Finance c) Ministry of Science & Technology d) Ministry of Industry & Information e) National Development & Reform Commission

4. Transform Policy Full Texts into Distribution-of-Attention Vectors

After collecting all the industrial policies based on the previous criteria, I then transformed each policy full text into a distribution-of-attention vector. As mentioned before, a distribution-of-attention vector records the allocation of attention of each industrial policy across 155 finely-segmented industry categories in the manufacturing sector based on the three-digit codes in the Chinese Industrial Classification for National Economic Activities (GB/T 4754-2002). For example, if a distribution-of-attention vector is written as (0.5 0.5 0 … 0), then it means the industrial policy corresponding to the vector allocates 50% of its attention to the first industry category and another 50% to the second while the remaining 153 industry categories receive zero attention from the industrial policy. It generally took four steps to transform a policy full text into a distribution-of-attention vector. The four steps and their related natural language processing (NLP) techniques are shown in *t*able 2.

Table 2: Steps of Transforming Policy Full Texts into Vectors

Steps	Main Computational Text Analysis Methods
Step One: Identify Manufacturing Phrases	Named Entity Recognition Technique, Conditional Random Fields (CRF), Supervised Learning
Step Two: Categorize Manufacturing Phrases into Industry Categories	Inverted Index, Levenshtein distance, Word Embedding, Cosine Similarity
Step Three: Calculate Amount of Attention	Word/Phrase Frequency Analysis
Step Four: Create Distribution-of-Attention Vector	N.A.

4.1 Step One: Identify Manufacturing Phrases

In step one, I need to first identify all the manufacturing phrases in industrial policies. There is a typical task in natural language processing called “Named Entity Recognition” (NER) which is exactly what I need to do in this step. Named Entity Recognition (NER) aims to recognize mentions of real-world objects belonging to predefined semantic types—such as person, location, organization, product—from unstructured text. In this research, the goal of NER is to identify from the policy full texts the manufacturing phrases which denote industry categories and products in the manufacturing sector.

I applied a widely used supervised machine learning model—conditional random field (CRF)—to accomplish the NER task. CRF is an algorithm specifically designed for dealing with sequential data. In the task of identifying manufacturing phrases in policy texts, it is important to take into account the context of (i.e., information appears before and after) the potential phrases.

CRF is best suited to such prediction tasks where contextual information or the state of the neighbors affect the current prediction.

Since CRF is a supervised machine learning technique, users need to first create a hand-labeled dataset to train the CRF model so it can later be used to predict unlabeled data. Therefore, I randomly selected 34,513 sentences for human coding. These sentences constitute 8.5% of all the sentences that appeared in the central-level and provincial-level ITUPs. I invited 5 research assistants to manually identify and label all the keywords/phrases which denote manufacturing industry categories and products in these sentences. After that, I divided the pre-labeled sentences into two parts: 80% of them in the training set and 20% of them in the test set. I later trained the CRF model by using the labeled sentences in the training set and then I tested the performance of the CRF model by comparing machine-labeled sentences with the human-labeled sentences in the test set. To evaluate the performance of the CRF model, there are two important metrics:

Recall Rate: number of manufacturing phrases correctly identified by the CRF model divided by the total number of manufacturing phrases identified by human beings.

Precision Rate: number of manufacturing phrases correctly identified by the CRF model divided by the total number of manufacturing phrases identified by the CRF model.

I calculated the recall rate and precision rate of the model. The precision rate is 0.855 and the recall rate is 0.803. This means that the CRF model has a satisfactory performance in identifying manufacturing phrases in unstructured policy texts.

Table 3: Precision Rate and Recall Rate

Metrics	Value
Precision Rate:	0.855
Recall Rate:	0.803

4.2 Step Two: Categorize Manufacturing Phrases into Industry Categories

After identifying all the manufacturing phrases in policy texts, now it's time to classify these phrases into one or more of the 155 industry categories based on the 3-digit codes in the Chinese Industrial Classification for National Economic Activities (GB/T 4754-2002).

A challenge here is that it is difficult and time-consuming for human beings to match manufacturing phrases with different industry categories. For example, ordinary people usually do not know that "molybdenum" belongs to the industry category "rare metals" (three-digit code: 333) and that "calcium carbide" to "basic chemical raw material manufacturing" (three-digit code: 261). As a result, it would be highly costly to create a hand-labeled training set from scratch for supervised machine learning.

To address this challenge, I chose not to use a supervised learning technique. Instead, I leveraged several "natural training sets" that provide information about the connection between manufacturing phrases and industry categories. In Table 4, I present these "natural training sets" in detail. I used these natural training sets to create a manufacturing-phrase dictionary that contains both manufacturing phrases and their corresponding industry categories.

Table 4: Natural Training Sets

Name	**Issue Year**	**Issue Agency**
Chinese Industrial Classification for National Economic Activities (GB/T 4754-2002)	2002	General Administration of Quality Supervision, Inspection and Quarantine; Chinese Standardization Administration;
Chinese Industrial Classification for National Economic Activities (GB/T 4754-2017)	2017	General Administration of Quality Supervision, Inspection and Quarantine; Chinese Standardization Administration;
Chinese High-tech Industry Classification	2017	National Bureau of Statistics
Chinese Classification for Strategic Emerging Industries	2018	National Bureau of Statistics

Product Catalog for Strategic Emerging Industries in China	2018	National Bureau of Statistics
Health Industry Classification	2019	National Bureau of Statistics
Energy Saving and Environmental Protection Industry	2021	National Bureau of Statistics
Chinese Industrial Enterprise Dataset	2011	Information provided by firms, data collected by National Bureau of Statistics

After creating a manufacturing-phrase dictionary, I matched the manufacturing phrases that appeared in industrial policies with the manufacturing phrases in the dictionary. The matching process involves two techniques. The first is Levenshtein distance and the second is word embedding. For each manufacturing phrase that appeared in an industrial policy, I matched it with the most similar phrase in the dictionary as long as their similarity exceeds a threshold. In Table 5, I showed the percentage of manufacturing phrases that were finally matched in central/provincial industrial policies by year.

Table 5: Match Rates

Year	Central Industrial Policies	Provincial Industrial Policies
2004	0.894	0.926
2005	0.832	0.904
2006	0.901	0.901
2007	0.920	0.926
2008	0.898	0.914
2009	0.923	0.924
2010	0.864	0.915
2011	0.890	0.920
2012	0.883	0.927
2013	0.907	0.895
2014	0.907	0.924
2015	0.858	0.914
2016	0.865	0.918
2017	0.858	0.908
2018	0.834	0.906
2019	0.839	0.907

4.3 Step Three: Calculate Amount of Attention

After categorizing each manufacturing phrase into one or more industry categories, it is relatively easy to calculate the amount of attention that an industrial policy pays to each of the 155 industry categories. I first calculated the total number of manufacturing phrases written as N matched in the policy. Then, for each industry category i, I calculated the number of matched manufacturing phrases that belong to the industry category written as m_i. Then, the amount of attention that the policy pays to industry category i equals $\frac{m_i}{N}$.

4.4 Step Four: Create Distribution-of-Attention Vectors

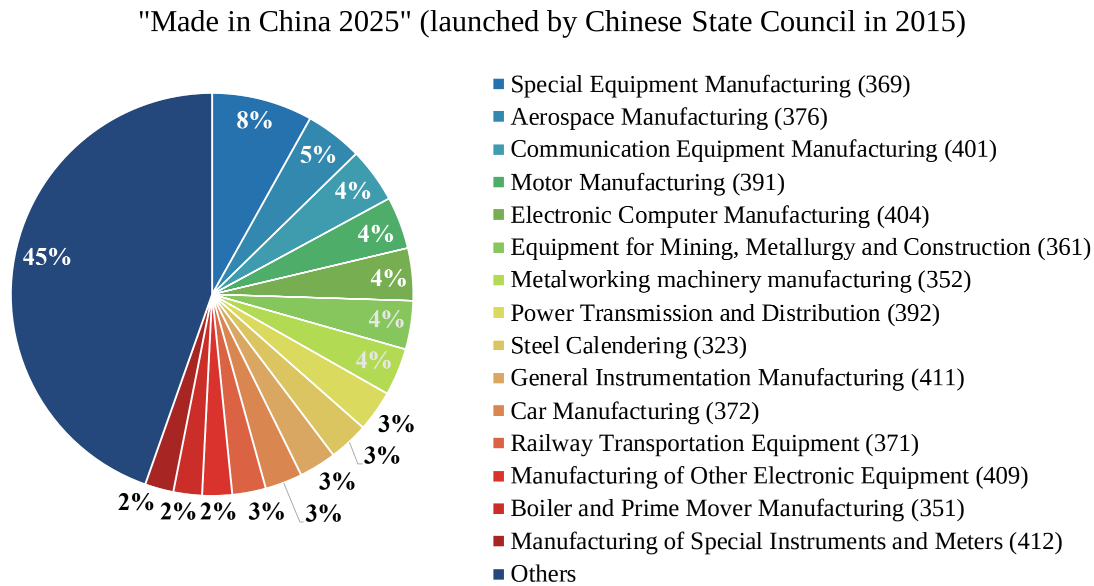
Now that I have calculated the amount of attention that an industrial policy pays to each of the 155 industry categories, it would be quite easy to create the distribution-of-attention vector corresponding to the policy. This can simply be done by creating a 155-dimensional vector and letting the value of the *i*th dimension equal the amount of attention paid to the *i*th industry category.

5. Example Applications of CIPAD

5.1 Quickly Identify the Most Frequently Mentioned Industry Categories in Each Policy

CIPAD transforms the full text of each industrial policy into a distribution-of-attention vector. This allows researchers to fast identify industry categories that receive the most attention from an industrial policy. Take the policy "Made in China 2025" issued by the Chinese State Council in 2015 as an example. Based on CIPAD, I can quickly extract the top-15 industry categories that are most frequently mentioned by "Made in China 2025." According to Figure 1, the industry category that received the most attention is "special equipment manufacturing," which receives eight percent of attention from the policy. The industry categories that rank the second and the third are "aerospace manufacturing" and "communication equipment manufacturing," which obtain five and four percent of the policy's attention, respectively. Industry categories outside the top-15 chart account for 45% of the attention, showing that “Made in China 2025” is a highly comprehensive industrial policy that targets diverse industry categories.

Figure 1: Top-15 Industry Categories in “Made in China 2025”



5.2 Compare the Similarities of Targeted Industry Categories between Industrial Policies

CIPAD also enables researchers to fast compare similarities between industrial policies based on the industry categories they mentioned. By transforming policy full texts into distribution-of-attention vectors, researchers can measure policy similarities by calculating cosine similarity between policies’ corresponding vectors. Cosine similarity ranges from 0 to 1 where 0 indicates no similarity at all and 1 indicates complete similarity. In Table 6, I demonstrate the top-

3 provincial industrial policies that are the most and the least similar to “Made in China 2025” and the cosine similarities between the above provincial industrial policies and “Made in China 2025.”

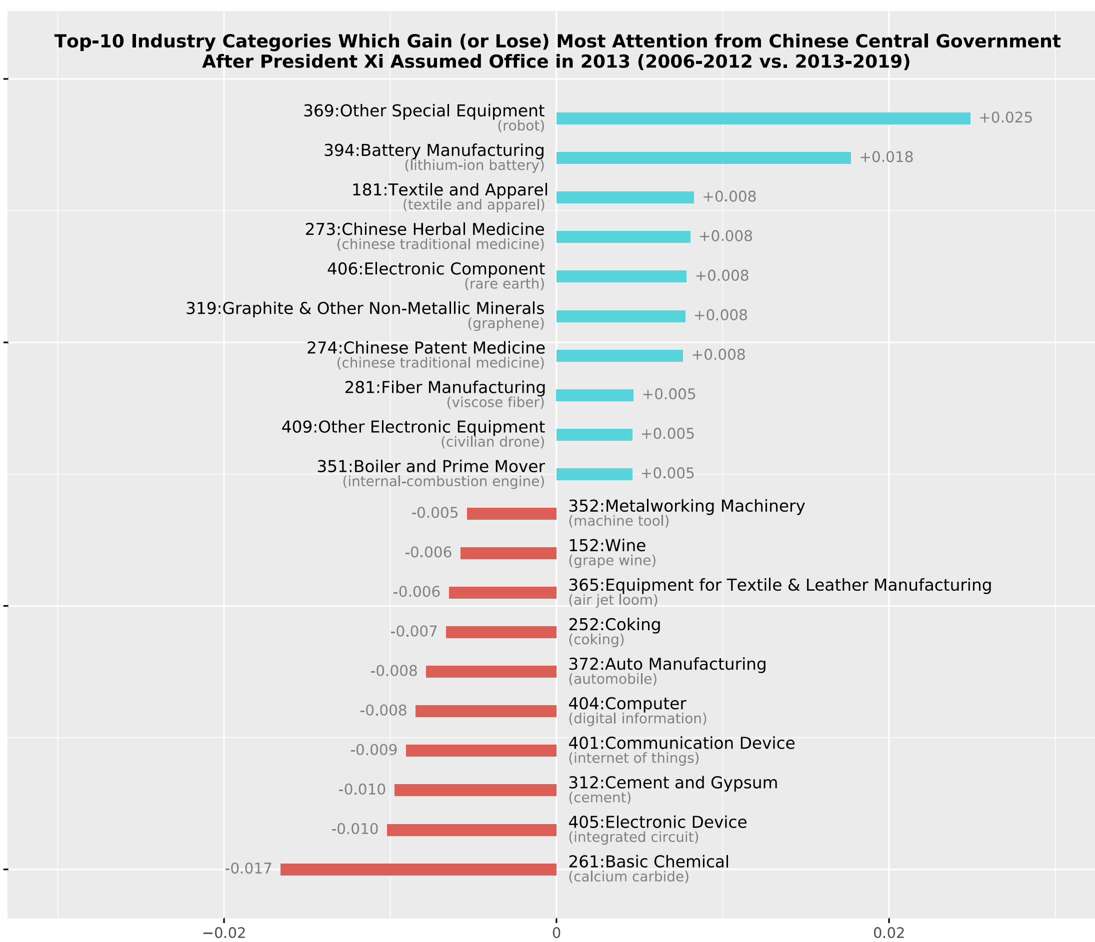
Table 6: Provincial Industrial Policies Most and Least Similar to “Made in China 2025”

Title	Time	Issue Agency	Cosine Simi.
Panel A: Provincial industrial policies that are most similar to “Made in China 2025”			
"Made in China 2025" Five-Year Action Plan	2015.11	Hunan Provincial Government	0.891
Opinions on Further Promoting "Made in China 2025"	2015.11	Henan Provincial Government	0.881
Implementation Plan for Transformation and Upgrading of Equipment Manufacturing Industry	2018.12	Shandong Provincial Government General Office	0.881
Panel B: Provincial industrial policies that are least similar to “Made in China 2025”			
Title	Time	Issue Agency	Cosine Simi.
Implementation Opinions on Promoting Supply-side Structural Reform in the Liquor Industry	2016.9	Guizhou Provincial Government General Office	0.001
Measures to Support The High-quality Development of the Tobacco Industry	2019.10	Yunnan Provincial Government	0.006
Guiding Opinions on Promoting the Inheritance and Development of the Silk Industry	2015.11	Zhejiang Provincial Government General Office	0.020

5.3 Track Changes in Government's Attention to Different Industry Categories over Time

Based on CIPAD, I can not only identify the attention allocation of each industrial policy, but can also calculate the government's attention allocation during a period of time by calculating the average distribution-of-attention vector based on all the policies adopted by the government. Figure 2 shows the top 10 industry categories that gained or lost the most attention from the Chinese central government after 2013 (i.e., 2006-2012 vs. 2013-2019). The gray words in parentheses are high-frequency key phrases corresponding to each industry category. For example, the increasing attention paid to "Other Special Equipment" after 2013 is largely due to Chinese central government's increasing attention to robots.

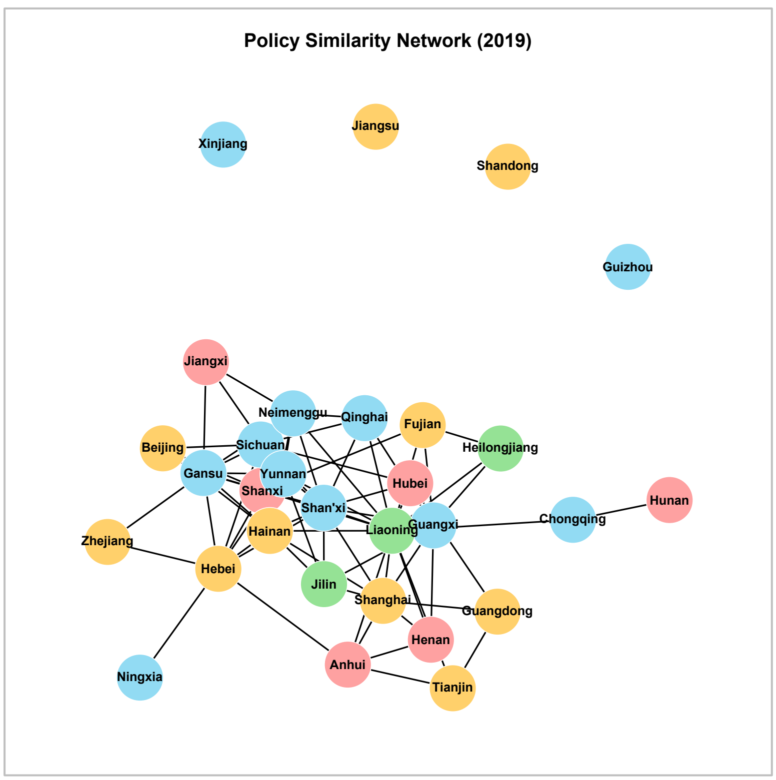
Figure 2: Top-10 Industry Categories which Gain or Lose Most Attention before and after 2013



5.4 Compare Similarities of Policy Attention between Different Governments

By calculating the average distribution-of-attention vector for each government during a period of time, CIPAD enables us to compare similarities of policy attention between different governments. In Figure 3, I draw the policy similarity network in 2019. Each node represents a provincial government. Provincial governments in different regions are highlighted by different colors. Two nodes are connected by a gray line if the two corresponding provincial governments share highly similar distribution-of-attention vectors (cosine similarity>0.8). It is shown by the figure that most provincial governments are densely linked with each other, suggesting high industrial policy similarity across Chinese provincial governments in 2019.

Figure 3: Policy Similarity Network (2019)



Chapter 2: Track Policy Convergence over Time from the Perspective of Policy Similarity Networks

1. Introduction

Policy convergence is an overall increase in the similarity of particular aspects (e.g., policy goals, policy content, policy instruments, policy styles, etc.) in a policy or a set of policies across a given group of jurisdictions over a given period of time (Bennett 1991; Knill 2006; Heichel et al. 2005). From cities' anti-smoking guidelines (Shipan and Volden 2006) to countries' trade regulations (Cao 2012; Drezner 2001), policy convergence is ubiquitous both within a nation and worldwide. Sometimes, even the reforms in a nation's fundamental institutions can be seen as part of the policy convergence process, such as the cross-national acquisition of women's suffrage rights in the twentieth century (Ramirez, Soysal, and Shanahan 1997; Finnemore and Sikkink 1998) and the worldwide economic liberalization movement in the past several decades (Simmons and Elkins 2004). Therefore, it is crucial for scholars to have proper theoretical frameworks to describe and examine the phenomenon of policy convergence.

Although the phenomenon of policy convergence is common, the concept of policy convergence has not received as much attention as some related concepts such as policy diffusion and policy learning. One potential reason could be the lack of rigorous measurement of the concept of policy convergence. For example, although "a given period of time" is a key dimension in the definition of policy convergence, many policy convergence studies do not provide a clear starting and ending point. Another potential reason could be the lack of appropriate statistical models to study the phenomenon. This hinders scholars from quantitatively examining the phenomenon of policy convergence.

In this study, I propose to measure, visualize, and examine the phenomenon of policy convergence from a policy similarity network perspective. For each point of time during a period, I construct a policy similarity network by treating each jurisdiction as a node and connecting two nodes with a line (i.e., edge/link) if the sets of policies that are currently in effect in the corresponding two jurisdictions are highly similar to each other in particular aspects. Then I measure policy convergence by checking whether there is an increase in the density of the policy similarity network from time t1 to time t2. Here, network density is the ratio of the number of actual links to the number of all potential links in a network. If the policy similarity network becomes increasingly denser from time t1 to time t2, then I say there is policy convergence between the two points of time.

There are at least three advantages to discussing the phenomenon of policy convergence from a policy similarity network perspective. First, policy similarity networks provide a straightforward way to visualize the dynamic of policy convergence across a group of jurisdictions over time. Second, the concept of network density helps scholars to rigorously and easily measure policy convergence. Increasing network density from time t1 to time t2 means there have been more pairs of jurisdictions that have highly similar policies between each other than before. This measurement aligns well with the definition of policy convergence. Third, by describing policy convergence from a network perspective, I am able to use various statistical models for network analysis to quantitatively examine the phenomenon of policy convergence. In this study, for example, I use the additive and multiplicative effects network models (AMEN models; Hoff 2015, 2018) to quantitatively analyze the underlying causes of policy convergence over time.

From a policy similarity network perspective, I examine the phenomenon of industrial policy convergence among 30 provincial governments (except for Tibet due to low industrialization) in mainland China between the period of 2005 and 2019. I compare industrial policy similarity between Chinese provinces based on an original dataset called the "Chinese Industrial Policy Attention Dataset" (CIPAD). It contains 612 central-level and 1907 provincial-level industrial policies launched between 2001 and 2019 in China. A novel design of CIPAD is that each industrial policy is transformed into a 155-dimensional distribution-of-attention vector. The distribution-of-attention vector records how an industrial policy allocates attention across 155 finely-segmented industry categories (e.g., automobile, shipbuilding, computer chips, etc.). Then scholars can easily compare similarity between industrial policies by calculating cosine similarity between the corresponding distribution-of-attention vectors. Here I define two provinces as having high industrial policy similarity if the average distribution-of-attention vectors corresponding to the sets of industrial policies in the two provinces have a cosine similarity higher than 0.8.

Then I constructed policy similarity networks for each year between 2005 and 2019 and tracked how network density changes over time. I find there is a surge in network density between 2015 and 2019, which hints at strong industrial policy convergence across Chinese provinces during this period of time. Then, I propose three potential causes underlying such dramatic industrial policy convergence between 2015 and 2019. The three potential causes include 1) convergence of local economic and industrial characteristics, 2) increasing susceptibility of provincial governments to central industrial policies, and 3) increasing susceptibility of provincial governments to policies adopted by "leading" peers. Data analysis shows that both similarity in industrial structure and co-susceptibility to central industrial policies are associated with high policy similarity between provinces. Further analysis shows that the increasing susceptibility of provincial governments to central industrial policies adopted by the State Council is likely to be the main reason for dramatic industrial policy convergence between 2015 and 2019.

This study has several contributions for research and practice. First, this study provides a network perspective to examine the phenomenon of policy convergence. By applying the concept of network density, scholars are able to measure policy convergence easily and rigorously. Second, this study shows how to leverage statistical models in network analysis literature to quantitatively study the causes of policy convergence. Third, this study, to the best of our knowledge, is among the first to discover significant industrial policy convergence across provincial governments between 2015 and 2019 in China. This study is also among the first to provide strong evidence that the main cause of Chinese industrial policy convergence during this period of time is the increasing susceptibility of provincial governments to central industrial policies issued by the Chinese State Council. In addition, this study shows that scholars should not treat the Chinese central government as a whole. Instead, there is much difference in terms of the role of different central agencies during the process of provincial industrial policy convergence in China. Although the increasing impact of the Chinese State Council contributes to fast policy convergence across provinces, there is no evidence that other central ministries, such as the National Development & Reform Commission and the Ministry of Finance, play any role here.

2. Examine Policy Convergence from a Policy Similarity Network Perspective

2.1 Definition of Policy Convergence

Policy convergence is defined as an overall increase in the similarity of some aspects of a certain policy or a type of policies across a given group of jurisdictions over a given period of time (Bennett 1991; Knill 2006). Here, a jurisdiction means a legal body or a government agency that exercises control over a specific geographical area, subject matter, or group of individuals.

The concept of policy convergence is closely related to but different from policy diffusion, which has been heavily discussed in policy process studies. By definition, policy diffusion refers to "one government's policy choices being influenced by the choices of other governments" (Shipan and Volden 2012). Therefore, policy convergence can possibly, but not necessarily, be a result of policy diffusion. However, the two concepts differ from each other in at least three important ways. First, policy diffusion focuses on each government's policy choices, while policy convergence focuses on a group of governments. Second, policy diffusion is concerned with the process during which the policy choice of one government is influenced by others, while policy convergence is concerned with the process through which the policy choices of governments become more similar to one another over time. Third, policy diffusion requires that policymakers are informed about the policy choices of others, while policy convergence can happen even when policymakers have no information about what others are doing.

Policy convergence is a common phenomenon both domestically and worldwide. Domestically, Schneider (2012) studies the convergence and divergence of punishment policy in terms of the use of incarceration across American states from 1890 through 2008. The author finds that the punishment policies among states cannot be described as a sustained convergence toward a common level of incarceration. Instead, there have been cycles, with some periods of convergence followed by periods of divergence. In another study, Kilwein and Brisbin (1997) examine the degree of doctrinal convergence between relatively autonomous state supreme courts. They find that the political context of state court decisions as well as the role of the U.S. Supreme Court all contribute to doctrinal convergence across state supreme courts. In terms of cross-national policy convergence, Drezner (2001) discusses how globalization leads to a convergence of environmental regulations and the regulation of labor worldwide. Similarly, Cao (2012) examines how global networks, including those based on trade, capital flows, and intergovernmental organizations, play a significant role in shaping economic policy convergence across nations. Mukand and Rodrik (2005) discuss the large-scale convergence of economic liberalization policies across nations in the 1980s and 1990s. They argue that national leaders may strategically adopt economic liberalization policies to signal that there is no corruption, even if such policies may not fit domestic circumstances.

Despite the prevalence of policy convergence, it has not received enough attention from scholars compared to other related concepts such as policy diffusion. One possible reason is that the approaches to conceptualize policy convergence are highly diverse, and the measurement of the concept often lacks clear and rigorous standards. This would likely hinder comparability across policy convergence studies (Heichel, Pape, and Sommerer 2005). Knill (2006) summarizes four types of policy convergence. The first type is called σ-convergence, which describes a decrease in variation of policies among a group of jurisdictions. The second type is called β-convergence, which describes the phenomenon when regions that lagged behind in the past catch up with leading jurisdictions over time. The third type is called γ-convergence, which describes how the rankings of different regions change over time. The fourth type is δ-convergence, which describes similarity changes by comparing policies of each region with an exemplary model. Another issue in the measurement of policy convergence is how to choose a clear time frame. As has been pointed out by Heichel, Pape, and Sommerer (2005), in genuine convergence studies, researchers should first measure the initial degree of similarity at a starting time point t1, and then compare it to a second measurement at time point t2. However, in many policy convergence studies, this procedure is not followed, or is conducted in an ambiguous way by giving a rough time period. Without clear and rigorous ways to define and measure the concept of policy convergence, studies in this area will be difficult to compare, and knowledge will be difficult to accumulate.

Another challenge of policy convergence studies is the lack of proper statistical models to quantitatively analyze the phenomenon of policy convergence. Most studies on policy convergence use case studies as the main approach (David M. Ostergren 1999; Gibson and Means 2001; Strunz et al. 2018), and very few studies use time-series data to describe and quantitatively examine the causes of policy convergence. This can be a critical research gap in policy convergence studies, since time-series data provides a good way to track how policy convergence gradually happens over time, and researchers can take advantage of the time variation in such data structure to explore the underlying causes of policy convergence.

In the next section, I propose a simple and straightforward way to measure policy convergence from a policy similarity network perspective. I will explain how to construct policy similarity networks, and how to rigorously describe policy convergence by tracking changes in the density of policy similarity networks over time. Moreover, I will explain how to analyze the causes of policy convergence by using the additive and multiplicative effects network model (AMEN model) proposed by Hoff (2015, 2018).

2.2 Policy Similarity Network, Network Density, and Policy Convergence

I this section, I explain how to conceptualize and measure policy convergence from a policy similarity network perspective. Recall that the definition of policy convergence is “an increase in the similarity between some key aspects (e.g., policy goals, policy content, policy instruments, policy styles, etc.) of a certain policy or a set of policies across a given group of jurisdictions over a given period of time.”

For each time point, I construct a policy similarity network by considering each jurisdiction as a node and connecting two nodes with a line (i.e., edge/link) if the policies that are currently in effect in the corresponding two jurisdictions are highly similar to each other in some key aspects in which I am interested. Then I define policy convergence as an increase in the density of the policy similarity network from time t_1 to time t_2. Here, network density is the ratio of the number of actual links to the number of all the potential links in a network.

The above conceptualization of policy convergence is simple and straightforward. By constructing a policy similarity network for each time point, I am able to observe the whole picture of policy similarity across jurisdictions. An increase in the density of the policy similarity network over time means that there have been more pairs of jurisdictions with highly similar policies than before. This measure aligns well with the aforementioned definition of policy convergence. In essence, a policy similarity network can be represented by an adjacency matrix. An adjacency matrix, as is shown by table 7, is a matrix with rows and columns labeled by nodes in the network, with E_{ijt} equal to 1 or 0 in position (n_i, n_j) according to whether node n_i and node n_j are connected in the network at time point *t* or not. It is worth noting that the adjacency matrix of each policy similarity network is a symmetric matrix, since the values in position (n_i, n_j) and in position (n_i, n_j) will always be the same.

Table 7: An Adjacency Matrix for Policy Similarity Network at Time t

	Jurisdiction 1	Jurisdiction 2	Jurisdiction 3	…	Jurisdiction N
Jurisdiction 1	NA	E_{12t}	E_{13t}	…	E_{iNt}
Jurisdiction 2	E_{21t}	NA	E_{23t}	…	E_{2Nt}
Jurisdiction 3	E_{31t}	E_{32t}	NA	…	E_{3Nt}
…	…	…	…	NA	…
Jurisdiction N	E_{N1t}	E_{N2t}	E_{N3t}	…	NA

Note: The above adjacency matrix satisfies the following conditions: 1) $E_{iit} = NA$. 2) $E_{ijt} = E_{jit}$. 3) $E_{ijt} \in \{0,1\}$ if $i \neq j$.

Based on the adjacency matrix, the density of the policy similarity network can be calculated as shown below, where N denotes the total number of jurisdictions in the network, and E_{ijt} equals either zero or one in position (n_i, n_j).

$$Network\ Density_t = \frac{\sum_{i \in N} \sum_{j(\neq i) \in N} E_{ijt}}{N(N-1)}$$

I define policy convergence as an increase in network density between two time points. In other words, policy convergence exists between time point t_1 and time point t_2 if:

$$Network\ Density_{t_2} > Network\ Density_{t_1}.$$

2.3 Choose Proper Statistical Models to Analyze the Phenomenon of Policy Convergence

Now that I have defined policy convergence from a policy similarity network perspective, I need to choose the proper network analysis models to examine the underlying mechanisms of policy convergence. Here, I propose using the additive and multiplicative effects network models (AMEN models; Hoff 2015, 2018) to achieve this goal. I will introduce what AMEN models are and compare them with exponential random graph models (ERGMs), another type of commonly used statistical model for network analysis. I will explain why I finally choose to use AMEN models instead of ERGMs in this study.

AMEN models provide a statistical modeling framework for dyadic data. A dyad refers to a pair of objects (i.e. nodes), and a quantity based on dyads is called a dyadic variable, such as friendship between two people, trade between two countries, etc. The measurements of a dyadic variable on a population of n nodes can be described by an $n \times n$ matrix, and the value of y_{ij} denotes the relationship from node *i* to node *j* (Hoff 2018). Dyadic data often have strong statistical dependencies. One type of statistical dependency comes from within-dyad correlation, that is, the correlation between y_{ij} and y_{ji}. A second type of statistical dependency is the correlation between observations in the same row or the column of the matrix. For instance, the correlation between y_{ij} and y_{ik}, or that between y_{ij} and y_{kj}. A third type of statistical dependency is the correlation between observations whose column is the row of the other, just as the relationship between y_{ij} and y_{jk}. Moreover, there are potentially third-order dependence patterns where the relationship between two nodes are determined by their relationships with a third node or a third object. Some typical third-order dependence patterns include transitivity, balance and clustering. For example, transitivity describes the phenomenon that if two nodes are both connected to a third node, then the two nodes themselves are likely to be connected as well.

AMEN models incorporate the above statistical dependencies by combining insights from both additive random effects models and multiplicative random effects models. A standard AMEN model can be written as below:

$$y_{i,j} = \beta_d^T x_{d,i,j} + \beta_r^T x_{r,i} + \beta_c^T x_{c,j} + a_i + b_j + {u_i}^T v_j + \epsilon_{i,j} \qquad (1)$$

$$(a_1, b_1), \dots, (a_n, b_n) \sim i.i.d.\, N_2(0, \begin{pmatrix} \sigma_a^2 & \sigma_{ab} \\ \sigma_{ab} & \sigma_b^2 \end{pmatrix}),$$

$$(\boldsymbol{u}_1, \boldsymbol{v}_1), \dots, (\boldsymbol{u}_n, \boldsymbol{v}_n) \sim i.i.d.\, N_{2r}(0, \boldsymbol{\psi}), \text{ with } \boldsymbol{\Psi}_{uv} = cov[\boldsymbol{u}_i, \boldsymbol{v}_i]$$

$$\{(\epsilon_{i,j}, \epsilon_{j,i}) : i < j\} \sim i.i.d.\, N_2(0, \sigma^2 \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix})$$

Here $x_{d,i,j}$ is a vector of characteristics of dyad {i , j}, $x_{r,i}$ is a vector of characteristics of node i as a sender which appears in each row of the matrix, and $x_{c,j}$ is a vector of characteristics of node j as a receiver which appears in each column of the matrix. Also notice that a_i and b_j are random effects corresponding to the sender i and the receiver j. The inclusion of a_i and b_j in the model represents within-column, within-row, and column-row correlation. Moreover, AMEN models contain a multiplicative effects term ${u_i}^T v_j$, in which u_i is a r-dimensional vector of latent, unobserved characteristics of node i, and v_j is a r-dimensional vector of latent, unobserved characteristics of node j. The product of u_i and v_j shows how similar u_i and v_j are as well as the magnitudes of the two vectors. By including a multiplicative effects term ${u_i}^T v_j$, the AMEN model takes third-order dependence patterns into consideration.

If I want to analyze changes in policy similarity network over time by using AMEN models, there are three things I need to pay attention to. First, in a policy similarity network, the dyadic outcome variable $y_{i,j}$ is a binary variable which equals one if the policies in region i and in region j are highly similarity to each other. However, the standard AMEN model is designed for continuous variable, so I need to adjust the previous model in a way that fits the binary outcome variable. Second, the adjacency matrix corresponding to each policy similarity network is symmetric, which means that $y_{i,j} = y_{j,i}$, so that I need include this information in the model as well. Third, to analyze changes in policy similarity network, I need to deal with repeated measurements of dyadic variables in multiple time points. By taking the aforementioned concerns into consideration, I adjust the AMEN model as below:

$$z_{i,j,t} = y_{i,j,t-1} + \beta_d^T x_{d,i,j,t} + \beta_n^T \left(x_{n,i,t} + x_{n,j,t}\right) + a_i + a_j + {u_i}^T \wedge u_j + \epsilon_{i,j,t} \qquad (2)$$

$$y_{i,j,t} = 1(z_{i,j,t} > 0)$$

$$a_1, \dots, a_n \sim i.i.d.\, N(0, \sigma_a^2)$$

$$\left\{\epsilon_{i,j,t}\right\} \sim i.i.d.\, N(0, \sigma_e^2)$$

Notice that I include the lagged value $y_{i,j,t-1}$ in the model to reflect the potential temporal dependence. The model also sets the restriction that the coefficient before $x_{n,i,t}$ and that before $x_{n,j,t}$ are the same, so that $y_{i,j,t}$ would equal $y_{j,i,t}$. Based on model (2), I will be able to analyze the following two research questions: first, what factors cause policy similarity across jurisdictions? Second, among the above factors, which of them contribute to overall increase in policy similarity (i.e. policy convergence) across jurisdictions over time? The first question could be analyzed by examining the magnitude and significance of the coefficients β_d and β_n, while the second question could be analyzed by comparing the time trends of network density before and after I control for the impact of the dyadic and nodal characteristics.

Besides AMEN models, another type of commonly used model for network analysis in social science research is exponential random graph models (ERGMs). A key assumption behind ERGMs is that a network "is generated by a stochastic process in which relational ties come into being in ways that may be shaped by the presence or absence of other ties" (Robins et al. 2007, page 177). Therefore, ERGMs help identify certain structural characteristics (e.g., reciprocated ties) and their related local social processes that contribute to the formation of the observed network. However, ERGMs may not be the best statistical model for this study due to the following reasons: First, a policy similarity network is not like a social network. In the policy similarity network, when two jurisdictions are linked together, it simply means they currently have highly similar policies, and this does not necessarily involve real-world social interactions between the two jurisdictions. Therefore, some typical hypotheses about how local social processes cause network formation in ERGMs are not likely to hold in the policy similarity network. Second, ERGMs focus on the detailed structural characteristics of an observed network. However, to examine the phenomenon of policy convergence, it is the overall network density rather than the detailed structures of the network that are of interest. Due to the above reasons, I finally choose to use AMEN models to examine the phenomenon of policy convergence in this study.

3. Industrial Policy Convergence across Provincial Governments in China

I examine the phenomenon of policy convergence in the context of provincial industrial policy-making in China from 2001 to 2019. Specifically, I focus on industrial policies in the manufacturing sector adopted by 30 provincial governments in mainland China (except for Tibet due to the lack of industrialization). I track how industrial policies converge across the 30 provincial governments over time by examining and visualizing the evolution of the corresponding policy similarity networks during that period. Then I examine the causes of industrial policy convergence across Chinese provincial governments by applying the AMEN model.

In this study, I use an original dataset called the "Chinese Industrial Policy Attention Dataset" (CIPAD). It contains 612 central-level and 1907 provincial-level industrial policies launched between 2001 and 2019 in China. Here I define industrial policies as the policies that intervene in specific industry categories in the manufacturing sector, with an explicit goal to either alter the share of output of these industry categories or increase their productivity and product quality. The central-level industrial policies are issued either by the State Council or by the following four central ministries: the National Development & Reform Commission (NDRC), the Ministry of Industry & Information Technology (MIIT), the Ministry of Finance (MF), and the Ministry of Science and Technology (MST). The State Council and the aforementioned central ministries are widely believed to play an essential role in Chinese industrial policy-making. Provincial-level industrial policies are issued by 30 provincial-level governments in mainland China. Tibet is not included in the sample due to its low degree of industrialization.

A novel design of CIPAD is that the dataset transforms each industrial policy into a distribution-of-attention vector with 155 dimensions. Each vector dimension records the proportion of attention an industrial policy pays to one of the 155 finely segmented industry categories in the manufacturing sector, and the sum of all the dimensions in a vector is one. Industry categories are classified based on the 3-digit codes in the Chinese Industrial Classification for National Economic Activities (GB/T 4754-2002).

CIPAD measures the distribution of policy attention by calculating the frequency of manufacturing key phrases belonging to each industry category in the full text of an industrial policy (Grimmer and Stewart 2013; Hollibaugh 2018). This generally involves three steps. For each policy, I first identified all the manufacturing key phrases in its full text. Manufacturing key phrases are defined as the phrases which denote certain manufacturing categories or products, such as “new energy vehicles,” “men’s running shoes,” “integrated circuit,” etc. Then, I classified each manufacturing key phrase into one (or more than one) of the 155 industry categories. Finally, I generated a distribution-of-attention vector by counting the frequency of the manufacturing key phrases classified into each industry category. The above steps look simple but can be very difficult to execute. I utilized a series of computational text analysis methods, such as named-entity recognition and word embedding, to complete the whole task. To the best of my knowledge, I am among the first to propose an automatic way of measuring how industrial policies distribute attention to finely segmented industry categories.

An advantage of transforming industrial policies into distribution-of-attention vectors is that I can measure the similarity between different industrial policies by comparing their corresponding vectors. Here, I uses cosine similarity to measure the similarity between two vectors. For example, given two 155-dimensional vectors *A* and *B*, cosine similarity between *A* and *B* is calculated as below:

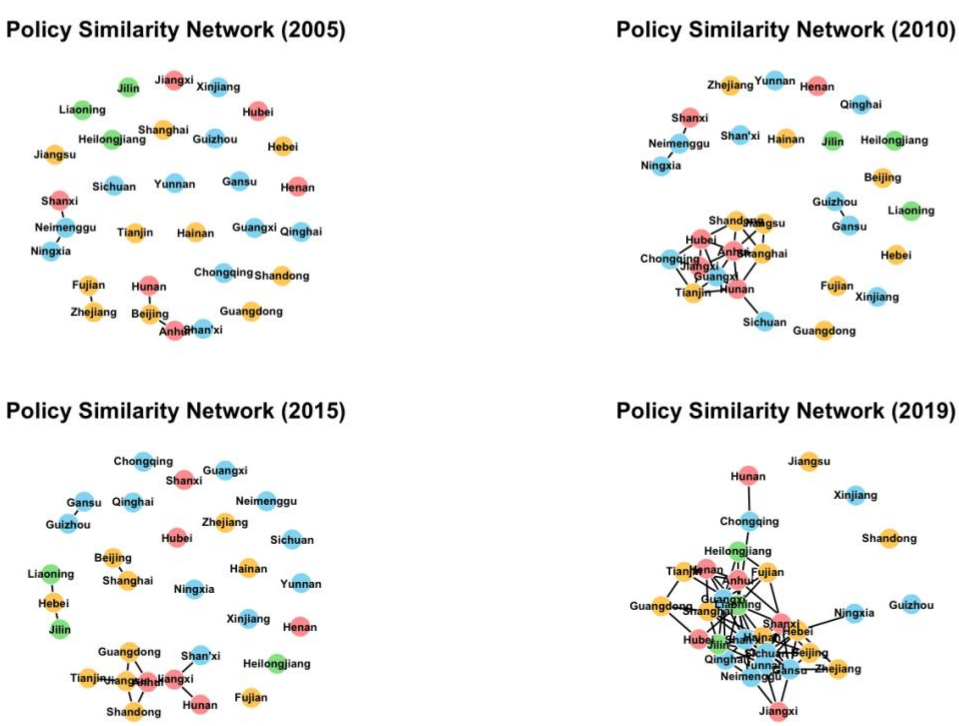
$$cosine\ similarity = \frac{A \cdot B}{\|A\|\|B\|} = \frac{\sum_{i=1}^{155} A_i B_i}{\sqrt{\sum_{i=1}^{155} A_i^2}\sqrt{\sum_{i=1}^{155} B_i^2}}$$

Not only can I measure similarity between a pair of industrial policies, but I can also measure overall policy similarity between different governments (e.g., horizontally between different provincial governments or vertically between central and provincial governments) at time point t. For each government, I first identify all the industrial policies that are currently in effect within the jurisdiction at time point t. Then I calculate an average distribution-of-attention vector for all these industrial policies. After that, I calculate policy similarity between two governments by calculating the cosine similarity between their corresponding average distribution-of-attention vectors.

I construct provincial industrial policy similarity networks for each year between 2005-2019 by considering each provincial government as a node and connecting two nodes with a line (i.e., edge/link) if there is high similarity between the sets of policies that are currently in effect in the two provinces. Two provinces are defined as having highly similar industrial policies if the cosine similarity of their average distribution-of-attention vectors is higher than 0.8. Another issue is how to identify policies that are currently "in effect." Sometimes, an industrial policy clarifies a clear time period during which the policy will be in effect. However, in some other cases, policies may fail to clarify in the full text how long the policies will be valid. Therefore, in this research, I assume that a policy stays in effect within five years after its issuance. For example, if an industrial policy is issued in 2001, then I assume the policy would stay in effect until 2005. That is why policy similarity networks start from the year 2005 since the earliest industrial policy I have in the dataset is issued in 2001.

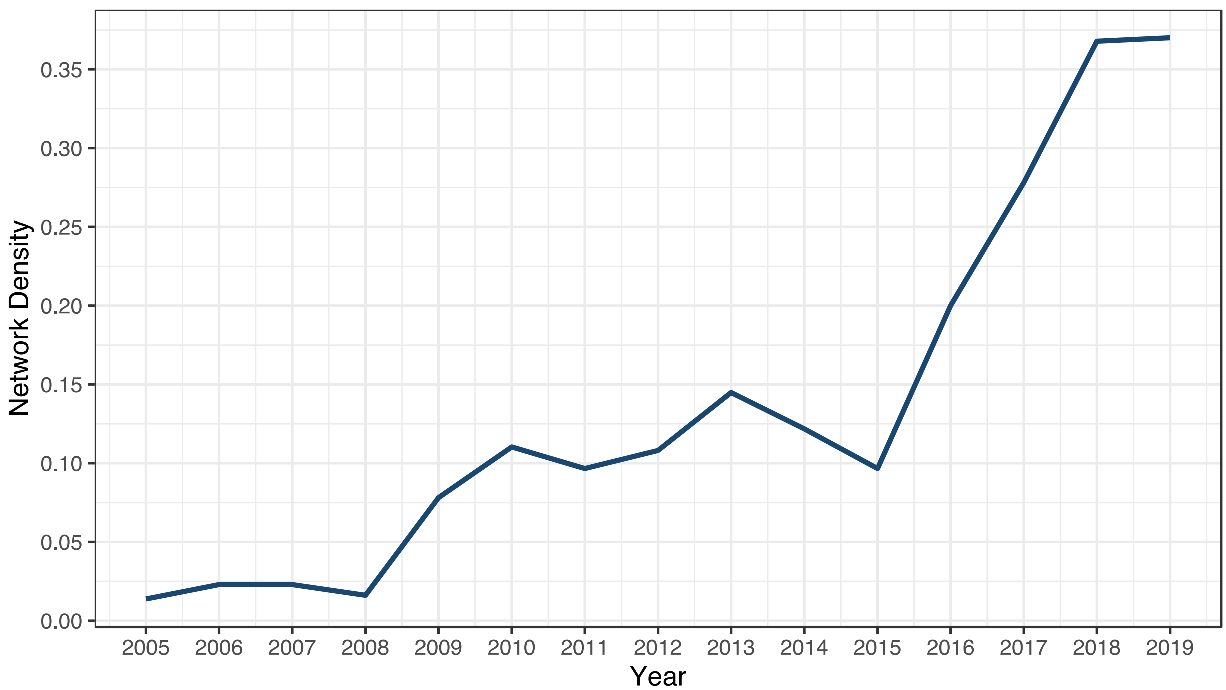
Figure 4 demonstrates the policy similarity networks in the years 2005, 2010, 2015, and 2019, respectively. Each node represents one of the 30 provinces in mainland China (except for Tibet), and different colors highlight provinces in different regions (red for middle, blue for west, yellow for east, and green for northeast). A grey line connects two nodes if the cosine similarity between the corresponding two provinces is higher than 0.8. If I compare the policy similarity network in 2015 with that in 2019, I can find an evident change between the two years. Compared with the network in 2015, the network in 2019 becomes much denser in the sense that a lot more pairs of provinces are linked together than before. This provides evidence that industrial policies converged across Chinese provincial governments from 2015 to 2019.

Figure 4: Policy Similarity Network in 2005, 2010, 2015, and 2019



To better track industrial policy convergence among provincial governments in China, I calculate the density of the policy similarity network in each year, and I use a line graph to show how network density changes over time. The result is shown in Figure 5. As the figure shows, from 2005 to 2019, the density of the policy similarity network kept increasing in most years, and the greatest increase started in 2015. This result shows a clear trend of policy convergence in terms of industrial policymaking among the 30 Chinese provinces between 2005 and 2019.

Figure 5: Time Trend of Network Density over Time



4. Theoretical Hypotheses: What Causes Provincial Industrial Policy Convergence in China?

Previous literature has discussed a number of factors that could potentially cause policy convergence over time (Knill 2006). Among all the discussions, the analytical framework proposed by Holzinger and Knill (2005) has received much attention. Holzinger and Knill (2005), by focusing on cross-national policy convergence, argue that there are at least five main causes of policy convergence, including independent problem-solving, imposition, harmonization, communication, and competition.

First, policy convergence can happen due to independent problem-solving, during which policymakers in different jurisdictions independently respond to parallel problem pressures and reach similar policies. This process does not necessarily involve information exchange between jurisdictions. Instead, policy convergence in this case can be seen as a natural result of the convergence of "circumstances" faced by policymakers, as long as policymakers are all rational enough to choose the policies that best fit the specific circumstances. Strunz et al. (2018), for example, argue that the convergence of environmental policies across jurisdictions can possibly be driven by economic convergence. This is due to a close connection between environmental pollution and economic development described by the so-called Environmental Kuznets Curve (Grossman and Krueger 1995). The Environmental Kuznets Curve suggests an inverse U-shaped relationship between a region's level of economic development (often measured by gross domestic product) and the level of pollution. One potential reason behind this phenomenon is that pollution first increases due to the process of industrialization but later decreases when the demand for higher environmental quality increases with citizens' rising income levels. Therefore, if there is a convergence of economic development across regions, it is likely that the environmental policies in these regions will also converge as a response to similar demands for environmental quality among the public.

Second, policy convergence may happen due to a process of imposition. In cross-national context, imposition means "countries or international organizations force other countries to adopt certain policies by exploiting asymmetries in political or economic power." (Knill 2006, page 770) For jurisdictions within a nation, I can define imposition as "government agencies or organizations forcing other subnational governments to adopt certain policies by exploiting asymmetries in political or economic power." When policy convergence is due to imposition, policy convergence can be seen as a result of policy diffusion caused by coercion. Shipan and Volden (2008) propose that coercion can be an important mechanism of policy diffusion. In the international setting, some countries may coerce other countries to adopt specific trade policies through threat of economic sanctions, or through international organizations such as World Trade Organization or the United Nations. When it comes to domestic policy diffusion, central government may leverage its political and economic power to coerce subnational governments to adopt certain policies, and one example is the U.S. government using highway funds to incentivize states to adopt lower speed limits and higher drinking age.

Third, policy convergence can happen through the mechanism of harmonization. Unlike imposition, harmonization describes a process when interdependent jurisdictions try to resolve common problems through cooperation. This process often involves international institutions in an international setting. Unlike imposition, harmonization does not rely on asymmetric power. Instead, it is often based on "sets of implicit or explicit principles, norms, rules, and decision-making procedures around which actors' expectations converge in a given area of international relations." (Kasner, 1983, page 2) An important assumption behind harmonization is the existence of interdependencies or externalities between different jurisdictions which push these jurisdictions to take action in an coordinated way. Drezner (2005), for example, discusses the convergence of anti-money laundering policies across nations through harmonization. The author argues that fast and effective policy harmonization happens when the great powers, in this case the US and the European Union, reach a consensus and decide to act in concert.

Fourth, policy convergence can be also due to competition between jurisdictions. This is especially the case when it comes to regulatory policies. In an integrated economy in which goods, workers, and capital can flow between jurisdictions, jurisdictions face pressure to design domestic regulatory policies in a way that exerts as little regulatory burdens on industries and firms as possible. This will likely lead to a "race to the bottom" situation, in which regulatory policies across jurisdictions converge towards lower regulatory standards, such as lower environmental protection standards, etc. Despite of the above discussion, it is worth noting that competition does not necessarily lead to policy convergence. By contrast, competition in some other cases may lead to policy diversity across jurisdictions. For example, when it comes to industrial policy making, it is possible that a region deliberately target an industry category that is different from those targeted by other regions to avoid fierce competition across regions. This example shows that policy types and conditions in which the policies are made may greatly influence the relationship between competition and policy convergence, and researchers need to examine the above relationship based on specific circumstances.

The fifth potential cause of policy convergence is communication across jurisdictions. Holzinger and Knill (2005) summarize four detailed mechanisms of policy convergence through communication. The first is lesson-drawing. Lesson-drawing describes a process when governments learn from the experience in other regions and adopt similar policies domestically. The second is transnational problem-solving, which refers to joint effort across nations to develop policies in response to similar domestic problems through transnational elite networks or policymaking communities. The third is emulation of policies. Holzinger and Knill (2005) define emulation as "mere desire for conformity with other countries rather than the search for effective solutions to given problems." (page 784) The fourth mechanism of policy convergence through communication is international policy promotion. Such mechanism describes the phenomenon when a government adopts a policy because that policy is promoted as “best practice” internationally by international institutions.

Holzinger and Knill’s framework provides a good basis for us to discuss the causes of industrial policy convergence in China. However, a potential shortcoming of the aforementioned framework is that it only explains why jurisdictions adopt similar policies but fail to explain why they don’t do so in the past. Time is an important factor in the definition of policy convergence. Policy convergence describes a process during which the overall level of policy similarity across jurisdictions increases, rather than a snapshot in which jurisdictions are currently having similar policies. For example, a researcher may argue that a number of subnational governments adopt similar policies due to top-down coercion from the central government. However, this does not necessarily lead to policy convergence, since the policies adopted by these subnational governments in the past may also be highly similar to each other due to the same coercive influence from the central government. Then there is no change in overall policy similarity across subnational governments before and after.

Based on the above discussion, here I argue that to analyze the causes of policy convergence, I need to answer the following two questions: first, what factors cause policy similarity between jurisdictions? Second, why does the overall policy similarity across all jurisdictions increase over time?

I propose three potential causes for the convergence of industrial policies across Chinese provincial governments between 2005 and 2019.

First, the convergence of Chinese provincial industrial policies could be due to the convergence of economic and industrial characteristics across provinces. For example, if the level of economic development and industrial structure becomes increasingly similar across Chinese provinces over time, it is likely that the provincial governments would also adopt increasingly similar industrial policies as a response.

H1a: Two provincial governments tend to adopt similar industrial policies if their jurisdictions have similar economic and industrial characteristics.

H1b: The economic and industrial characteristics of Chinese provinces converge over time.

H1c: The convergence of economic and industrial characteristics across provinces causes provincial industrial policy convergence in China.

Second, the convergence of Chinese provincial industrial policies could be due to a process of imposition led by Chinese central government. Chinese central government has superior power over provincial governments, both politically and economically. Therefore, if the Chinese central government increasingly leverages such asymmetric power to impose its own preferences on provincial governments, the latter will become more likely to adopt industrial policies that follow what have already been suggested by the central government. As a result, provincial industrial policies will naturally converge towards the existed central industrial policies.

H2a: Two provincial governments tend to adopt similar industrial policies if both of them are susceptible to central industrial policies.

H2b: Chinese provincial governments become increasingly susceptible to central industrial policies over time.

H2c: The increasing susceptibility of provincial governments to central industrial policies causes provincial industrial policy convergence in China.

The third driver of policy convergence that I would like to discuss here is the existence of "leading" jurisdictions whose policies are likely to be imitated by other jurisdictions. If the influence of such "leading" jurisdictions increases over time, it is possible that the overall policy similarity across all the jurisdictions will also increase accordingly, since more jurisdictions will choose to imitate what have been done by the "leader" jurisdictions.

H3a: Two provincial governments tend to adopt similar industrial policies if both of them are susceptible to the industrial policies adopted by "leading" provinces.

H3b: Chinese provincial governments become increasingly susceptible to the industrial policies adopted by "leading" provinces.

H3c: The increasing susceptibility of provincial governments to the industrial policies adopted by "leading" provinces causes provincial industrial policy convergence in China.

5. Data and Methods

In this section, I will discuss how to examine the underlying causes of industrial policy convergence in China. As mentioned before, to analyze the causes of policy convergence, I need to answer the following two questions: first, what factors cause policy similarity between jurisdictions? Second, why does the overall policy similarity across all jurisdictions increase over time?

5.1 Measure Policy Similarity between Provinces

I use a dummy variable $\boldsymbol{PolicySimi_{ijt}}$ to measure whether or not the industrial policies that are currently in effect in province i and in province j are highly similar at time t. $\boldsymbol{PolicySimi_{ijt}}$ is a dyadic variable. . $\boldsymbol{PolicySimi_{ijt}}$ equals 1 if there is high policy similarity between the two provinces, and 0 otherwise. It measures the relationship between each pair of the

30 provinces in mainland China. Therefore, in each year, I will have 30*29=870 observations of this variable. Also notice that $\boldsymbol{PolicySimi_{ijt}} = \boldsymbol{PolicySimi_{jit}}$. I need to incorporate this information in our statistical model.

5.2 Measure Similarity of Economic and Industrial Characteristics between Provinces

To test hypothesis H1a, H1b, and H1c, I need to measure the similarity of economic and industrial characteristics between provinces. Here I propose two characteristics that can be closely related to industrial policymaking process by provincial governments. The first characteristic is the level of economic development. This characteristic is measured by the log form of GDP of each province in each year, written as $\boldsymbol{LnGDP_{it}}$. The second characteristic is industrial structure. Here I use the value added ratio of the secondary industry in each province in each year to reflect the industrial structure in each province. This variable is written as $\boldsymbol{IndRatio_{it}}$.

I measure similarity in the level of economic development by calculating the absolute value of the difference in $LnGDP_{it}$ between each pair of provinces in each year. That is:

$$\boldsymbol{GDPDiff_{ijt}} = |LnGDP_{it} - LnGDP_{jt}|$$

The similarity of industrial structure in provinces is measured by calculating the absolute value of the difference in $IndRatio_{it}$ between each pair of provinces in each year. That is:

$$\boldsymbol{IndDiff_{ijt}} = |IndRatio_{it} - IndRatio_{jt}|$$

5.3 Measure Provincial Susceptibility to Central Industrial Policies

To test hypothesis H2a, H2b, and H2c, I need to measure to what extent Chinese provincial governments are susceptible to central industrial policies. When it comes to industrial policies adopted by Chinese central government, I distinguish two types of central agencies. The first is the Chinese State Council. Chinese State Council is constitutionally the highest administrative organ of the country. The State Council and provincial governments have a superior-subordinate relationship administratively. The second is central ministries under the State Council. A number of central ministries are believed to play an important role in industrial policymaking in China: the National Development & Reform Commission (NDRC), the Ministry of Industry & Information Technology (MIIT), the Ministry of Finance (MF), and the Ministry of Science & Technology (MST). Although the top leaders in the above central ministries have the same administrative level as that of the top leaders in provincial governments, these central ministries may use their power in resource allocation to influence the policymaking behaviors of provincial governments.

To measure a province's susceptibility to central industrial policies adopted by the State Council and by the central agencies, I measure the proportion of all industrial policies currently in force in a province that are highly similar to at least one industrial policy already issued by the State Council or by the central ministries within the past five years. The higher the proportion, the greater the province is susceptible to central industrial policies. I use the variables $\boldsymbol{ImpactSC_{it}}$ and $\boldsymbol{ImpactCM_{it}}$ to denote a province i's susceptibility to industrial policies launched by the State Council and those by the central ministries.

Also notice that I are interested in whether two provinces are both susceptible to central industrial policies. Therefore, I need to create a dyadic variable to measure the co-susceptibility of both provinces, that is:

$$\boldsymbol{MultiImpactSC_{ijt} = ImpactSC_{it} \times ImpactSC_{jt}}$$

$$\boldsymbol{MultiImpactCM_{ijt} = ImpactCM_{it} \times ImpactCM_{jt}}$$

5.4 Measure Provincial Susceptibility to Industrial Policies of Leading Provinces

Hypothesis H3a proposes that when both provincial governments are susceptible to the industrial policies of leading provinces, the two jurisdictions tend to have highly similar policies. Here I create a variable $\boldsymbol{PeerInfl_{it}}$ to denote a provincial government's susceptibility to the influence of leading peers. This variable is measured by calculating the proportion of all industrial policies currently in force in a province that are highly similar to at least one industrial policy already issued by leading provinces within the past five years. The leading provinces I choose here include Zhejiang, Shanghai, Beijing, Shandong, Guangdong, and Jiangsu. The six provinces are chosen as the "leading provinces" in industry development based on "White Paper on High-quality Development of Manufacturing Industry" issued in 2021.

Similarly, I also need to create a variable to measure the co-susceptibility of a pair provinces to the industrial policies of leading provinces. This is done by calculating the product of $PeerInfl_{it}$ and $PeerInfl_{jt}$ for each pair of provinces i and j, that is:

$$\boldsymbol{MultiPeerInfl_{ijt} = PeerInfl_{it} \times PeerInfl_{jt}}$$

Besides the above variables, I also include the lagged value of the dependent variable $\boldsymbol{PolicySimi_{ijt-1}}$ in the model to reflect the potential temporal dependence. The summary statistics of all the variables is shown in Table 8. It is also worth noting that the time period I focus in the regression model is from 2009 to 2019. The reason why the time period starts in 2009 rather than in 2005 is because to measure the susceptibility of a provincial government to central industrial policies, I need to the provincial industrial policies to all the central industrial policies within the past five years. For example, if I want to measure the susceptibility of a province in year 2009, I will need to compare the policies it adopts in that year to all the existed central industrial policies adopted between 2005 and 2009. That's why the sample data for regression starts from the year of 2009.

Table 8: Summary Statistics of Key Variables

Variable Name	Definition	Mean/ Proportion	Std. Dev.
Dependent Variable			
$PolicySimi_{ijt}$	Dummy Variable. Indicate whether province i and province j have highly similar industrial policies at time t.	0.078	
Independent Variables A. Dyadic Variables			
$PolicySimi_{ijt-1}$	Lagged value of the dependent variable.	0.062	
$GDPDiff_{ijt}$	Differences in Log Form of GDP	0.972	0.753
$IndDiff_{ijt}$	Differences in the proportion of added value of the secondary industry.	0.081	0.070
$MultiImpactSC_{ijt}$	Extent to which both provinces are susceptible to the impact of the State Council.	0.136	0.121
$MultiImpactCM_{ijt}$	Extent to which both provinces are susceptible to the impact of central ministries.	0.256	0.144
$MultiPeerInfl_{ijt}$	Extent to which both provinces are susceptible to the impact of leading provinces	0.355	0.231
B. Nodal Variables			
$LnGDP_{it}$	Policy Convergence Index from National Development & Reform Committee to a follower province.	9.634	0.912
$IndRatio_{it}$	Policy Convergence Index from Ministry of Industry & Information Technology to a follower province.	0.351	0.082
$ImpactSC_{it}$	Extent to which province i is susceptible to the impact of the State Council	0.346	0.193
$ImpactCM_{it}$	Extent to which province i is susceptible to the impact of central ministries.	0.495	0.173
$PeerInfl_{it}$	Extent to which province i is susceptible to the impact of leading provinces.	0.592	0.263

5.5 Model Specification

In this article, I use the AMEN model to examine the causes of policy convergence. The question of what causes policy convergence can be decomposed into two sub-questions. first, what factors cause policy similarity between jurisdictions? Second, why does the overall policy similarity across all jurisdictions increase over time?

The AMEN model is as follows:

$$z_{i,j,t} = y_{i,j,t-1} + \beta_d^T x_{d,i,j,t} + \beta_n^T \left(x_{n,i,t} + x_{n,j,t}\right) + a_i + a_j + {u_i}^T \wedge u_j + \epsilon_{i,j,t}$$

$$y_{i,j,t} = 1(z_{i,j,t} > 0)$$

The vector of dyadic variables $x_{d,i,j,t}$ includes $PolicySimi_{ijt-1}$, $GDPDiff_{ijt}$, $IndDiff_{ijt}$, $MultiImpactSC_{ijt}$, $MultiImpactCM_{ijt}$, and $MultiPeerInfl_{ijt}$. The vector of nodal variables for province i, denoted as $x_{n,i,t}$, includes $LnGDP_{it}$, $IndRatio_{it}$, $ImpactSC_{it}$, $ImpactCM_{it}$, and $PeerInfl_{it}$, and the same for $x_{n,j,t}$. $a_1, \dots, a_n \sim i.i.d.\, N(0, \sigma_a^2)$. $\{\epsilon_{i,j,t}\} \sim i.i.d.\, N(0, \sigma_e^2)$.

I test hypothesis H1a, H2a, and H3a by estimate the value of β_d, which is a vector of coefficients for all the dyadic variables $x_{d,i,j,t}$. The magnitude and significance of β_d shows how the dyadic variables correlate with the likelihood that two provinces are in high policy similarity with each other.

To test the remaining hypotheses, I compare the time trend of network density (i.e. mean value of $y_{i,j,t}$ by year) before and after I control for the value of $x_{d,i,j,t}$.

6. Results

6.1 Explain industrial policy similarity between Chinse provincial governments

Table 9 reports the regression results. Besides controlling for the lagged value of policy similarity and all the nodal variables, in model (1) I include the dyadic variables $GDPDiff_{ijt}$ and $IndDiff_{ijt}$, In model (2) the dyadic variables $MultiImpactSC_{ijt}$ and $MultiImpactCM_{ijt}$, model (3) the dyadic variable $MultiPeerInfl_{ijt}$. In model (4) I include all the aforementioned dyadic variables.

The regression results of model (1) show that, similarity of the level of economic development and similarity of industrial structure are both associated with high policy similarity between two provinces. In model (4) the coefficient of $IndDiff_{ijt}$ remains significant, but the coefficient of $GDPDiff_{ijt}$ is no longer significant anymore.

Model (2) examines whether two provinces who are both susceptible to central industrial policies tend to have high policy similarity between each other. As has been mentioned before, I distinguish two types of central agencies. The first is the State Council, and the second is the central ministries under the control of the State Council. Results of model (2) show that when both provinces are susceptible to the impact of the State Council, they are more likely to have highly similar industrial policies. By contrast, the coefficient of $MultiImpactCM_{ijt}$ is negative and insignificant. Therefore, I find no evidence that the impact of the central ministries plays a role in causing high industrial policy similarity between provincial governments. The above results remain stable when I include other dyadic variables in the model, as is shown in the results of model (4).

In Model (3), the coefficient of the variable $MultiPeerInfl_{ijt}$ is positive and significant. This shows some evidence that when two provinces who are both susceptible to the impact of leading provinces, they are more likely to have highly similar policies. However, in model (4) the coefficient of $MultiPeerInfl_{ijt}$ is no longer significant after I include other dyadic variables into the model.

Based on the above discussion, it is safe to conclude that at least two factors are associated with the high policy similarity between provinces. First, similarity in local industrial structure. Second, susceptibility of both provinces to central industrial policies adopted by the State Council. In the next section, I will further discuss whether these two factors explain the phenomenon of industrial policy convergence across provinces in China.

Table 9: Regression Results of AMEN Model

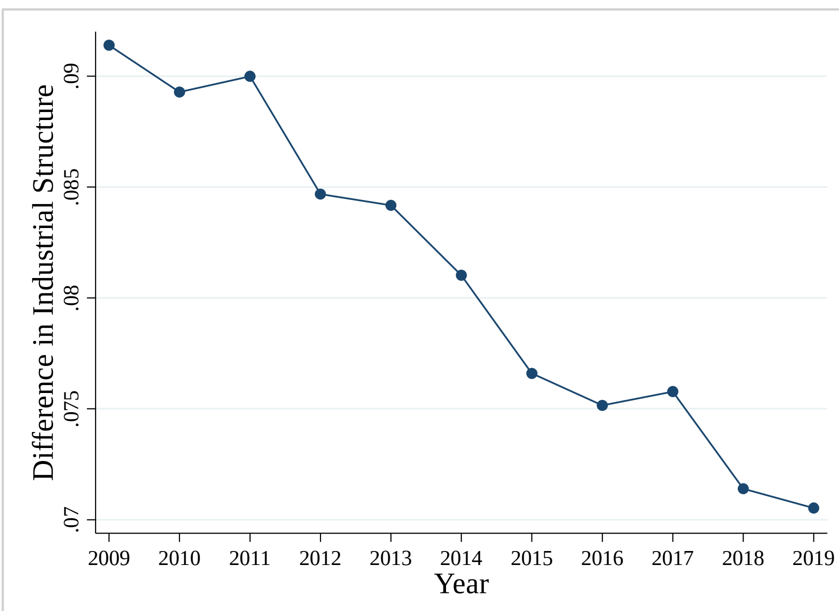
	(1)	(2)	(3)	(4)
$GDPDiff_{ijt}$	-0.199*			-0.145
	(0.084)			(0.090)
$IndDiff_{ijt}$	-1.915*			-2.124**
	(0.762)			(0.790)
$MultiImpactSC_{ijt}$		4.114**		3.986**
		(1.372)		(1.529)
$MultiImpactCM_{ijt}$		-1.418		-2.036
		(1.546)		(1.571)
$MultiPeerInfl_{ijt}$			2.114**	1.412
			(0.675)	(0.885)
$PolicySimi_{ijt-1}$	1.399***	1.383***	1.348***	1.352***
	(0.101)	(0.100)	(0.092)	(0.094)
$LnGDP_{it}$	-0.254**	-0.194*	-0.229**	-0.239**
	(0.082)	(0.084)	(0.084)	(0.076)
$IndRatio_{it}$	0.077	0.078	0.155	0.172
	(0.698)	(0.739)	(0.823)	(0.782)
$ImpactSC_{it}$	1.131***	-0.516	1.050***	-0.387
	(0.293)	(0.598)	(0.296)	(0.653)
$ImpactCM_{it}$	-0.891***	-0.284	-0.963***	0.093
	(0.269)	(0.844)	(0.271)	(0.806)
$PeerInfl_{it}$	1.696***	1.787***	2.114**	0.869
	(0.337)	(0.339)	(0.675)	(0.535)
N				

6.2 What causes industrial policy convergence across Chinese provincial governments?

In the previous section, I find two factors that are associated with high policy similarity between provinces. The first factor is similarity of industrial structure between provinces. The second factor is co-susceptibility of both provinces to central industrial policies adopted by the State Council. In this section, I will further discuss whether these two factors contribute to overall policy convergence among provincial governments in China over time.

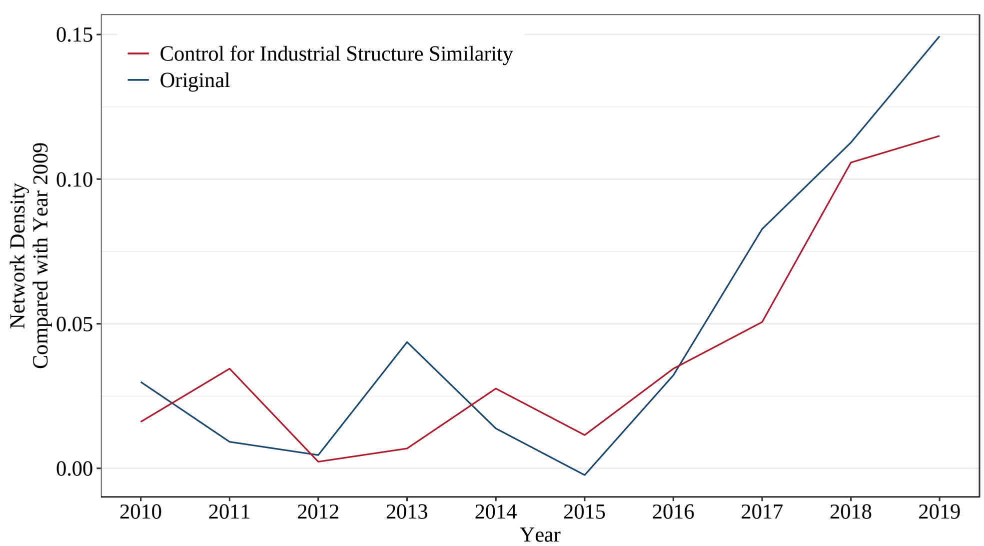
One potential reason of industrial policy convergence in China is that there is convergence of provincial industrial structure over time, and such convergence in industrial structure contributes to industrial policy convergence. I examined whether there is convergence in the industrial structure across Chinese provinces over time by drawing a line graph to track changes in the average difference in the proportion of secondary industry between provinces over time. As is shown by figure 6, the difference in industrial structure between provinces does decrease over time.

Figure 6: Difference in Industrial Structure between Provinces, by Year



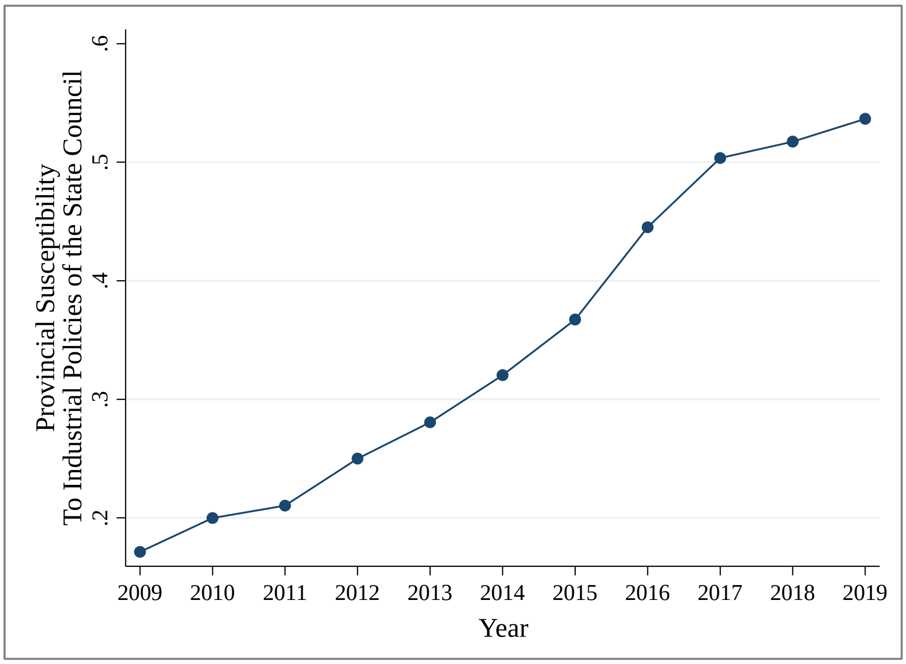
I further examined whether the increasing similarity in industrial structure across provinces contributes to industrial policy convergence over time. To do so, I compared the time trends of industrial policy convergence before and after controlling for the similarity in industrial structure across provinces over time. This is done by calculating how the time trend of industrial policy convergence would be like if the provincial similarity in industrial structure always equals the value in the starting year (i.e., 2009). Figure 7 shows both the original time trend of network density (denoted by the blue line) and the simulated time trend of network density (denoted by the red line) after controlling for industrial structure similarity. As is shown by the figure, the simulated time trend of network density looks similar to the original time trend, and the fast increase in network density after year 2015 still exists. This result implies that the increasing similarity in provincial industrial structure is unlikely the main reason why there is industrial policy convergence across Chinese provincial governments over time, especially for the period after 2015.

Figure 7: Original versus Simulated Time Trend of Network Density after Controlling for Industrial Structure Similarity



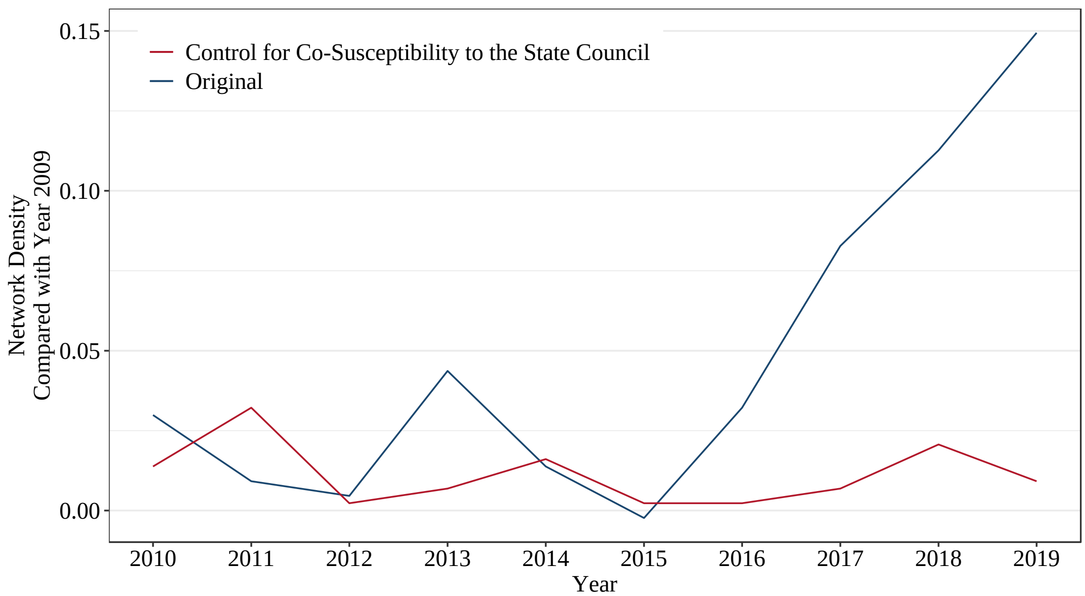
Then I examined whether the susceptibility of provinces to central industrial policies adopted by the State Council helps explain industrial policy convergence in China. I first check whether, on average, each province becomes increasingly susceptible to coercive impact from the State Council over time. As is shown by figure 8, there is an evident increasing trend in terms of the overall susceptibility of a provincial government to the industrial policies adopted by the State Council.

Figure 8: Time Trend of Provincial Susceptibility to Central Industrial Policies



Now the question is whether the increasing susceptibility of each pair of provinces to the industrial policies of the State Council explains provincial industrial policy convergence in China. To address this question, I repeated the practice before by comparing the original time trend of network density to the simulated time trend of network density after controlling for the susceptibility of each province to the industrial policies of the State Council as well as the co-susceptibility of each pair of provinces. The result is shown in figure 9. The blue line shows the original time trend of network density, and the red line shows the simulated time trend of network density after controlling for the (co-)susceptibility of provinces to industrial policies of the State Council. I find that the surge in network density after year 2015 disappears in the simulated time trend. This results supports the hypothesis that the increasing (co-)susceptibility of provinces to industrial policies issued by the State Council is associated with industrial policy convergence across Chinese provinces particularly between 2015 and 2019.

Figure 9: Original versus Simulated Time Trend of Network Density after Controlling for Provincial Susceptibility to the State Council



7. Conclusion

In this study, I examined the phenomenon of industrial policy convergence across provincial governments in China. An innovation of this study is that I measure and examine the phenomenon of policy convergence from a policy similarity network perspective. For each year between 2009 and 2019, I construct a policy similarity network by considering each provincial government as a node and connecting two nodes with a line (i.e., edge/link) if the industrial policies that are currently in effect in the two provinces are highly similar to each other in terms of the industry categories they target. The measurement of policy similarity is based on the particular finely-segmented industry categories that the policies target. Then I define policy convergence as an increase in the density of the policy similarity network from time t1 to time t2.

Following the above definition, I find a clear trend of industrial policy convergence across Chinese provinces, especially between 2015 and 2019. To examine the underlying causes of policy convergence, I argue that researchers should explain not only what factors contribute to policy similarity between jurisdictions, but also the reason why the overall policy similarity across jurisdictions increases over time. Then I address the above two questions by applying the AMEN model proposed by Hoff (2015, 2018) to test three potential causes of industrial policy convergence in China. I find that the increasing susceptibility of provincial governments to central industrial policies adopted by the State Council is likely to be the main reason for industrial policy convergence between 2015 and 2019.

This study is among the first to examine the phenomenon of policy convergence from a policy similarity network perspective. I apply such a policy similarity network in the study of industrial policy convergence across provincial governments in China. However, it is still unclear whether such a policy similarity network perspective will work in other situations. Scholars, in the future, may explore more real-world applications in different economic, political, and policy contexts to test the usefulness of such a network perspective. It is also worthwhile for scholars to explore how to use other network analysis tools, such as clustering algorithms, to dig deeper into the phenomenon of policy convergence.

8. References

Aghion, Philippe, and Jean Tirole. "Formal and real authority in organizations." Journal of political economy 105, no. 1 (1997): 1-29.

Bennett, Colin J. "What is policy convergence and what causes it?." British journal of political science 21, no. 2 (1991): 215-233.

Cao, Xun. "Global networks and domestic policy convergence: A network explanation of policy changes." World Politics 64, no. 3 (2012): 375-425.

Drezner, Daniel W. "Globalization and policy convergence." International studies review 3, no. 1 (2001): 53-78.

Finnemore, Martha, and Kathryn Sikkink. "International norm dynamics and political change." International organization 52, no. 4 (1998): 887-917.

Gilardi, Fabrizio. "Four ways I can improve policy diffusion research." State Politics & Policy Quarterly 16, no. 1 (2016): 8-21.

Grimmer, Justin, and Brandon M. Stewart. "Text as data: The promise and pitfalls of automatic content analysis methods for political texts." Political analysis 21, no. 3 (2013): 267-297.

Grossman, Gene M., and Alan B. Krueger. "Economic growth and the environment." The quarterly journal of economics 110, no. 2 (1995): 353-377.

Hayek, Frederick A. "The use of knowledge in society." In Knowledge management and organizational design, pp. 7-15. Routledge, 2009.

Heichel, Stephan, Jessica Pape, and Thomas Sommerer. "Is there convergence in convergence research? An overview of empirical studies on policy convergence." Journal of European public policy 12, no. 5 (2005): 817-840.

Hollibaugh, Gary E. "The use of text as data methods in public administration: A review and an application to agency priorities." Journal of Public Administration Research and Theory 29, no. 3 (2019): 474-490.

Holzinger, Katharina, and Christoph Knill. "Causes and conditions of cross-national policy convergence." Journal of European public policy 12, no. 5 (2005): 775-796.

Huang, Zhangkai, Lixing Li, Guangrong Ma, and Lixin Colin Xu. "Hayek, local information, and commanding heights: Decentralizing state-owned enterprises in China." American Economic Review 107, no. 8 (2017): 2455-78.

Ingraham, Patricia W. "Toward more systematic consideration of policy design." Policy Studies Journal 15, no. 4 (1987): 611.

Knill, Christoph. "Introduction: Cross-national policy convergence: concepts, approaches and explanatory factors." Journal of European public policy 12, no. 5 (2005): 764-774.

Nowlin, Matthew C. "Theories of the policy process: State of the research and emerging trends." Policy studies journal 39 (2011): 41-60.

Ramirez, Francisco O., Yasemin Soysal, and Suzanne Shanahan. "The changing logic of political citizenship: Cross-national acquisition of women's suffrage rights, 1890 to 1990." American sociological review (1997): 735-745.

Shipan, Charles R., and Craig Volden. "Bottom-up federalism: The diffusion of antismoking policies from US cities to states." American journal of political science 50, no. 4 (2006): 825-843.

Shipan, Charles R., and Craig Volden. "Policy diffusion: Seven lessons for scholars and practitioners." Public Administration Review 72, no. 6 (2012): 788-796.

Shipan, Charles R., and Craig Volden. "The mechanisms of policy diffusion." American journal of political science 52, no. 4 (2008): 840-857.

Sidney, Mara S. "Policy formulation: design and tools." In Handbook of public policy analysis, pp. 105-114. Routledge, 2017.

Simmons, Beth A., and Zachary Elkins. "The globalization of liberalization: Policy diffusion in the international political economy." American political science review 98, no. 1 (2004): 171-189.

Weinter, David L. "The craft of policy design: Can it be more than art?." Review of Policy Research 11, no. 3-4 (1992): 370-388.

Yihua Yu, 2009. "CHINA_SPATDWM: Stata module to provide spatial distance matrices for Chinese provinces and cities," Statistical Software Components S457059, Boston College Department of Economics.

Chapter 3: The Dilemma of Political Control: Top-Down Inspection and Its Impact on Bureaucrats' Use of Discretion in Policymaking

1. Introduction

A challenge of policy control of bureaucracy is how to direct bureaucratic agencies to behave in accordance with the assigned goals while simultaneously granting them enough discretion to apply their expertise in policymaking (Terry M. Moe 2012). Previous literature mainly discusses how political leaders (i.e. legislative, judicial, and executive actors with formal political authority) should delegate the right amount of discretion to bureaucrats to balance the needs of political control and bureaucratic autonomy (Epstein and O'Halloran 1999; Gailmard and Patty 2012; Huber and Shipan 2002).

Even if bureaucrats are legally granted sufficient discretion to make decisions, whether bureaucrats would prefer to use that discretion in policymaking is a separate consideration. At one extreme, bureaucrats abstain from using any of their discretion by always adopting "center-following policies" that are similar to the baseline policies already proposed by political leaders. At the other extreme, bureaucrats make full use of their discretion by always adopting "local-initiated policies" that are quite different from those proposed by political leaders.

The issue of bureaucrats' preference for using discretion in policymaking has been largely neglected in the literature. Previous studies often assume that, as long as bureaucrats take actions within statutory constraints, there are no additional costs for them to use discretion by adopting local-initiated policies relative to center-following ones. In the real world, however, bureaucrats may need to think twice before exercising their discretion even if they are legally allowed to do so. First, adoption of local-initiated policies that are quite different from pre-existing baseline policies may easily attract the attention of political leaders and increase the likelihood of ex post oversight.

Second, frequent adoption of local-initiated policies can be seen as a sign of disobedience if disloyalty is a big concern for political leaders. Third, adopting local-initiated policies makes it more difficult for bureaucrats to shift blame if the policies turn out to be failures.

In this article, I attempt to fill the gap in the literature by discussing how bureaucrats adjust their preference for using discretion in policymaking in response to political control from above. More specifically, I examine how bureaucrats react to top-down inspections from political leaders. Top-down inspection as a political control instrument is common across political systems and national contexts (Ding et al. 2022; Downe and Martin 2007; Gates and Knowles 1984; Lindgren 2014). It often involves a political leader authorizing a specific institution to conduct on-site inspections of bureaucratic agencies and report findings back to her. Bureaucrats found to be shirking, fraudulent, or corrupt during the inspection are likely to face further investigation or even sanctions.

I argue that in an under-institutionalized accountability system, top-down inspections as a political control instrument can cause widespread decrease in bureaucrats' preference to use discretion in policymaking by provoking their risk-avoidance strategies. An under-institutionalized accountability system has two characteristics that are widely observed in non-democratic and developing countries. First, formal institutions to regulate bureaucrats are ambiguous, incomplete, or inadequately developed, making them difficult to enforce in reality. Second, enforcement processes to hold bureaucrats accountable lack consistency and transparency, and short-term goals of enforcement agencies take precedence over formal institutions (L. Chen 2022; Zhang 2021). Insufficient or inadequately developed formal rules to regulate bureaucrats, combined with highly uncertain accountability enforcement processes, result in bureaucrats behaving according to "circumstances" rather than "rules." However, selective adherence to rules according to circumstances can make bureaucrats extremely vulnerable to top-down inspections from political leaders. As a result, bureaucrats are likely to adopt various risk-avoidance strategies when faced with the risk of inspection, including staying low-key by reducing adoption of local-initiated policies, and showing obedience by increasing adoption of center-following policies. Both two risk-avoidance strategies decrease bureaucrats' preference for using discretion in policymaking. I further propose that top-down inspections not only impact bureaucrats who are being inspected, but also impact uninspected bureaucrats. By observing their peers being inspected, uninspected bureaucrats can be influenced by the chilling atmosphere and feel that the next inspection is just around the corner. As a result, they would also reduce their preference for using discretion in policymaking.

I place the above arguments in the context of provincial industrial policymaking in China. While Chinese provincial governments have no inherent power, they are granted by Chinese central authority a great deal of discretion in local governance (Xu 2011). In terms of industrial policymaking, for example, provincial governments have much freedom to stipulate industrial policies that differ much from those proposed by central agencies (Tan 2020). Provincial governments can also decide which specific industry categories (e.g., shipbuilding, automobiles, computers, etc.) to target in an industrial policy. However, whether provincial governments use their discretion is another matter. Here I distinguish two types of provincial industrial policies: "center-following" and "local-initiated." The former refers to provincial industrial policies that target the industry categories already proposed by central industrial policies. The latter, by contrast, refers to those that target the industry categories not yet proposed by any central industrial policy. Then a provincial government's preference to use discretion can be measured by the quantity difference between local-initiated policies and central-following ones adopted by the provincial government in each period of time.

Since the second quarter of 2013, the Central Commission for Discipline Inspection (CCDI) in China has repeatedly conducted disciplinary inspections on both central agencies and subnational governments with the main goal to combat corruption. The disciplinary inspections since 2013 are widely believed as “unprecedented” regarding the total number and the rank of public officials investigated and charged with misconduct or corruption during the inspections. From 2013 to 2019, CCDI conducted nine rounds of disciplinary inspections on provincial governments. During each round of inspections, CCDI dispatches inspection teams to a portion of the 31 provinces in mainland China, and each inspection team stay “on-site” for around two months. The inspection teams collect information and report findings back to the central authority.

It is worth noting that central disciplinary inspections aim to fight misconduct and corruption among public officials. However, such inspections do not directly set any additional constraint on public officials’ use of discretion legally granted to them when they make decisions in policymaking. Therefore, it would be interesting to examine how such central disciplinary inspections could indirectly discourage public officials to use their discretion in policymaking even when their use of discretion is legally allowed.

I study the effects of central disciplinary inspections on provincial governments’ preference for using discretion in industrial policymaking by analyzing the Chinese Industrial Policy Attention Dataset (CIPAD). The CIPAD is an original dataset containing detailed information for 612 central-level and 1907 provincial-level industrial policies stipulated between 2001 and 2019 in China. A novel design of the CIPAD is leveraging computational text analysis methods to transform the full text of each industrial policy into a distribution-of-attention vector.

Each distribution-of-attention vector describes the allocation of an industrial policy's attention to 155 finely segmented manufacturing industry categories. By transforming each policy full text into a distribution-of-attention vector, I can fast compare similarity between different industrial policies in terms of the manufacturing industry categories they target. This also enables us to easily distinguish center-following and local-initiated policies adopted by provincial governments.

Methodologically, I use two different identification strategies to examine the impact of central inspections on provincial governments' preference to use discretion. The first strategy is based on a pre-post comparison design, with an assumption that, after properly controlling for observed variables, a provincial government's preference to use discretion in industrial policymaking would have remained the same as that of the pre-event reference period in the absence of an inspection. The second strategy is two-way fixed effects model with spatial spillovers. Here I use uninspected far-away-enough provinces as the comparison group.

Empirical analysis shows that provincial governments significantly reduce their preference to use discretion in industrial policymaking during periods when the CCDI sends inspection teams to provincial governments. This is evidenced by the decreased number of local-initiated industrial policies compared to center-following ones adopted by provincial governments during inspection active periods. Interestingly, I find that the negative effect of central disciplinary inspections on provincial governments' preference for using discretion is more substantial for uninspected provinces who are observing their peers being inspected than for provinces being inspected themselves. This result may be due to the fact that provinces who are undergoing inspection have less operating space to strategically adjust their policymaking behaviors. Moreover, I find evidence that central disciplinary inspections are associated with increasing industrial policy homogeneity across provinces. This is shown by an increase in the similarity of distribution-of-attention vectors between different provinces during inspection active periods than during inspection inactive periods.

By examining how bureaucrats voluntarily decrease their preference to use discretion in response to political control from above, this study contributes to a large literature on political control of bureaucracy (Carpenter 1996; Epstein and O'Halloran 1999; Gailmard and Patty 2012; Huber and Shipan 2002; Terry M. Moe 2012; Volden 2002). Previous studies often assume that, as long as bureaucrats act within the limit of discretion, there are no extra costs for them to actively use their discretion in policymaking by moving away from the baseline policies proposed by political leaders (Gailmard and Patty 2012; Terry M. Moe 2012). Our study shows, however, that bureaucrats may strategically reduce use of discretion as a risk-avoidance strategy when political control creates a chilling environment (Gueorguiev 2018). Therefore, political leaders should pay more attention to the potential effect of political control on bureaucrats' preference to use discretion, even when political control instruments themselves do not constrain bureaucrats' decision-making freedom.

This study also speaks to a burgeoning literature on policy experimentation and policy learning. (S. Wang and Yang 2023) mainly focus on policy experiments sponsored by central government. By examining China's policy experimentation since 1980, they find that China's policy experimentation is characterized by positive sample selection and local politicians' strategic efforts. (Xu 2011) takes the privatization of state-owned enterprises as an example and suggests that locally initiated experiments also play a vital role in advancing China's economic reforms. Mukand and Rodrik (2005) discuss how politicians' tendency to avoid blame of corruption impacts their choices in policy experimentation, and how the above process helps explain a worldwide convergence of economic liberalization policies in the late 20th century. Although our study does not directly analyze the phenomenon of policy experimentation and policy learning, I believe the distinction between center-following and local-initiated policies in our study can shed light on the above discussions. Center-following policies, since they imitate the baseline policies proposed by central government, are likely to have lots of similar policies adopted by other regions who also follow the same central policies. As a result, center-following policies offer limited new information to policy learning process. By contrast, local-initiated policies can come from more diverse sources and are less likely to have been tried by other regions, thus providing new information for other regions to learn from.

Moreover, this study adds to the literature on developmental states by discussing how state-led developmental strategies can be shaped by complex interactions between central and subnational governments. Previous studies, when discussing about the role of government in "developmental states," often view central and subnational governments of a state as one single actor(Evans 1989; Haggard 2018; Routley 2012). In real-world situation, however, subnational governments may have both de jure and de facto power to stipulate local developmental policies which may or may not follow the baseline policies proposed by central government. This is particularly true for countries with large geographical areas. In the context of China, for example, scholars have noticed the divergence between central and local governments in terms of economic intervention and industrial policymaking. Tan (2020) finds that Chinese central government and subnational governments adopt very different strategies in response to the entry of WTO, with the former adopting more regulatory strategies and the latter adopting more developmental or directive strategies. Chen (2018) studies local governments' behaviors in economic policymaking responding to national paradigm change from FDI attraction to indigenous industry upgrading. The author finds that the success or failure of new central policies is greatly impacted by local bureaucrats' self-interest. This study joins the above discussion by examining how local governments strategically adjust their choices between center-following and local-initiated industrial policies in response to political control from central government.

2. Political Control and Bureaucratic Discretion

Political control of bureaucracy is an important issue in governance. Although political leaders have formal authority over bureaucratic agencies, it is hard to assume that bureaucratic agencies would automatically behave in consistence with the goals set by their political leaders (Hammond and Knott 1996; Terry M. Moe 1987; Weingast 1984). As a result, political leaders often need to employ certain mechanisms, processes, and strategies of political control to influence and direct the behavior of bureaucratic agencies within a governmental system.

Political control of bureaucracy can take various forms (Wood and Waterman 1991). One common mechanism of political control is using statutory constraints (such as administrative procedures) to directly limit bureaucrats' behaviors (Bawn 1997; Hill and Brazier 1991; McCubbins, Noll, and Weingast 1987, 1989; Xiao and Zhu 2022). Another frequently used mechanism of political control is oversight, which involves monitoring bureaucratic behaviors with rewards or punishments (McCubbins and Schwartz 1984). Measurable performance indicators have also become an important tool of control since the New Public Management (NPM) movement in 1980s (Verbeeten and Speklé 2015). In addition, scholars have found that budget (Bolton and Thrower 2019; Carpenter 1996) and personnel appointments (Jiang and Zeng 2020; Landry, Lü, and Duan 2018; Wood and Waterman 1991; Xu 2011) can serve as powerful devices of political control as well.

A challenge of political control of bureaucracy is how to induce bureaucrats to act in consistence with their political leaders while simultaneously granting them enough discretion to make decisions (Epstein and O'Halloran 1994, 1999; Gailmard and Patty 2012; Huber and Shipan 2002). Sufficient bureaucratic discretion is a prerequisite for effective governance (Moe 1990, 2012). Bureaucrats need enough discretion to apply their expertise in policy process. Previous studies have discussed how "red tapes" restricts talented bureaucrats' ability (Bozeman 1993; Duflo et al. 2018; Gore 1993; Mascarenhas 1993) to pursue societal welfare outcomes (Grandy and Hiatt 2020). Bureaucratic discretion also enhances bureaucrats' responsiveness to diverse needs of society and allows them to fast respond to emerging challenges (Xu 2011). Moreover, bureaucratic discretion also incentivizes bureaucrats to work harder. This is because discretion mentally helps bureaucrats to get proactive motivations at work (Parker and Ohly 2008) and enable bureaucrats to obtain rents from their expertise (Dessein 2002; Gailmard and Patty 2012).

The issue of balancing political control and bureaucratic discretion has been closely examined in the literature on delegation. Scholars mainly focus on discussing the optimal level of discretion that should be granted to bureaucratic agencies. Epstein and O'Halloran (Epstein and O'Halloran 1994, 1999) develop a straightforward approach to model Congress delegation. The authors find that both policy uncertainty and alignment of preferences between legislature and bureaucracy influence the level of delegation. Volden (2002) extended Epstein-O'Halloran model by considering the role of both Congress and the president. He shows that, in a separation of powers system, bureaucratic agencies tend to get more discretion than in a system of single power. Huber and Shipan (2002) develop a comparative theory of delegation by thoroughly discussing how different institutional contexts matter. They show that legislative capacity, existence of veto player, and cost of other non-statutory control mechanisms all impact level of delegation. Besides, Gailmard (2002) examines legislature's delegation choice when bureaucrats can subvert legislative limit on discretion at some cost. Interestingly, the author finds that bureaucrats would like the subversion of legislative limit difficult since only then would Congress delegate discretion at first hand.

3. Bureaucrats' Preference to Use Discretion in Policymaking: Center-Following versus Local-Initiated Policy

Previous discussions largely focus on the scenario when political leaders directly use political control instruments to limit bureaucrats' discretion, such as adoption of statutory constraints by Congress. Nevertheless, few studies investigate how political control mechanisms could cause bureaucrats to voluntarily curtail the exercise of discretion even when bureaucrats are granted the freedom to make decisions. This distinction arises from the fact that bureaucrats may formally possess discretion, yet their actual preference to exercise it constitutes a separate consideration.

In this study, I examine bureaucrats' preference to use discretion in policymaking by distinguishing two types of policies. The first type is called "center-following policies," which refer to policies adopted by a bureaucratic agency when similar policies have already been proposed by political leaders. The other type is "local-initiated policies," which refer to policies adopted by a bureaucratic agency when there doesn't exist any similar policy that has been proposed by political leaders. Bureaucrats' preference to use discretion in policymaking is then embodied by their choice between center-following and local-initiated policies. In one extreme, bureaucrats abstain from using any of their discretion by always adopting center-following policies. In the other extreme, bureaucrats make full use of their discretion by always adopting local-initiated policies.

The issue of bureaucrats' preference to use discretion in policymaking has largely been neglected in the previous literature. A formal model of delegation often assumes that political leaders set a baseline policy, $\mathbf{p}$, and a level of discretion, $\mathbf{d}$ (Moe 2012). Then a bureaucratic agency choose a policy of its own, $\boldsymbol{p_A}$, that meets the requirement of $|\boldsymbol{p_A} - \boldsymbol{p}| < \boldsymbol{d}$. An implicit assumption of the model is that, as long as bureaucrats take actions within the scope of discretion granted to them, there is no extra cost (benefit) for them to adopt a policy that is quite different from (similar to) the baseline policy pre-determined by political leaders.

In real-world situations, however, bureaucrats might need to think twice before they adopt local-initiated policies that are quite different from baseline policies proposed by their political leaders even if bureaucrats do have the formal authority to do so. There are several reasons behind this argument. First, adopting a local-initiated policy can increase the likelihood of receiving ex post investigations. This is because local-initiated policies, since being quite different from pre-existing baseline policies, are likely to arouse political leaders' suspicion and make them wonder why bureaucrats adopt them. Second, adopting a local-initiated policy could be regarded as a signal of disobedience when subordinates' disloyalty is a big concern for political leaders. Therefore, bureaucrats might prefer to adopt more center-following policies rather than local-initiated ones to show their loyalty (Lü and Landry 2014). Third, adopting a local-initiated policy makes it difficult for bureaucrats to shift blame if the policy turns out to be failure (Hood 2011; Weaver 1986). This is because failure of a center-following policy could at least be partly attributed to the baseline policy set by political leaders. By contrast, failure of a local-initiated policy is likely to be fully attributed to bureaucrats' own decisions.

The above discussion shows that bureaucrats' use of discretion should not be taken for granted. There are multiple types of costs that potentially come along with bureaucrats' decision to exercise their discretion. Therefore, both scholars and practitioners should have better understanding about how bureaucrats' preference to use discretion varies across contexts.

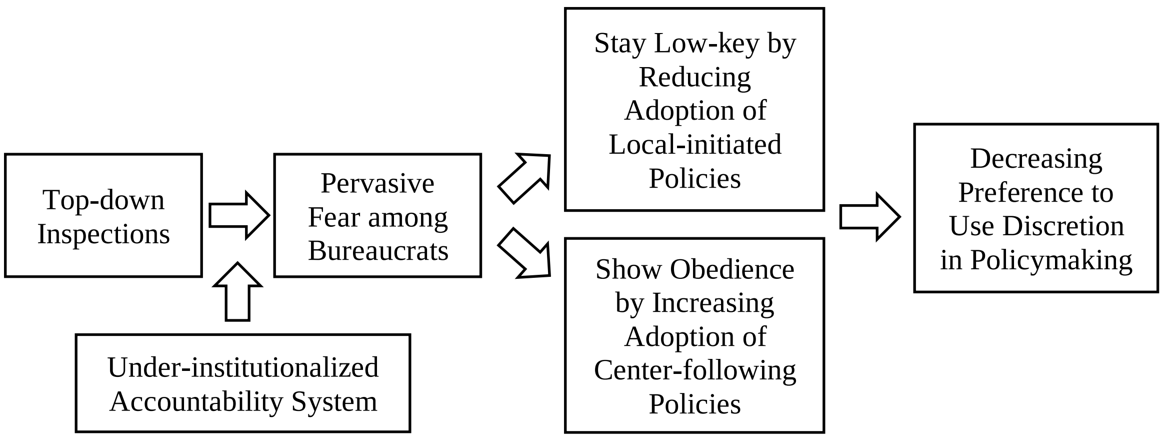
4. Top-Down Inspection as A Political Control Instrument in An Under-Institutionalized Accountability System

As a political control instrument, top-down inspections aim to ensure the actions undertaken by bureaucratic agencies align with the goals of political leaders. In essence, top-down inspection exerts control over bureaucracy by mitigating information asymmetry between political principals and subordinate agencies. It is common that political leaders authorize a specific institution to conduct inspections and report findings to it. Top-down inspections often encompass on-site visits, during which inspectors physically demonstrate their presence in the inspected agency. Such on-site visits facilitate inspectors to better collect information and conduct investigations. Individuals or entities who are found to be fraudulent, shirking, or involve in corruptive activities are likely to receive further investigations, interventions, or even sanctions.

The utilization of top-down inspection as a political control method is observed across diverse political systems and national contexts. In the United States, for example, the federal government passed The Inspector General Act in 1978. The purpose of the Act is to create independent inspectors general within federal agencies to prevent and detect fraud, abuse, waste and inefficiency. The inspectors general report directly to agency head and to Congress (Gates and Knowles 1984). In China, the central committee of Chinese Communist Party has routinized strict disciplinary inspections since 2013 (Fang 2022). Inspection teams conduct on-site visits to central ministries and local governments, with an aim to combat corruption and ensure the enforcement of party discipline.

In this study, I argue that top-down inspections, when conducted in an under-institutionalized accountability system, can cause widespread decrease in bureaucrats' preference to use discretion in policymaking. Figure 10 demonstrates the causal mechanism of our argument.

Figure 10: Causal Mechanism of Bureaucrats' Decreased Preference to Use Discretion



An under-institutionalized accountability system is characterized by two phenomena: First, formal institutions to regulate bureaucrats are ambiguous, incomplete, or inadequately developed, making them difficult to enforce in reality. Second, enforcement processes to hold bureaucrats accountable lack consistency and transparency, and short-term goals of enforcement agencies take precedence over formal institutions (L. Chen 2022; Zhang 2021).

Due to insufficient or inadequately developed formal institutions to regulate bureaucrats, as well as inconsistent accountability enforcement processes, bureaucrats are likely to behave according to "circumstances" rather than "rules." However, selective compliance with formal rules according to circumstances make bureaucrats highly vulnerable to top-down inspections from above. Even those "clean" bureaucrats who are not involved in corruptive practices could be worried about their situation, since they might occasionally sidestep some burdensome formal procedures to get work done, and they are uncertain about the consequences once their informal practices are identified during inspections.

As a result, top-down inspections are likely to provoke large-scale risk-avoidance strategies among bureaucrats. One strategy to avoid risk is to stay low-key by reducing the adoption of local-initiated policies. Adopting local-initiated policies can be risky by attracting inspectors' attention and increasing likelihood of ex post investigations. This is because local-initiated policies, since they are quite different from baseline policies suggested by political leaders, could easily arouse inspectors' suspicion and make them wonder why bureaucrats adopt them. By contrast, adopting center-following policies is relatively safe since bureaucrats are simply following what have already been suggested by their superiors. Another strategy to avoid risk is to show obedience by increasing the adoption of center-following policies. Remember that a main goal of top-down inspections as a political control method is to ensure bureaucratic agencies take actions that are aligned with the goals of political leaders. Therefore, a natural and straight-forward way for bureaucrats to protect themselves is to demonstrate their obedience by imitating what has been proposed by political leaders, which leads to increasing adoption of central-following policies. Both the above two risk-avoidance strategies decrease bureaucrats' preference for local-initiated policies relative to center-following ones.

Hypothesis 1: In an under-institutionalized accountability system, bureaucrats would decrease their preference for local-initiated policies compared to center-following ones when their working place is being inspected.

Another question is whether top-down inspections only impact bureaucrats who are undergoing inspections, or such inspections would have a spillover effect on uninspected bureaucrats. In this study, I argue that top-down inspections are likely to have a chilling effect on uninspected bureaucrats as long as bureaucrats cannot know in advance when they will be inspected. By watching their peers to be inspected, uninspected bureaucrats would feel that the next inspection is around the corner. As a result, uninspected bureaucrats would also decrease preference for local-initiated policies as a risk-avoidance strategy.

Hypothesis 2: In an under-institutionalized accountability system, uninspected bureaucrats who are observing their peers to be inspected would also decrease their preference for local-initiated policies compared to center-following ones.

5. Institutional Background

5.1 Disciplinary inspections in China since 2013

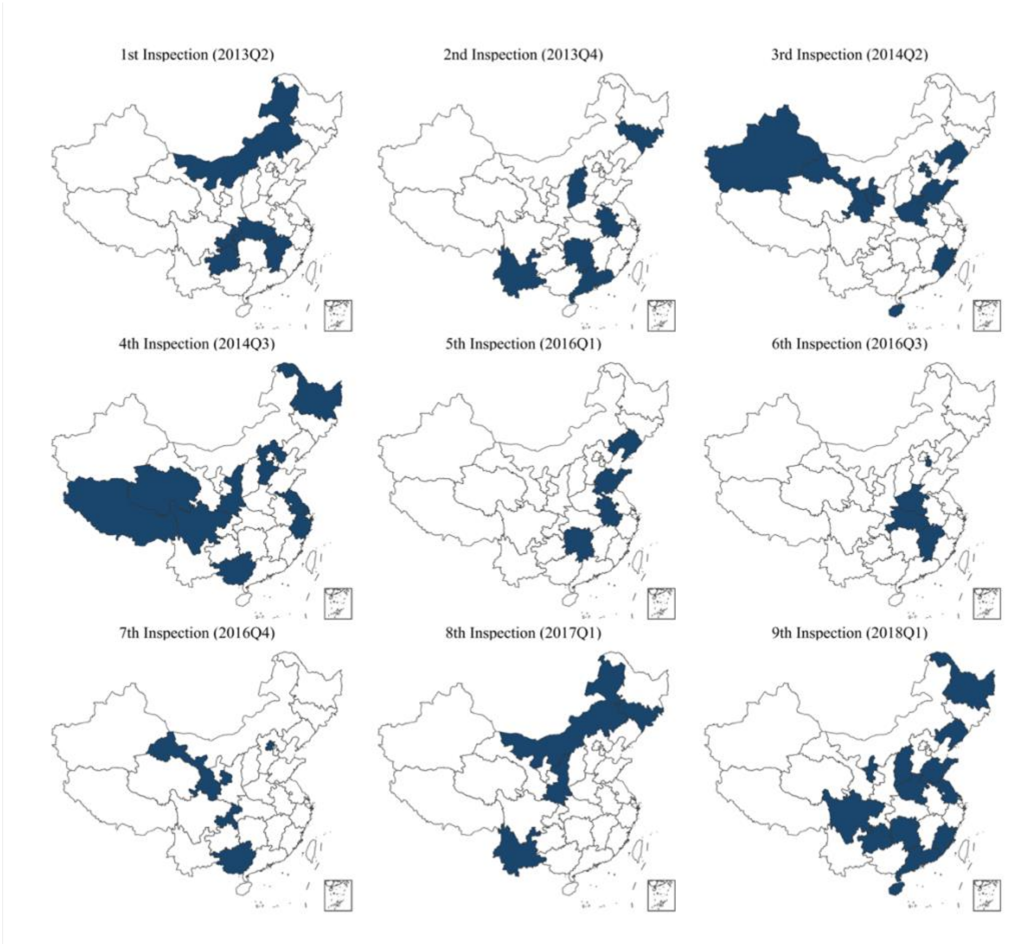
Since President Xi Jinping took office in China in the end of 2012, top-down inspections have increasingly become an important governing tool inside the Chinese government. The most frequently mentioned type of central inspections in both media and academia in China since late 2012 is probably the disciplianry inspections conducted by the Central Commission for Discipline Inspection (CCDI) since 2013. The starting point was May 17, 2013, when Wang Qishan, the previous head of the CCDI, announced that CCDI would begin to conduct regular disciplinary inspections on both central agencies and subnational governments, with the primary objective of these inspections being combatting corruption and ensuring enforcement of party rules.

The CCDI-led disciplinary inspections since the second quarter of 2013 (i.e. 2013Q2) are unprecedented for the following reasons. First, the disciplinary inspections since 2013 have far greater influence than those in the past regarding the total number of public officials investigated and charged with misconduct and corruption. Between 2013 and 2022, at least 226 sub-provincial (ministerial) or higher level public officials were finally transferred to Supreme Procuratorate for corruption investigation. By contrast, this number was only 65 between 2003 and 2012. Second, the disciplinary inspections since 2013 are sensational considering that they even cracked down some top leaders in Chinese central authority. In July 2014, CCDI started the investigation to Zhou Yongkang, who was a previous national-level leader. Zhou Yongkang was reported to be the first Politburo Standing Committee member who was ever charged with corruption since 1949, the founding year of the People's Republic of China.

The disciplinary inspections since 2013 are not a one-time campaign. From 2013 to 2019, CCDI launched nine rounds of inspections that conducted on-site visits to subnational governments. In each round of inspection, CCDI dispatches inspection teams to a portion of the 31 provinces in mainland China, with each inspection team stays in a province for around two months. Figure 11 demonstrates the provinces being inspected during each round of inspection. Table 13 in the appendix shows the detailed lists of provinces being inspected.

For a long time, China grappled with pervasive misconduct and corruption in its governmental agencies (Ang 2020; Wedeman 2005). Although evidence shows that the disciplinary inspections since 2013 have strongly curbed the spread of corruption (T. Chen and Kung 2019), people are worried that the enforcement processes to hold bureaucrats accountable are subject to human manipulations and political interventions (Zhu and Zhang 2017). This, in turn, introduces significant uncertainty into accountability enforcement processes.

Figure 11:Provinces Being Inspected in Nine Rounds of Central Disciplinary Inspections That Target Subnational Governments from 2013 to 2019



Both media and academia noticed that the intense disciplinary inspections since 2013 caused widespread fear inside government (T. Chen and Kung 2019; W. Chen, Keng, and Zhang 2023; E. H. Wang 2022). However, it is still unclear to what extent such fear changed Chinese bureaucrats' preference to use discretion in policymaking. This study attempts to address the question in the context of provincial industrial policymaking in China.

5.2 Central and Provincial Industrial Policymaking in China

A significant characteristic of Chinese industrial policies is that they often target specific industry categories (e.g. automobile, shipbuilding, computer chips…) rather than impacting the whole economy (Aghion et al. 2015; L. Chen and Naughton 2016; Hausmann, Hwang, and Rodrik 2007; Liu 2019; Prud'homme 2016). Such industrial policies that focus on a number of selected industry categories are often called "targeted industrial policies" in literature.

Both Chinese central and provincial governments adopt targeted industrial policies every year. Most central-level targeted industrial policies are issued by the following five central agencies: the State Council, the National Development & Reform Commission (NDRC), the Ministry of Science & Technology (MST), the Ministry of Industry & Information Technology (MIIT), and the Ministry of Finance (MF). On the provincial level, Most influential targeted industrial policies are issued either directly by provincial governments themselves or by their general offices. This study does not discuss other targeted industrial policies issued by departments under provincial governments, as they are considered to be less influential.

In terms of selecting specific industry categories to target, provincial industrial policies might or might not choose industry categories that have already been proposed in central industrial policies. On the one hand, choosing industry categories proposed in central industrial policies has a better chance for provincial governments to obtain support and resources from central government. On the other hand, industry categories proposed by central government are not necessarily suitable for local context. Provincial governments might also worry about fierce inter-governmental competition and industrial overcapacity if most provinces choose to follow the same central industrial policies. Therefore, it would be interesting to examine whether provincial governments prefer to adopt "center-following" industrial policies that target industry categories already proposed in central industrial policies or to adopt “local-initiated” ones targeting industry categories not mentioned in previous central policies.

The adoption of targeted industrial policies in China merits special attention for the following reasons: First, recent years have witnessed a resurgence of targeted industrial policies worldwide, and China is one of the key players in this trend. A vivid example is “Made in China 2025,” which selectively supports the development of aerospace, biotech, electric vehicles, robots, and other advanced manufacturing categories. Similarly, the United States and Europe have also adopted their own targeted industrial policies in the past a few years, such as the CHIPS and Science Act enacted by the U.S. Congress and the European Chips Act proposed by the European Commission to encourage semiconductor production. Second, there is much controversy regarding the effectiveness of targeted industrial policies on a region’s economic development. Supporters argue that targeted industrial policies could help address certain types of market failures, such as externalities, monopoly, etc., while critics argue that targeted industrial policies tend to “pick winners” and are likely to fail due to “government failures” (Harrison and Rodríguez-Clare 2010; Juhász, Lane, and Rodrik 2023; Krugman 1995; J. Lin and Chang 2009; J. Y. Lin 2011; Liu 2019; Tassinari et al. 2019). I believe a better understanding about the policy process behind adoption of targeted industrial policies could shed light on the previous discussion.

6. Data and Methods

6.1 Chinese industrial policy attention dataset (CIPAD)

The data on central and provincial targeted industrial policymaking in China are drawn from the Chinese Industrial Policy Attention Dataset (CIPAD), an original dataset containing detailed information for 612 central-level and 1907 provincial-level targeted industrial policies in manufacturing sector from 2001 to 2019.

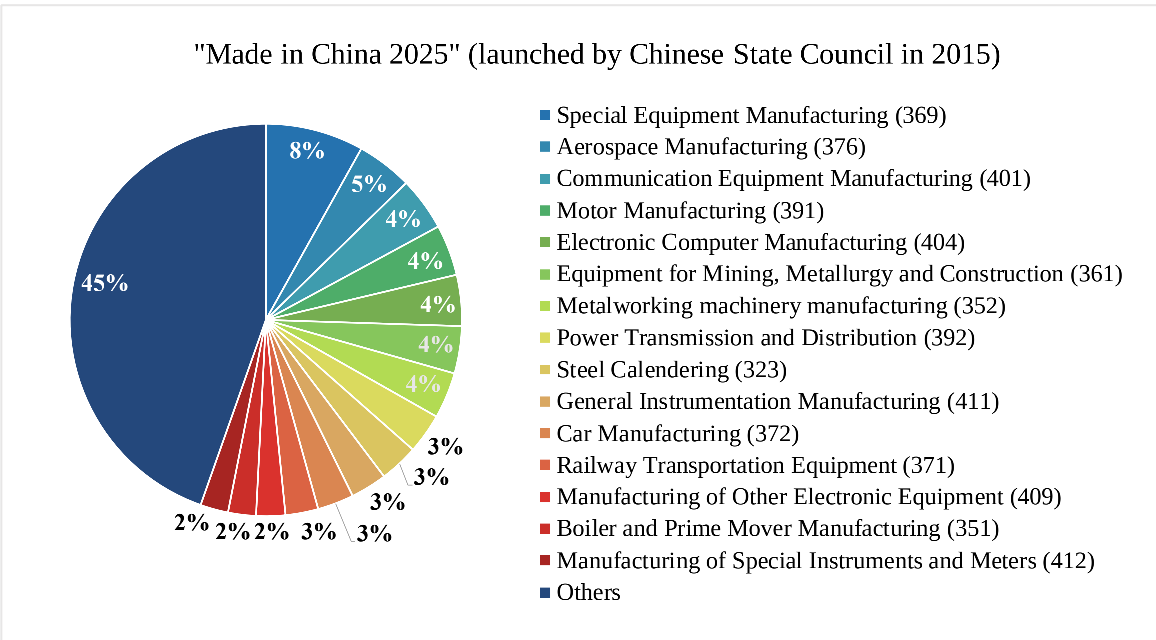
A novel design of CIPAD is that, by using computational text analysis techniques, the full text of each targeted industrial policy is transformed into a distribution-of-attention vector. A distribution-of-attention vector can be written as $(x_1, x_2, \ldots, x_{155})$, with $x_i \in [0,1]$ and $\sum_1^{155} x_i = 1$. Each vector describes the attention allocation of an industrial policy to 155 finely segmented industry categories in manufacturing sector, and x_i equals the proportion of attention paid to the ith industry category. The 155 industry categories are based on the three-digit codes in Chinese Industrial Classification for National Economic Activities (GB/T 4754-2002). For instance, three-digit code "372" denotes auto manufacturing, and "266" denotes special chemical products. To the best of our knowledge, this dataset stands out as one of the first to identify industry categories as granular as three-digit levels in full texts of industrial policies.

CIPAD transforms a policy full text into a distribution-of-attention vector by three steps. The first step is to identify in policy full text all the manufacturing key phrases which describe either industry categories or products within industry categories. The second step is to categorize each manufacturing key phrase into one or more than one of the 155 industry categories. Then the third step is to calculate the proportion of attention that a policy pays to each industry category by counting the ratio of the manufacturing key phrases classified into that industry category. Appendix B provides an example of transforming a policy into a distribution-of-attention vector. Appendix C introduces the computational text analysis methods I use to construct the dataset.

CIPAD allows researchers to fast identify industry categories that receive the most attention from a targeted industrial policy. Take the policy "Made in China 2025" issued by Chinese State Council in 2015 as an example. Based on CIPAD, I can fast extract the top-15 industry categories. According to figure 12, the industry category that received the most attention is "special equipment manufacturing" which receives eight percent of attention from the policy.

The industry categories that rank the second and the third are "aerospace manufacturing" and "communication equipment manufacturing," which obtain five and four percent of the policy's attention respectively. Industry categories outside the top-15 chart account for 45% of attention, showing that "Made in China 2025" is a highly comprehensive industrial policy that targets diverse industry categories.

Figure 12: Attention Allocation of "Made in China 2025"



CIPAD also enable researchers to fast compare similarity between industrial policies in terms of the industry categories they mentioned. By transforming policy full texts into distribution-of-attention vectors, researchers can measure policy similarity by calculating cosine similarity between policies' corresponding vectors. Cosine similarity ranges from 0 to 1, where 0 indicates no similarity at all, and 1 indicates complete similarity. In table 10, I demonstrate the top-3 provincial industrial policies that are the most and the least similar to "Made in China 2025" after the adoption of the latter. According to panel A of table 10, the provincial industrial policy that is most similar to "Made in China 2025" is an action plan stipulated by Hunan Provincial

Government to implement the central policy. By contrast, provincial industrial policies that are least similar to "Made in China 2025" are those focusing on industry categories like liquor, tobacco, and silk, which are barely mentioned in "Made in China 2025."

Table 10: Provincial Industrial Policies Most and Least Similar to "Made in China 2025"

Title	Time	Issue Agency	Cosine Simi.
Panel A: Provincial industrial policies that are most similar to "Made in China 2025"			
"Made in China 2025" Five-Year Action Plan	2015.11	Hunan Provincial Government	0.891
Opinions on Further Promoting "Made in China 2025"	2015.11	Henan Provincial Government	0.881
Implementation Plan for Transformation and Upgrading of Equipment Manufacturing Industry	2018.12	Shandong Provincial Government General Office	0.881
Panel B: Provincial industrial policies that are least similar to "Made in China 2025"			
Title	Time	Issue Agency	Cosine Simi.
Implementation Opinions on Promoting Supply-side Structural Reform in the Liquor Industry	2016.9	Guizhou Provincial Government General Office	0.001
Measures to Support The High-quality Development of the Tobacco Industry	2019.10	Yunnan Provincial Government	0.006
Guiding Opinions on Promoting the Inheritance and Development of the Silk Industry	2015.11	Zhejiang Provincial Government General Office	0.020

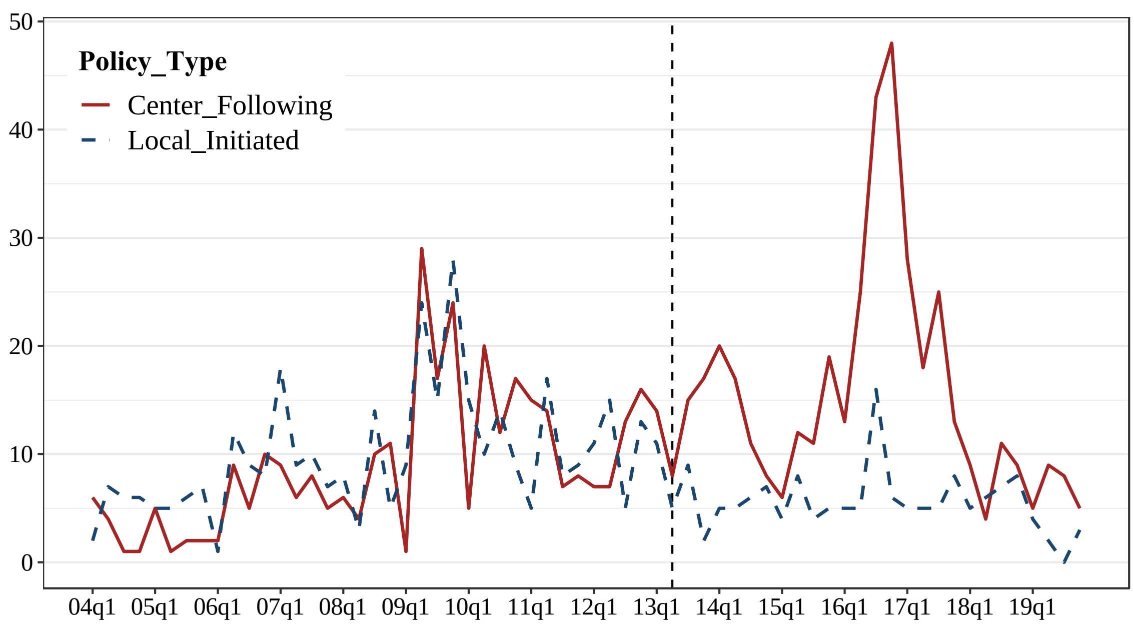
Note: The table presents the top-3 provincial industrial policies that are most similar and least similar to "Made in China 2025." Cosine similarity between distribution-of-attention vectors corresponding to each pair policies are shown in the last column of the table.

6.2 Preference to Use discretion: "Center-following" versus "Local-initiated" Policies

Based on CIPAD, I can now fast distinguish "center-following" and "local-initiated" industrial policies adopted by provincial governments in China. Here I define a provincial industrial policy as "center-following" if the distribution-of-attention vector of the policy is similar to (i.e. cosine similarity>0.8) that of at least one central industrial policy issued within the past three years. I define a provincial industrial policy as "local-initiated" if it is not similar to any central industrial policy issued within the past three years.

Figure 13 compares the time trends of the number of center-following policies and local-initiated ones adopted by the Chinese provincial governments between 2004 and 2019. Time points are year-by-quarter. The solid red line denotes center-following policies, while the dashed blue line denotes local-initiated policies. The vertical solid line shows the initiation of central disciplinary inspections in May 2013. Figure 13 shows that, the number of center-following policies and that of local-initiated policies adopted over time used to share similar time trends before 2013Q2, which is the starting point of central disciplinary inspections. However, 2013Q2 witnessed a big divergence between the time trends of two types of policies. Since then, the number of center-following policies have remained greater than that of local-initiated ones in most time.

Figure 13: Time Trends of the Number of Center-Following and Local-Initiated Industrial Policies by Provincial Governments from 2004 to 2019



To measure provincial governments' preference to use discretion in policymaking, I calculate the difference between the number of local-initiated policies and that of central-following ones adopted by each provincial government in each quarter of year based on function (1). Here *i* denotes each provincial government; *t* denotes each year-by-quarter time point.

$$Preference\ to\ Use\ Discretion_{it} = NumLocalInitiated_{it} - NumCentralFollowing_{it} \quad (1)$$

In robustness check, I use another way to measure preference to use discretion, that is, to calculate the proportion of local-initiated policies to the total number of policies adopted by a provincial government in each quarter of year. This is shown by function (2):

$$Preference\ to\ Use\ Discretion_{it} = \frac{NumLocalInitiated_{it}}{NumLocalInitiated_{it} + NumCentralFollowing_{it} + 1} \quad (2)$$

It is notably that I add one to the denominator to address the problem that the denominator may equal zero when a provincial government adopts no industrial policy. As I will discuss later, the results remain largely the same when I applied the alternative way to calculate provincial governments' preference to use discretion.

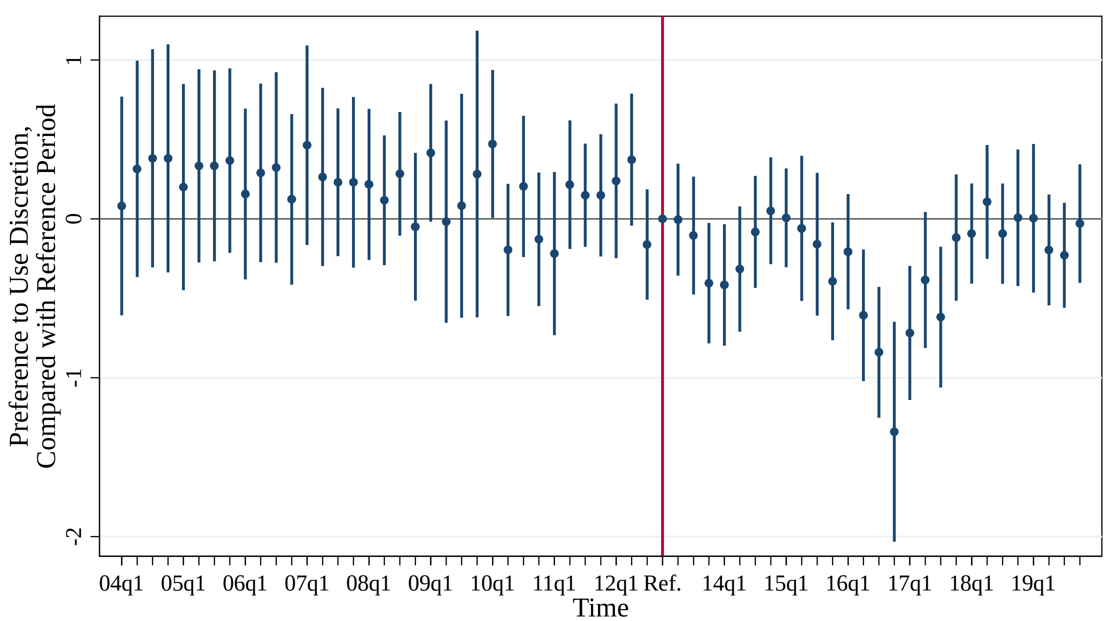
6.3 Baseline model: Pre-Post Comparison Design

The biggest challenge in this study is how to choose comparison group so that the spillover effect of disciplinary inspections on uninspected provinces is appropriately modeled. One strategy to deal with this issue is by conducting pre-post comparison. For each province (either inspected or uninspected), I compare post-event periods with a pre-event reference period that is right before the time when central disciplinary inspections were initiated in 2013Q2. The key assumption of pre-post comparison as an identification strategy is that, after properly controlling for observed variables, a provincial government's preference to use discretion in industrial policymaking (i.e. $NumLocalInitiated_{it} - NumCentralFollowing_{it}$) would have remained the same as that of the pre-event reference period in the absence of an inspection.

This assumption is plausible in the context of this study because empirical evidence shows that Chinese provincial governments' preference to use discretion in industrial policymaking was quite stable before the initiation of disciplinary inspections in 2013Q2. In figure 14, I choose two quarters (i.e. 2012Q4 and 2013Q1) right before the initiation of disciplinary inspections (i.e. 2013Q2) as the pre-event reference period. Then I compare provincial governments' preference to use discretion in each year-by-quarter between 2004 and 2019 with that of the reference period (2012Q4 and 2013Q1) by estimating the following equation:

$$Preference\ to\ Use\ Discretion_{it} = \sum_{j \in \{04Q1,\ldots,12Q3,13Q2,\ldots,19Q4\}} \gamma_j \cdot D_{j,t} + \alpha_i + \beta \cdot X_{it} + \epsilon_{it} \quad (3)$$

Figure 14 Compare Each Year-by-Quarter with the Pre-Event Reference Period



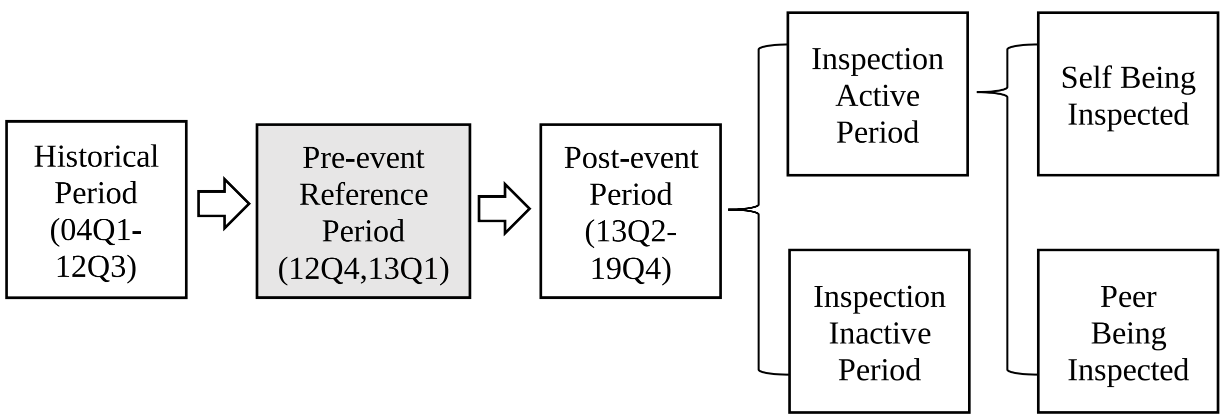
In equation (3), $D_{j,t} = 1$ if time point *t*=*j*; α_i controls for provincial fixed effect; X_{it} are control variables including provincial GDP (ln), industrial added value, and age and tenure of provincial governor and party chief. Variable descriptions and summary statistics are shown in Table 14. Robust standard errors clustered at the province level. The y axis of figure 14 shows the estimated values of γ_j. The x axis shows year-by-quarter time point j. As is shown by the figure, for a long historical period between 2004Q1 and 2012Q3, provincial governments' preference to use discretion remained statistically indifferent (95% confidence interval) from that of the pre-event reference period (i.e. 2012Q4 and 2013Q1) in most time points except one. The only time point that is statistically significant is above zero. This means by choosing the pre-event reference period as the comparison group, I are more likely to underestimate rather than overestimate the negative effect of central disciplinary inspections. It is only after the initiation of central inspections in 2013Q2 that the time points appear to be significantly lower than zero. These results give us confidence to choose the pre-event reference period as the comparison group.

Therefore, I apply the pre-post comparison design as the identification strategy in our study. I choose two quarters (i.e. 2012Q4 and 2013Q1) right before the initiation of central disciplinary inspections as the pre-event reference period. Then, I compare different post-event time points with the pre-event reference period. Figure 15 presents the diagram of the pre-post comparison design in our study. As is shown by the figure, I divide post-event period (i.e. >=2013Q2) into *inspection active period* and *inspection inactive period*. The former indicates the time points when at least one province is being inspected, and the later the opposite. Then I compare the two subperiods to the pre-event reference period based on function (4). The variable $Historical\,Period_t$ indicates the historical period (2004Q1-2012Q3) before the pre-event reference period. By comparing historical period with pre-event reference period, I are able to test whether provincial governments' preference to use discretion used to remain quite constant before the initiation of central disciplinary inspections.

$$Preference\ to\ Use\ Discretion_{it} = Inspection\ Active\ Period_t + Inspection\ Inactive\ Period_t + Historical\ Period_t + \alpha_i + \beta \cdot X_{it} + \epsilon_{it} \quad (4)$$

To distinguish between the scenarios when a province itself is undergoing inspection and when inspection is happening outside a province, I further divide *inspection active period* into *self being inspected* and *peer being inspected*. *Self Being Inspected* refers to the time points when a province itself is undergoing inspection. By contrast, *Peer Being Inspected* refers to the time points when the inspection is happening in other provinces rather than in a province itself. I estimate the new model by replacing the variable $Inspection\ Active\ Period_t$ in function (4) with the two variables $Self\ \ Being\ Inspected_{it}$ and $Peer\ Being\ Inspected_{it}$.

Figure 15: Diagram of the Pre-Post Comparison Design



6.4 Alternative identification strategy: two-way fixed effects model with spatial spillovers

In robustness check, I adopt a two-way fixed effects model with spatial spillovers as an alternative identification strategy to examine the robustness of the results.

As I mentioned before, disciplinary inspections could have a spillover effect on uninspected provinces. That means I could not directly use uninspected provinces as the comparison group. To address the issue, here I adopt a less strict assumption: for each round of inspection, uninspected provinces that are located far away enough from all the provinces being inspected would not be impacted by the inspection. The criterion for two provinces to be considered "far enough apart" is that the distance between their capitals is greater than 1000 km. As a reference, 1000 km is similar to the distance between Beijing and Shanghai, or between New York City and Chicago.

Based on the above assumption, I are able to conduct a two-way fixed effects model by using uninspected far-away-enough provinces as the comparison group. It is worth noting that provinces being inspected are different for each round of inspection, so the comparison group is also changing for each round of inspection. I identify the direct effect and spillover effect (Butts 2023) of disciplinary inspections based on the function below:

$$Preference\ to\ Use\ Discretion_{it} = \tau D_{it} + \gamma(1 - D_{it})S_{it} + \beta \cdot X_{it} + \mu_i + \lambda_t + \epsilon_{it} \quad (5)$$

D_{it} is a dummy variable indicating whether a province is being inspected. S_{it} is a dummy variable indicating whether a province is located near (i.e. distance<=1000km) a province that is being inspected. X_{it} are control variables including provincial GDP (ln), industrial added value, and age and tenure of provincial governor and party chief. μ_i is province fixed effect, and λ_t is year-by-quarter fixed effect. Robust standard errors clustered at the province level. τ is the direct effect of anti-corruption inspection on a province being inspected, and γ is the spillover effect of anti-corruption inspection on an uninspected province located nearby.

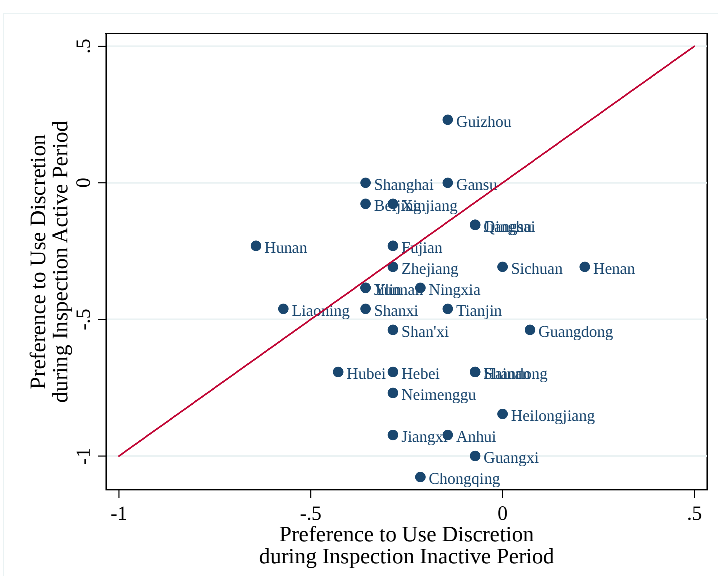
Recent literature shows that TWFE estimation with staggered adoption and heterogenous treatment effect may fail to produce readily interpretable results (de Chaisemartin and D’Haultfœuille 2020; Imai and Kim 2021). To address the concern, here I apply two-stage TWFE suggested by (Butts and Gardner 2021; Gardner 2022). Two-stage TWFE, as its name suggests, contains two stages. The first stage is to estimate group and period fixed effects by only using the subsample of untreated observations. In the second stage, the estimated fixed effects are subtracted from observed outcomes, after which treatment effects are estimated by using the whole sample. Butts and Gardner (2021) designed a Stata package for the above two-stage procedure.

7. Main Results

7.1 Baseline

To examine how provincial governments' preference to use discretion in industrial policymaking changes due to central disciplinary inspections, I first draw a scatter plot to do some descriptive analysis. In figure 16, the x axis and the y axis measure a provincial government's preference for using discretion during "inspection inactive period" and "inspection active period" respectively. Each dot represents a province. Figure 16 shows that most dots are located below the 45 degree reference line. This means for most provinces, their preference to use discretion during inspection active period is lower than that during inspection inactive period. This result suggests a

Figure 16: Compare Preference to Use Discretion during Inspection Active and Inactive Periods



strong correlation between central disciplinary inspections and provincial governments' willingness to use discretion in policymaking.

Table 11 presents the results of the pre-post comparison model (2012Q4 and 2013Q1). Model 1 shows that, during inspection active period, provincial governments' preference to use discretion is 0.352 (or 39.8% of a standard deviation) lower than that in the pre-event reference period. The magnitude of the decline is substantial and is statistically significant at the 0.01 level. By contrast, decrease in preference to use discretion during inspection inactive period is 0.111, which is much less in magnitude and is statistically insignificant.

Table 11: Baseline Results of the Pre-Post Comparison Model

	Preference to Use Discretion		
VARIABLES	(1)	(2)	(3)
Inspection Inactive Period	-0.111	-0.111	-0.109
	(0.115)	(0.115)	(0.115)
Inspection Active Period	-0.352**		
	(0.117)		
Self under Inspection		-0.243	-0.243
		(0.183)	(0.183)
Peer under Inspection		-0.382**	
		(0.109)	
Inspection within 500km			-0.321*
			(0.122)
Inspection within 1000 km			-0.533***
			(0.134)
Inspection over 1000km			-0.193
			(0.194)
Historical Period	0.105	0.104	0.103
	(0.130)	(0.130)	(0.130)
Province Fixed Effects	√	√	√
Province Economic controls	√	√	√
Province leader controls	√	√	√
Observations	1,920	1,920	1,920
R-squared	0.059	0.060	0.061

Note: This table presents the effects of central disciplinary inspections on provincial governments' preference to use discretion in industrial policymaking. Province economic controls include provincial GDP (ln) and industrial added value. Province leader controls include the age and tenure of the party chief and the governor of each province. Robust standard errors clustered at province level are reported in parentheses. *** p<0.001, ** p<0.01, * p<0.05.

Model 2 further divides inspection active period into two variables: *Self Under Inspection* and *Peer Under Inspection*. The first variable indicate the scenario when a province itself is being inspected, and the second variable indicates that a province is not being inspected but its peers are. To our surprise, although the coefficients of both variables are negative, the coefficient of *Peer Under Inspection* is larger in magnitude and is the only one that is statistically significant. This result suggests that the impact of central disciplinary inspections is stronger for uninspected provinces who are observing their peers being inspected than for provinces themselves being inspected. A possible explanation of this result is that provinces being inspected are under close supervision by inspection teams, so they don't have much operating space to change their policymaking behaviors. By contrast, provinces that are not being inspected have more opportunities to adjust their behaviors when they observe other provinces undergoing inspections.

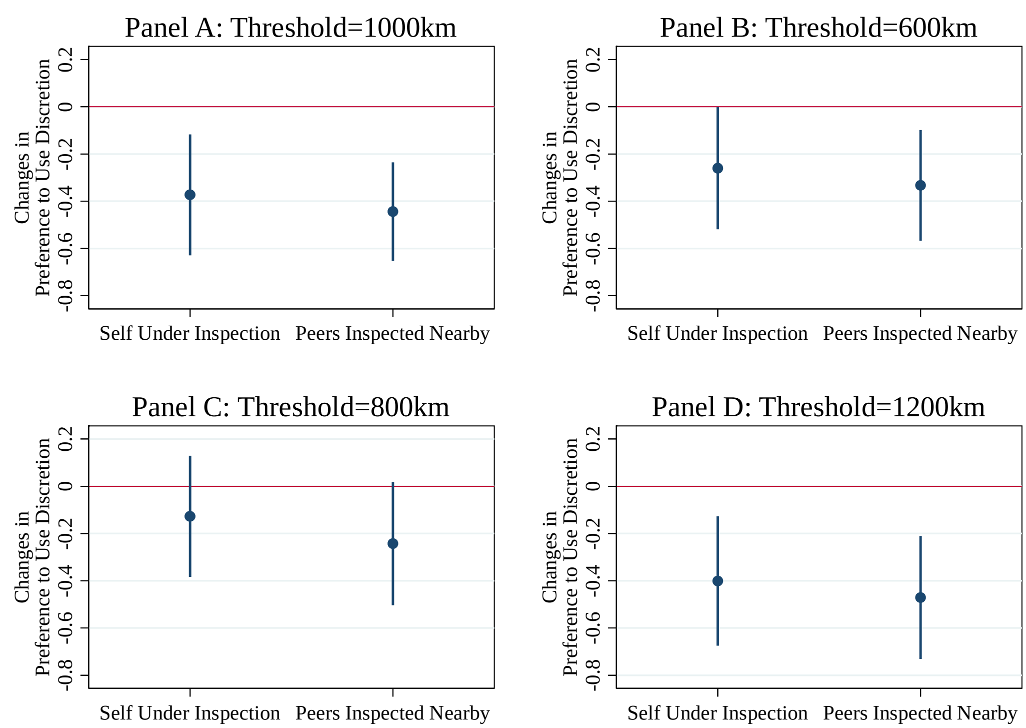
Model 3 takes a step further by considering whether the effect of central disciplinary inspections on uninspected provinces is associated with the distance between the latter and the nearest province being inspected. Model 3 replace the variable *Pees Under Inspection* with three new variables: *Inspection within 500km*, *Inspection within 1000km*, and *Inspection over 1000km*. Interestingly, I find that an uninspected province would be impacted by central disciplinary inspections only if the inspections take place within 1000km of it. This result suggests that the spillover effect of central disciplinary inspections may not be able to reach the uninspected provinces that are located too far away from where the inspections happen.

7.2 Robustness Check

In the last section, I find that the spillover effect of central disciplinary inspections on uninspected provinces may be limited by distance. This inspires us to use a TWFE model with spatial spillovers to identify the effect of central disciplinary inspections.

Figure 17 reports the results of TWFE model with spatial spillovers. Panel A of figure 17 shows the effects of disciplinary inspections on provinces being inspected and on uninspected provinces with peers being inspected nearby. Panel A of figure 17 reconfirms our finding that central disciplinary inspections decrease provincial governments' preference to use discretion in policymaking, and the negative effect of inspections is stronger for uninspected provinces than for provinces being inspected. The only difference between the results of the TWFE model and those of the pre-post comparison model is that the effect of inspections on provinces being inspected is significantly negative in the TWFE model.

Figure 17: Results of the TWFE Model with Spatial Spillovers



A concern of TWFE model with spatial spillovers is whether a distance threshold of 1000km is appropriate, and whether the results would be different if I change the threshold. To check the robustness of the results in TWFE model, in panel B, C, D of figure 17, I changed the distance threshold to 600km, 800km, and 1200km respectively. I find the results are generally stable. The coefficients in panel C become insignificant, but the direction and the magnitude of the coefficients are consistent with the previous results.

I also examine whether the results would change if I use an alternative way to measure provincial governments' preference to use discretion. This time I measure preference for using discretion based on function (2) by calculating the proportion of local-initiated policies to total number of policies. In Figure 13, I present the time trend of provincial governments' preference to use discretion over time. As is shown by the figure, after the initiation of disciplinary inspections, provincial governments' preference to use discretion remain at a relatively low level, with most values lower than 0.1. Figure 13 also shows much fluctuation of the value by using the new measure. In this case, pre-post comparison is no longer an appropriate method. I apply the TWFE model with spatial spillovers instead. Figure 14 shows the regression results by using four different distance thresholds. I find the results are largely the same by using the alternative way of measuring provincial governments' preference to use discretion in policymaking.

Moreover, I test the robustness of our results by adjusting the time period of our sample data. In the previous analyses, I choose our sample period to be between 2004 and 2019. However, there might be concern that the sample period is too long and might be impacted by some significant events like the global financial crisis in 2007 and 2008. Here I change the sample period from 2004-2019 to 2011-2019. Then I reran the pre-post comparison model. The regression results are reported in Table 15 in the appendix. The results are quite the same as before.

7.3 Central disciplinary inspections and increasing policy homogeneity across provinces

A key difference between center-following and local-initiated policies is that the sources of the latter tend to be more diverse than those of the former. Center-following policies are largely attributed to a top-down diffusion process in which bureaucratic agencies imitate what has been proposed by their superior authority, while local-initiated policies may come from various channels, such as governments' own indigenous inventions, horizontal diffusion from other governments, or bottom-up diffusion from grassroots agencies.

As a result, by decreasing bureaucrats' preference to adopt local-initiated policies compared to center-following ones, top-down inspections can lead to increasing policy homogeneity among bureaucratic agencies. In the context of provincial industrial policymaking in China, this means that provincial industrial policies adopted during the inspection active period tend to be more similar to each other across provinces than during the inspection inactive period.

To illustrate this point, for each provincial industrial policy, I calculate the number of provinces that have adopted similar policies in the past three years. I then calculate the composition of these values among local-initiated policies and center-following policies, respectively. The results are shown in table 12. For local-initiated policies, 67.89% of them are pure indigenous innovations in the sense that no other provincial government (and also no other central agency, since it is local-initiated) has adopted a similar policy before. By contrast, for center-following policies, this number is only 21.91%. On the other hand, only 0.19% of local-initiated policies have been adopted by more than 10 provinces prior to their own adoption, but this number is as high as 15.03% for center-following policies. Therefore, by reducing provincial governments' preference for local-initiated policies compared to central-following ones, central disciplinary inspections are likely to lead to increasing policy homogeneity across provinces.

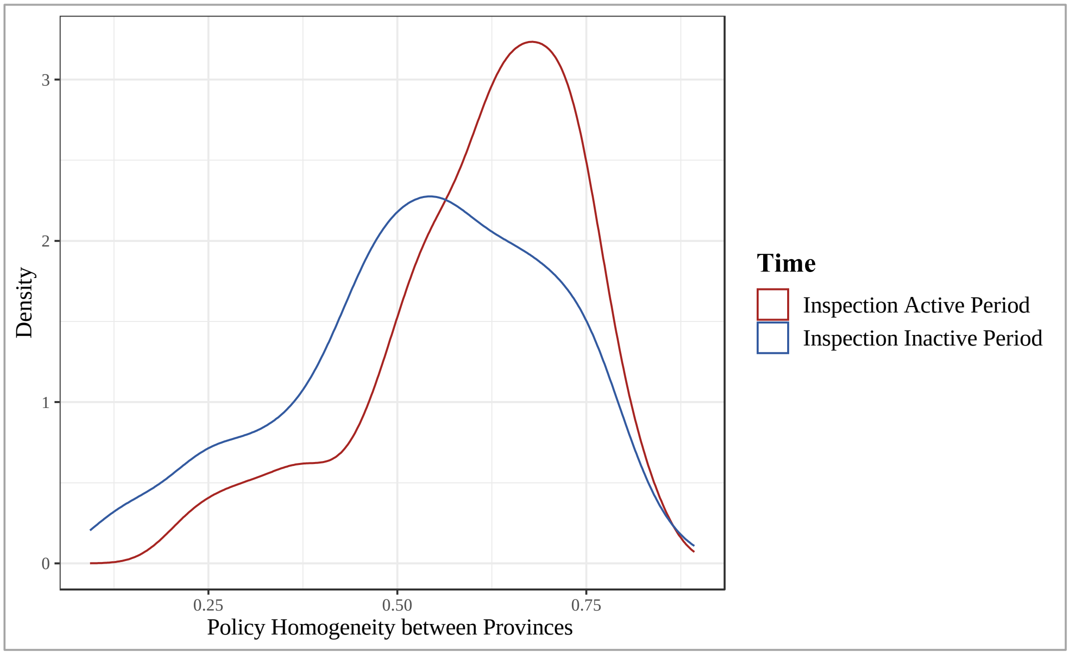
Table 12: Composition of the Number of Provinces Adopting Similar Policies Prior to the Adoption of A Policy Itself

Num. of Provinces Adopting Similar Policies	**Center-Following Policy**	**Local-Initiated Policy**
0	21.91%	67.89%
1	13.94%	16.05%
2	9.03%	7.35%
3	10.09%	3.68%
4	7.17%	3.09%
5	7.30%	0.77%
6	5.84%	0.39%
7	2.92%	0.19%
8	4.38%	0.19%
9	2.39%	0.19%
More than 10	15.03%	0.19%
Grand Total	**100.00%**	**100.00%**

Note: This table calculates, for central-following and local-initiated policies respectively, the composition of number of provinces that have already adopted similar policies prior to the adoption of a policy itself.

In figure 18, I take a step further by calculating the overall policy homogeneity between provinces during inspection active period and inspection inactive period respectively. Policy homogeneity between provinces is measured by similarity of the average distribution-of-attention vectors corresponding to provinces during each period of time. Figure 18 shows that, during inspection active period, the density distribution of policy homogeneity across provinces shifts towards the right compared to that during inspection inactive period. This result suggests strong correlation between central disciplinary inspections and industrial policy homogeneity across provinces in China.

Figure 18: Density Distribution of Policy Homogeneity between Provinces



8. Conclusion

In this study, I examine how bureaucrats actively adjust their preference for using discretion in policymaking in response to political control from above. More specifically, I examine how top-down inspections as a political control instrument would impact bureaucrats' willingness to adopt local-initiated policies compared to center-following ones. I argue that, in an under-institutionalized accountability system, top-down inspections can cause widespread decrease in bureaucrats' preference for local-initiated policies compared to center-following ones not only for bureaucrats being inspected but also for uninspected bureaucrats who are influenced by the chilling environment.

I place our arguments in the context of provincial industrial policymaking in China. By analyzing an original dataset of 612 central-level and 1907 provincial-level industrial policies stipulated between 2001 and 2019, I find strong evidence that provincial governments substantially decrease their use of discretion in industrial policymaking during the time when Chinese central authority conduct disciplinary inspections on provincial governments. Moreover, I find that the effect of central disciplinary inspections is even stronger for uninspected provinces who are observing their peers being inspected than for the provinces being inspected themselves. Extensive analysis shows that central disciplinary inspections are associated with increasing policy homogeneity across provinces due to decreasing preference for provincial governments to use discretion in policymaking.

Our study questions an implicit assumption that has received little scrutiny in the literature on political control of bureaucracy. This assumption is that there are no additional costs for bureaucrats to actively exercise their discretion as long as they take actions within statutory constraints. Our study shows, however, that bureaucrats can be quite cautious about using their discretion when faced with the risk of top-down inspections in an under-institutionalized accountability system. Future research may explore more scenarios in which bureaucrats voluntarily curtail their preference to use discretion in policymaking.

Our study also discusses the challenge of political control of bureaucracy in developing and non-democratic countries. Due to lack of ability to enact high-quality laws and regulations and the absence of an independent judiciary, developing and non-democratic countries often struggle with an under-institutionalized accountability system. Such a system is characterized by incomplete or inadequately developed institutions to regulate bureaucrats, as well as inconsistent and non-transparent enforcement processes to hold bureaucrats accountable. This results in a bureaucracy that is guided more by “circumstances” than by “rules.” However, bureaucrats’ selective adherence to rules can make them highly vulnerable to any top-down inspection or investigation. As a result, bureaucrats would actively adopt various risk-avoidance strategies to protect themselves, and these risk-avoidance strategies can complicate the process of political control and lead to unintended consequences. Future research on the challenge of governing bureaucrats in an under-institutionalized accountability system could be of great academic importance and policy relevance.

9. Appendix A: Tables and Figures

Table 13: Detailed Lists of Provinces Being Inspected during the Nine Rounds of Disciplinary inspections from 2013 to 2019

ID	Time Period	Provinces Being Inspected
1	2013Q2-2013Q3	Hubei, Neimenggu, Chongqing, Guizhou, Jiangxi
2	2013Q4	Jilin, Shanxi, Anhui, Hunan, Guangdong, Yunnan
3	2014Q2	Beijing, Tianjin, Liaoning, Fujian, Shandong, Henan, Hainan, Gansu, Ningxia, Xinjiang
4	2014Q3	Guangxi, Shanghai, Qinghai, Zhejiang, Hebei, Shan’xi, Heilongjiang, Sichuan, Jiangsu
5	2016Q1-2016Q2	Liaoning, Anhui, Shandong, Hunan
6	2016Q3	Tianjin, Jiangxi, Henan, Hubei
7	2016Q4	Beijing, Chongqing, Guangxi, Gansu
8	2017Q1-2017Q2	Neimenggu, Jilin, Yunnan, Shan’xi
9	2018Q1-2018Q2	Fujian, Henan, Sichuan, Guizhou, Liaoning, Heilongjiang, Jiangsu, Shandong, Hunan, Ningxia, Guangdong, Hainan, Heibei, Shanxi

Table 14: Variable Descriptions and Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Inspection Active Period	1920	.203	.402	0	1
Inspection Inactive Period	1920	.219	.414	0	1
Self under Inspection	1920	.044	.206	0	1
Peer under Inspection	1920	.159	.366	0	1
Inspection within 500km	1920	.081	.272	0	1
Inspection within 1000 km	1920	.057	.232	0	1
Inspection over 1000km	1920	.021	.143	0	1
Historical Period	1920	.547	.498	0	1
Party Chief Older Than 60	1920	.579	.494	0	1
Governor Older Than 60	1920	.283	.451	0	1
Tenure of Party Chief	1920	3.202	2.427	1	18
Tenure of Governor	1920	2.958	1.82	1	10
GDP (log form)	1920	9.308	1.034	6.095	11.59
Industry Value Added	1920	6516.435	6813.714	98.4	39141.8

Table 15: Results of the Pre-Post Comparison Model, 2011-2019

	Preference to Use Discretion		
VARIABLES	(1)	(2)	(3)
Inspection Inactive Period	-0.191	-0.188	-0.182
	(0.130)	(0.132)	(0.132)
Inspection Active Period	-0.407**		
	(0.114)		
Self under Inspection		-0.291	-0.290
		(0.179)	(0.180)
Peer under Inspection		-0.437***	
		(0.107)	
Inspection within 500km			-0.371**
			(0.118)
Inspection within 1000 km			-0.578***
			(0.138)
Inspection over 1000km			-0.274
			(0.193)
Historical Period	0.153	0.152	0.152
	(0.135)	(0.135)	(0.136)
Province Fixed Effects	√	√	√
Province Economic controls	√	√	√
Province leader controls	√	√	√
Observations	1,080	1,080	1,080
R-squared	0.059	0.061	0.065

Note: This table presents the effects of central disciplinary inspections on provincial governments' preference to use discretion in industrial policymaking by using the data sample between 2011 and 2019. Province economic controls include provincial GDP (ln) and industrial added value. Province leader controls include the age and tenure of the party chief and the governor of each province. Robust standard errors clustered at province level are reported in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$.

Figure 19: Time Trend in Provincial Governments' Preference for Using Discretion in Policymaking, Using the Alternative Measure

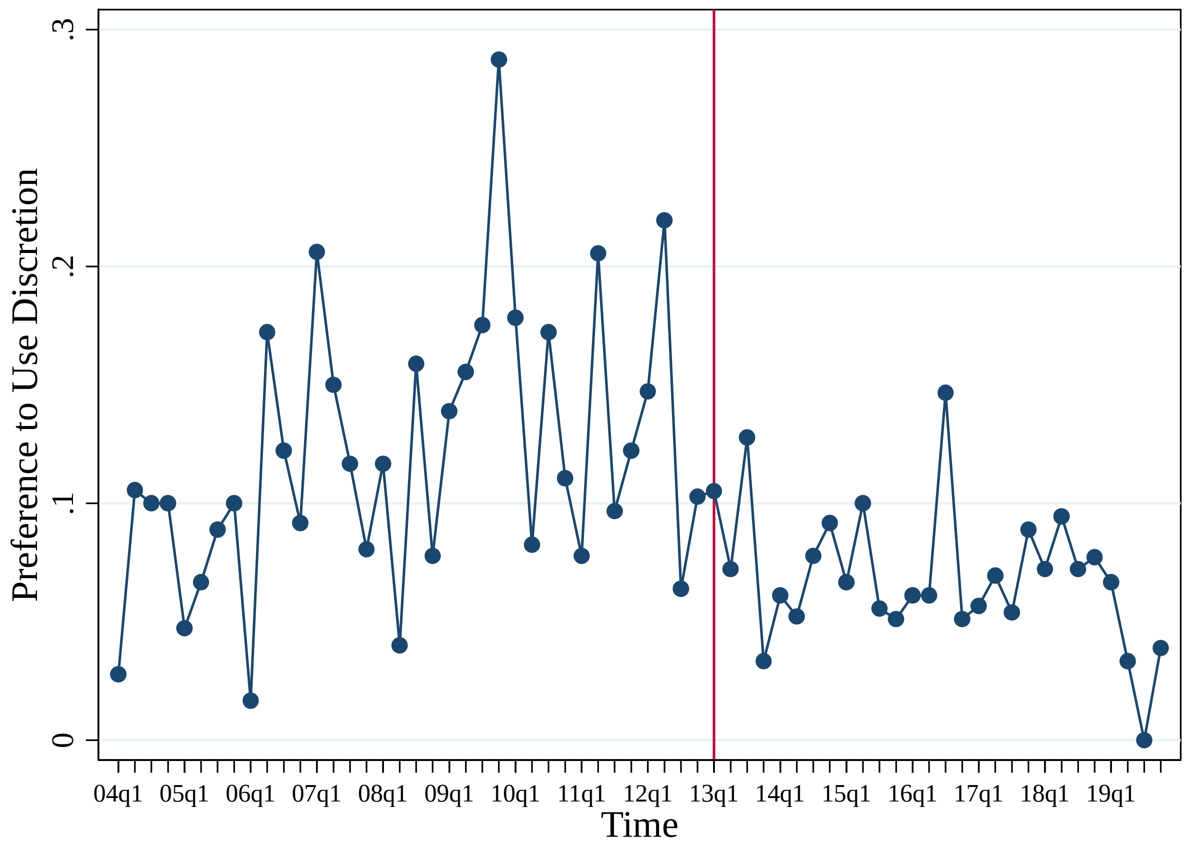
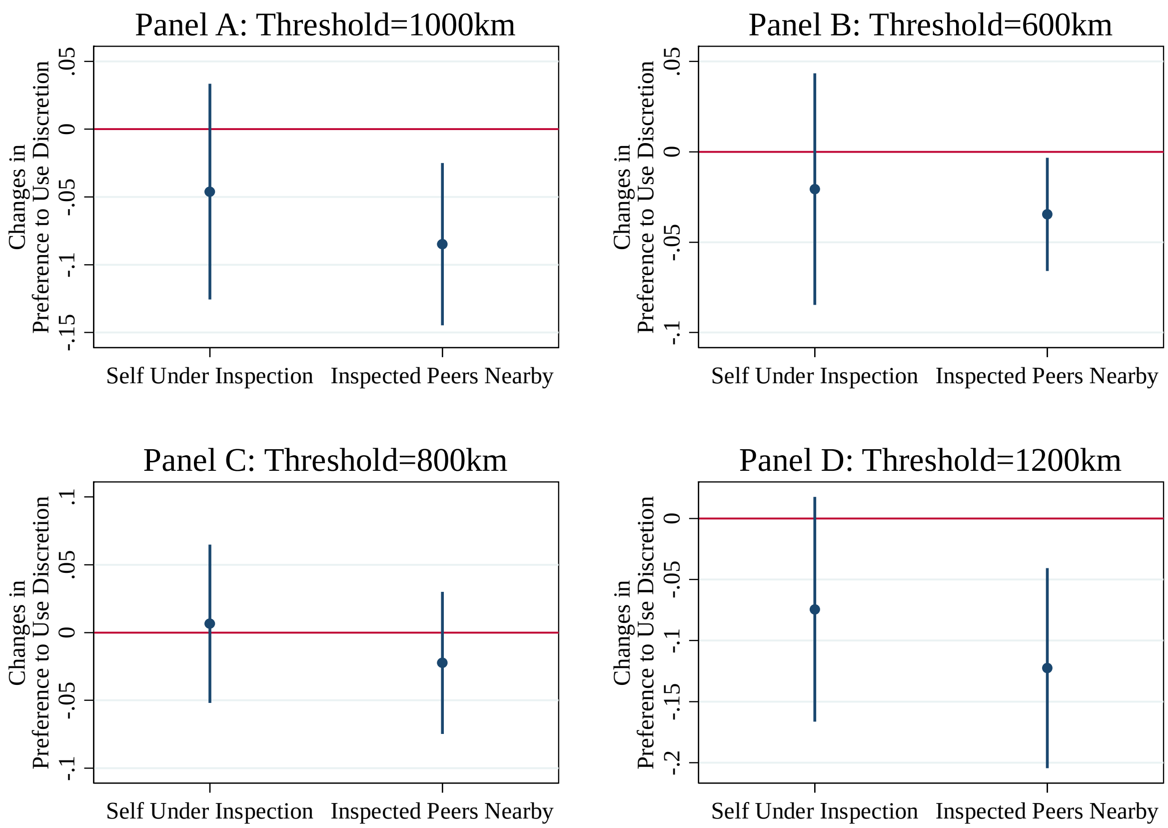


Figure 20: Results of the TWFE Model with Spatial Spillovers, Using the Alternative Measure



10. Appendix B: Transforming Policies into Distribution-of-Attention Vectors

In this section, I show an example of how to transform an industrial policy into a distribution-of-attention vector which records the amount of attention the policy pays to each of the 155 industry categories. Our example industrial policy is "Three-Year Plan for Chongqing's Equipment Manufacturing Industry" adopted by Chongqing government in 2012.

STEP ONE: identify all the manufacturing phrases which denote specific manufacturing industry categories in the policy text. The following sentence is an excerpt from the example industrial policy. All the identified manufacturing phrases are highlighted in red.

"重点发展千亿级**摩托车**产业集群和**风电成套装备**、**轨道交通装备**、**环保安全装备**、**船舶零部件**、**航空航天装备**、**能源装备**、**内燃机**、**大型铸锻件**及**关键基础件**等 10 个百亿级产业集群，**重大装备总装**及配套本地化率达到 80%以上。

STEP TWO: categorize each manufacturing phrase into one (or more than one) of the 155 industry categories. The 155 industry categories are based on the 3-digit codes in Chinese Industrial Classification for National Economic Activities (GB/T 4754-2002).

Table 16： Categorize manufacturing phrases into industry categories

Manufacturing Phrases	Industry Category (with 3-digit code)
摩托车 Motorcycle	373:摩托车制造 Motorcycle Manufacturing
风电成套装备 Wind-Power Equipment	351:锅炉及原动机制造 391: 电机制造 Boiler & Prime Mover Manufacturing; Motor Manufacturing
轨道交通装备 Rail Transportation Equipment	371:铁路运输设备制造，399:其他电器机械制造 Railroad Transportation Equipment; Other Electrical Machinery
环保安全装备 Environmental Protection & Safety Equipment	369: 环保、社会公共安全及其他专用设备制造 Environmental Protection, Public Safety and Other Special Equipment Manufacturing
船舶及零部件 Ship & Ship Parts	367: 农林牧渔专用机械制造，375: 船舶及浮动装置制造

	Special Machinery Manufacturing for Agriculture, Forestry, Animal Husbandry and Fishery; Ship and Floating Device Manufacturing
……	

STEP THREE: calculate the amount of attention that a policy pays to each industry category by counting the ratio of the manufacturing phrases classified into that industry category.

Table 17: Calculate Distribution of Attention

Three-Year Plan for Chongqing's Equipment Manufacturing Industry				
Total num. of manufacturing phrases identified in the policy full text: 518				
3-Digit Code	Industry Category	Example Manufacturing Phrases Identified in the Policy Full Text	Frequency	Ratio
369	环保、社会公共安全及其他专用设备制造 Environmental Protection, Public Safety and Other Special Equip.	环保安全装备、大型烟气脱硫装备 Environmental Protection & Safety Equipment, Large-Scale Flue Gas Desulfurization Equipment	41	0.079
375	船舶及浮动装置制造 Ship and Floating Device Manufacturing	船舶及零部件、小型游船、工程船、海洋工程装备 Ship & Ship Parts, small tourist boats, engineering ships, marine engineering equipment	31	0.060
392	输配电及控制设备 Power Transmission and Distribution and Control Equipment	超高压变压器、特高压输变电装备、智能电网装备 UHV transformers, UHV power transmission equipment, smart grid equipment	35	0.068
…				

STEP FOUR: create a 155-dimension vector, and the value of each dimension equals the amount of attention that the industrial policy pays to the corresponding industry category. The 155-dimension vector of the example industrial policy should be like this, and the sequence of the values depend on the sequence of the 3-digit codes of the corresponding industry categories:

$$(x_1, \dots, 0.079, \dots, 0.060, \dots, 0.068, \dots,\ x_{155})$$

11. References

Aghion, Philippe et al. 2015. "Industrial Policy and Competition." *American Economic Journal: Macroeconomics* 7(4): 1–32.

Ang, Yuen Yuen. 2020. *China's Gilded Age: The Paradox of Economic Boom and Vast Corruption*. Cambridge: Cambridge University Press.

Bawn, Kathleen. 1997. "Choosing Strategies to Control the Bureaucracy: Statutory Constraints, Oversight, and the Committee System." *The Journal of Law, Economics, and Organization* 13(1): 101–26.

Bolton, Alexander, and Sharece Thrower. 2019. "The Constraining Power of the Purse: Executive Discretion and Legislative Appropriations." *The Journal of Politics* 81(4): 1266–81.

Bozeman, Barry. 1993. "A Theory Of Government 'Red Tape.'" *Journal of Public Administration Research and Theory*.

Butts, Kyle. 2023. "Difference-in-Differences Estimation with Spatial Spillovers." http://arxiv.org/abs/2105.03737 (January 9, 2024).

Butts, Kyle, and John Gardner. 2021. "{did2s}: Two-Stage Difference-in-Differences." *arXiv.org*. https://arxiv.org/abs/2109.05913v2 (January 10, 2024).

Carpenter, Daniel P. 1996. "Adaptive Signal Processing, Hierarchy, and Budgetary Control in Federal Regulation." *American Political Science Review* 90(2): 283–302.

de Chaisemartin, Clément, and Xavier D'Haultfœuille. 2020. "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects." *American Economic Review* 110(9): 2964–96.

Chen, Ling. 2018. *Manipulating Globalization: The Influence of Bureaucrats on Business in China*. Stanford, CA: Stanford University Press.

———. 2022. "Getting China's Political Economy Right: State, Business, and Authoritarian Capitalism." *Perspectives on Politics* 20(4): 1397–1402.

Chen, Ling, and Barry Naughton. 2016. "An Institutionalized Policy-Making Mechanism: China's Return to Techno-Industrial Policy." *Research Policy* 45(10): 2138–52.

Chen, Ting, and James Kai-sing Kung. 2019. "Busting the 'Princelings': The Campaign Against Corruption in China's Primary Land Market*." *The Quarterly Journal of Economics* 134(1): 185–226.

Chen, Wei, Shu Keng, and Siyi Zhang. 2023. "China's Bureaucratic Slack: Material Inducements and Decision-Making Risks among Chinese Local Cadres." *The China Journal* 89: 70–94.

Dessein, Wouter. 2002. "Authority and Communication in Organizations." *Review of Economic Studies* 69(4): 811–38.

Duflo, Esther, Michael Greenstone, Rohini Pande, and Nicholas Ryan. 2018. "The Value of Regulatory Discretion: Estimates From Environmental Inspections in India." *Econometrica* 86(6): 2123–60.

Epstein, David, and Sharyn O'Halloran. 1994. "Administrative Procedures, Information, and Agency Discretion." *American Journal of Political Science* 38(3): 697.

———. 1999. *Delegating Powers: A Transaction Cost Politics Approach to Policy Making under Separate Powers*. Cambridge: Cambridge University Press.

Evans, Peter B. 1989. "Predatory, Developmental, and Other Apparatuses: A Comparative Political Economy Perspective on the Third World State." *Sociological Forum* 4(4): 561–87.

Fang, Hanming, Jing Wu, Rongjie Zhang, and Li-An Zhou. "Understanding the Resurgence of the SOEs in China: Evidence from the Real Estate Sector."

Gailmard, Sean. 2002. "Expertise, Subversion, and Bureaucratic Discretion." *The Journal of Law, Economics, and Organization* 18(2): 536–55.

Gailmard, Sean, and John W. Patty. 2012. "Formal Models of Bureaucracy." *Annual Review of Political Science* 15(1): 353–77.

Gardner, J. 2022. "Two-Stage Differences in Differences." https://www.semanticscholar.org/paper/Two-stage-differences-in-differences-Gardner/8c98f4e69eb0f287ea4ab0b9d8adfa240feb7ed6 (January 15, 2024).

Gates, Margaret J., and Marjorie Fine Knowles. 1984. "The Inspector General Act in the Federal Government: A New Approach to Accountability." *Alabama Law Review* 36(2): 473–514.

Gore, Albert. 1993. *From Red Tape to Results: Creating a Government That Works Better and Costs Less, Report of the National Performance Review*. Collingdale, PA: Diane Publishing.

Grandy, Jake B., and Shon R. Hiatt. 2020. "State Agency Discretion and Entrepreneurship in Regulated Markets." *Administrative Science Quarterly* 65(4): 1092–1131.

Gueorguiev, Dimitar D. 2018. "Dictator's Shadow." *China Perspectives* 2018(1–2): 17–26.

Haggard, Stephan. 2018. *Developmental States*. Cambridge University Press.

Hammond, T. H., and J. H. Knott. 1996. "Who Controls the Bureaucracy?: Presidential Power, Congressional Dominance, Legal Constraints, and Bureaucratic Autonomy in a Model of Multi-Institutional Policy-Making." *Journal of Law, Economics, and Organization* 12(1): 119–66.

Harrison, Ann, and Andrés Rodríguez-Clare. 2010. "Trade, Foreign Investment, and Industrial Policy for Developing Countries." In *Handbook of Development Economics*, Elsevier, 4039–4214.

Hausmann, Ricardo, Jason Hwang, and Dani Rodrik. 2007. "What You Export Matters." *Journal of Economic Growth* 12(1): 1–25.

Hill, Jeffrey S., and James E. Brazier. 1991. "Constraining Administrative Decisions: A Critical Examination of the Structure and Process Hypothesis." *The Journal of Law, Economics, and Organization* 7(2): 373–400.

Hood, Christopher. 2011. *The Blame Game: Spin, Bureaucracy, and Self-Preservation in Government*. Princeton University Press.

Huber, John D., and Charles R. Shipan. 2002. *Deliberate Discretion?: The Institutional Foundations of Bureaucratic Autonomy*. Cambridge University Press.

Imai, Kosuke, and In Song Kim. 2021. "On the Use of Two-Way Fixed Effects Regression Models for Causal Inference with Panel Data." *Political Analysis* 29(3): 405–15.

Jiang, Junyan, and Yu Zeng. 2020. "Countering Capture: Elite Networks and Government Responsiveness in China's Land Market Reform." *The Journal of Politics* 82(1): 13–28.

Juhász, Réka, Nathaniel Lane, and Dani Rodrik. 2023. *The New Economics of Industrial Policy*. SocArXiv. preprint. https://osf.io/gsyq4 (August 7, 2023).

Krugman, Paul R., ed. 1995. *Strategic Trade Policy and the New International Economics*. 7. pr. Cambridge, Mass.: MIT Press.

Landry, Pierre F., Xiaobo Lü, and Haiyan Duan. 2018. "Does Performance Matter? Evaluating Political Selection Along the Chinese Administrative Ladder." *Comparative Political Studies* 51(8): 1074–1105.

Lin, Justin, and Ha-Joon Chang. 2009. "Should Industrial Policy in Developing Countries Conform to Comparative Advantage or Defy It? A Debate Between Justin Lin and Ha-Joon Chang." *Development Policy Review* 27(5): 483–502.

Lin, Justin Yifu. 2011. "New Structural Economics: A Framework for Rethinking Development1." *The World Bank Research Observer* 26(2): 193–221.

Liu, Ernest. 2019. "Industrial Policies in Production Networks*." *The Quarterly Journal of Economics* 134(4): 1883–1948.

Lü, Xiaobo, and Pierre F. Landry. 2014. "Show Me the Money: Interjurisdiction Political Competition and Fiscal Extraction in China." *American Political Science Review* 108(3): 706–22.

Mascarenhas, R. C. 1993. "Building an Enterprise Culture in the Public Sector: Reform of the Public Sector in Australia, Britain, and New Zealand." *Public Administration Review* 53(4): 319.

McCubbins, Mathew D., and Thomas Schwartz. 1984. "Congressional Oversight Overlooked: Police Patrols versus Fire Alarms." *American Journal of Political Science* 28(1): 165–79.

McCubbins, Matthew D., Roger G. Noll, and Barry R. Weingast. 1987. "Administrative Procedures as Instruments of Political Control." *The Journal of Law, Economics, and Organization* 3(2): 243–77.

———. 1989. "Structure and Process, Politics and Policy: Administrative Arrangements and the Political Control of Agencies." *Virginia Law Review* 75(2): 431–82.

Moe, T. M. 1990. "Political Institutions: The Neglected Side of the Story." *Journal of Law, Economics, and Organization* 6(special): 213–53.

Moe, Terry M. 1987. "An Assessment of the Positive Theory of 'Congressional Dominance.'" *Legislative Studies Quarterly* 12(4): 475.

———. 2012. "Delegation, Control, and the Study of Public Bureaucracy." *The Forum* 10(2).

Parker, Sharon K., and Sandra Ohly. 2008. "Designing Motivating Jobs: An Expanded Framework for Linking Work Characteristics and Motivation." In *Work Motivation*, Routledge, 260–311.

Prud'homme, Dan. 2016. "Dynamics of China's Provincial-Level Specialization in Strategic Emerging Industries." *Research Policy* 45(8): 1586–1603.

Routley, Laura. 2012. "Developmental States: A Review of the Literature."

Tan, Yeling. 2020. "Disaggregating 'China, Inc.': The Hierarchical Politics of WTO Entry." *Comparative Political Studies* 53(13): 2118–52.

Tassinari, Mattia, Elisa Barbieri, Giovanni Morleo, and Marco Rodolfo Di Tommaso. 2019. "Targeted Industrial Policy and Government Failures: Insights from the South Korean Experience." *International Journal of Emerging Markets* 16(2): 221–40.

Verbeeten, Frank H. M., and Roland F. Speklé. 2015. "Management Control, Results-Oriented Culture and Public Sector Performance: Empirical Evidence on New Public Management." *Organization Studies* 36(7): 953–78.

Volden, Craig. 2002. "Erratum: A Formal Model of the Politics of Delegation in a Separation of Powers System." *American Journal of Political Science* 46(2): 476.

Wang, Erik H. 2022. "Frightened Mandarins: The Adverse Effects of Fighting Corruption on Local Bureaucracy." *Comparative Political Studies* 55(11): 1807–43.

Wang, Shaoda, and David Y Yang. 2023. "Policy Experimentation in China: The Political Economy of Policy Learning."

Weaver, R. Kent. 1986. “The Politics of Blame Avoidance.” *Journal of Public Policy* 6(4): 371–98.

Wedeman, Andrew. 2005. “Anticorruption Campaigns and the Intensification of Corruption in China.” *Journal of Contemporary China* 14(42): 93–116.

Weingast, Barry R. 1984. “The Congressional-Bureaucratic System: A Principal Agent Perspective (with Applications to the SEC).” *Public Choice* 44(1): 147–91.

Wood, B. Dan, and Richard W. Waterman. 1991. “The Dynamics of Political Control of the Bureaucracy.” *American Political Science Review* 85(3): 801–28.

Xiao, Shiyang, and Xufeng Zhu. 2022. “Bureaucratic Control and Strategic Compliance: How Do Subnational Governments Implement Central Guidelines in China?” *Journal of Public Administration Research and Theory* 32(2): 342–59.

Xu, Chenggang. 2011. “The Fundamental Institutions of China’s Reforms and Development.” *Journal of Economic Literature* 49(4): 1076–1151.

Zhang, Changdong. 2021. *Governing and Ruling: The Political Logic of Taxation in China*. Ann Arbor, MI: University of Michigan Press.

Zhu, Jiangnan, and Dong Zhang. 2017. “Weapons of the Powerful: Authoritarian Elite Competition and Politicized Anticorruption in China.” *Comparative Political Studies* 50(9): 1186–1220.

Chapter 4: Market Failure, Government Failure, and Institutional Context: The Underlying Logic of Targeted Industrial Policymaking in China

1. Introduction

Targeted industrial policies are designed to intervene in specific industry categories, rather than have a general impact on the entire economy. Targeted industrial policies have been adopted by countries all over the world, and their performances are mixed and controversial. On the one hand, all East Asian countries that experienced fast growth previously adopted certain types of targeted industrial policies in their history. South Korea, for example, adopted the Heavy and Chemical Industry (HCI) Drive, which targeted steel, nonferrous metals, electronics, machinery, chemicals, etc., between the period of 1972 to 1979. Lane (2022) finds evidence that HCI in South Korea promoted the expansion and dynamic comparative advantage of both the directly targeted industries and the upstream and downstream industries. Similarly, China has also adopted a large number of targeted industrial policies in the past twenty years. Liu (2019) shows that Chinese targeted industrial policies tend to support industry categories that have higher distortion centrality, and these industrial policies improve aggregate efficiency by 6.7%. On the other hand, some other literature argues that governments lack the necessary knowledge and capability to pick winners, and industrial policies could become tools of rent-seeking and collusion and do no good for national development. In one study, Ngo (2008) examines the passenger car industry in China and discusses the “Big Three and Small Three” policy within the industry. He shows how such kinds of industrial policies pick “winners” in a way that provides massive opportunities for corrupt activities and illicit exchanges between government and firms in China. In another study, Wei et al. (2023) examined a large pro-innovation industrial policy in China. The program is called InnoCom, which offers large subsidies to successful applicant firms to encourage innovation in the industry. The authors find that Chinese bureaucrats who select firms are faced with "a mild form of government failure" in the sense that they give a higher score to applicant firms who have more patent counts but cannot differentiate the quality of patents. The authors estimate that even a mild government failure in the InnoCom program could cause a negative social return that is as high as 19.7% of the total subsidy. This study shows that government officials' inability to pick winners would greatly impact the outcome of an industrial policy.

Whether the government is benevolent and capable enough to make good industrial policies or not is an empirical question. It would be greatly helpful if researchers could provide more empirical evidence on how governments make decisions during the industrial policymaking process. Moreover, previous literature tends to discuss the question in a vacuum and pays no attention to the institutional context in which an industrial policy is made. After all, whether or not the government has the ability and motive to launch the right industrial policies relies on the institutional environment faced by government agents.

To address the above research gap, in this study I examine the underlying logic of targeted industrial policymaking in China. Specifically, I focus on supportive targeted industrial policies in the manufacturing sector adopted by 30 provincial governments (except Tibet) in mainland China between 2003 and 2017. The definition of supportive targeted industrial policies is given in Table 1. I also compare supportive, restrictive, and regulatory targeted industrial policies in the table. This research is based on an original dataset called the "Chinese Industrial Policy Attention Dataset" (CIPAD). It contains 612 central-level and 1907 provincial-level targeted industrial policies launched between 2001 and 2019 in China. A novel design of CIPAD is that it transforms each industrial policy full text into a distribution-of-attention vector. Each vector records the allocation of government attention to 155 finely-segmented industry categories in the manufacturing sector.

In this way, I am able to know which industry categories receive the most and the least government attention in each industrial policy and in each year. Then I examine how provincial governments selectively choose specific industry categories to support. I develop several hypotheses based on two contradictory assumptions about government behavior. The first assumption is that the government behaves as a benevolent and omniscient ruler, and it selectively supports industry categories to address three types of market failure: 1) Intra-industry Coordination Failures, 2) Inter-industry Externalities, and 3) Imperfect Competition and Existence of Rents. The second assumption is that the government behaves as a self-interested agent. I propose two main motives for a self-interested government agent. The first motive is to obtain private gains by involving in rent-seeking activities with special interest groups. The second motive is to pursue job promotion or re-election within the governmental system. Here I further propose that in the institutional context of China, provincial leaders who want to get promoted would adopt an "output-oriented strategy" when selecting particular industry categories to support. An output-oriented strategy here means that the government tends to support industry categories which either have already created large value-added output within the jurisdiction or in other jurisdictions.

I test the above hypotheses by examining Chinese provincial industrial policies in three subperiods: 2003-2007, 2008-2012, and 2013-2017. Data analysis shows that provincial governments in China tend to support the industry categories which have revealed comparative advantage or which are dominated by high-income nations. At the same time, data analysis results support the output-oriented strategy. There is strong evidence that provincial governments support industry categories which either create large value-added within the province or in other provinces. The results of this study show that government behaviors are quite complex in the sense that they partially show governments' intention to address market failure while at the same time embody government agents' intention for pursuing self-interest. This study contributes to previous literature by conducting a comprehensive analysis of the underlying logic of industrial policymaking in China.

Table 18: Definition of Supportive Targeted Industrial Policies

Typology	**Definition**
Supportive Targeted Industrial Policies	Industrial policies that provide exclusive resources (e.g. subsidy, land, human capital, loans…) to specific industry categories to boost the output or the productivity of the latter.
Restrictive Targeted Industrial Policies	Industrial policies that exert exclusive restrictions (e.g. total output limit) to specific industry categories to constrain the production of the latter (usually due to concerns of environment protection, resource savings, social risks…)
Regulatory Targeted Industrial Policies	Industrial policies that set standards/regulations to govern the production of specific industry categories, with a neutral stance (i.e. no intention to exclusively support/constrain specific industry categories.)

2. Government as a Benevolent and Omniscient Policymaker

Supporters who believe targeted industrial policies are important for national development often argue that the existence of market failure makes industrial policies necessary. The implicit assumption behind this argument is that government agents would behave as benevolent rulers who design and issue industrial policies that address the potential market failures. Generally speaking, there are three types of market failure that are frequently discussed in industrial policy literature. These three types of market failure include 1) Intra-industry Coordination Failures, 2) Inter-industry Externalities, and 3) Imperfect Competition and Existence of Rents.

2.1 Intra-industry Coordination Failures

One important reason that might justify the use of industrial policies is the existence of coordination failures within an industry. The existence of such coordination failures implies that collective action, either conducted by a benevolent government or by a group of private actors, might contribute to productivity growth in the corresponding industry. One important source of coordination failures is learning-by-doing spillovers between firms within the same industry (Thompson 2010). That is, the knowledge and experience that one firm accumulates through production might spread to other firms and boost the latter's productivity. If this is the case, then firms might produce less than the socially optimal level (Irwin and Klenow 1994), and policies which induce the industry to increase total output could be welfare enhancing (Harrison and Rodríguez-Clare 2010). In fact, literature has found much evidence of learning-by-doing spillovers in a number of industry categories, such as the semiconductor industry (Irwin and Klenow 1994), the wind power industry (Nemet 2012), and the shipbuilding industry (Thornton and Thompson 2001), which provides reasons for government interventions.

That said, real-world intra-industry coordination failures are not limited to what I have discussed above, and the types of collective actions to address industry-level coordination failures can be highly diverse and varied according to specific circumstances (Hausmann and Rodrik 2003; Hernández et al. 2010; J. Y. Lin 2011). As a result, it is extremely challenging to directly test whether policymakers target the industry categories with severe coordination failures. Here I examine a concomitant condition that should be satisfied if a good-will and capable policymaker wants to address intra-industry coordination failures in a way that brings economic welfare gains to a region. The condition is that the policymaker targets the industry categories in which the region either already has a comparative advantage or will possibly gain a comparative advantage after the coordination failures are resolved (Harrison and Rodríguez-Clare 2010; J. Lin and Chang 2009; J. Y. Lin 2011; Lucas 1988). The intuition behind this condition is straightforward: Given that an industry is near perfect-competition in the world market, then if a region is far from achieving a comparative advantage in that industry, its opportunity cost of production would be much higher than the relative world price of the products. Therefore, even if a policy successfully resolves the intra-industry coordination failures (thus increases the productivity and decreases the opportunity cost of production), such changes are not enough to bridge the huge gap between costs and benefits, and a welfare-maximizing region would still choose not to produce in that industry.

Hypothesis 1: Policymakers launch industrial policies that target the industry categories in which the region either already has a comparative advantage or has a latent comparative advantage.

2.2 Inter-industry Externalities

Another reason for governments to launch industrial policies is the existence of inter-industry externalities. A number of literature has emphasized that the development of some specific industry categories might create large spillover effects that boost the productivity of many other industry categories. Such positive spillover effects might arise from R&D efforts and knowledge that can be transferred across sectors, increased human capital, improved institutional environments, etc. Greenwald and Stiglitz (2006) build a trade model in which one developed country and one less developed country produce two types of goods: industrial good and agricultural good. The authors assume that a country's productivity growth in both the industrial sector and the agricultural sector depends on the relative size of the industrial sector within that country. Then the authors show that government support for the industrial sector can increase the less developed country's long-term economic welfare, even if the less developed country's comparative advantage remains in agriculture. Similar ideas have been reiterated in Hidalgo et al. (2007), who see economic growth as a process of updating the products that a region produces. They argue that the technology, capital, institutions and skills to make newer products might be more easily adapted from some products than from others. Therefore, what a region specializes today might influence what the region produces tomorrow and finally influence the region's long-term growth trajectory. The potential existence of such inter-industry externalities provides theoretical justification for many industrial policies in the real world. As pointed out by Borrus, Tyson and Zysman (1986) in a case study which compares the semiconductor industry between the United States and Japan, "If the United States loses its ability to compete effectively in semiconductors, it may lose its ability to innovate in both the semiconductor industry and in related electronics industries and its ability to diffuse electronics-based product and process innovations in a whole variety of actual and potential user industries."

Hypothesis 2: Policymakers launch industrial policies that target the industry categories which generate large positive externalities to the productivity of other industry categories.

2.3 Imperfect Competition and Existence of Rents

Besides the above reasons, governments might also use industrial policies to secure a larger share of "rent" for their own jurisdictions. "Rent" here means "payment to an input higher than what that input could earn in an alternative use." (Krugman, 1986, page 12) If I continue assuming that the market is near perfect-competition in most cases, then the competitive price would be the benchmark, and "rent" becomes "payment in excess of competitive price." (Stratford 2022) Rent leads to high profits or high wages of incumbent firms, while at the same time new competitors cannot easily enter the industry. The key rationale of industrial policies here is that there exist a few industries which enjoy substantial amounts of rent out there due to investment constraints, economies of scale, steep learning curve, and so on. Then government support for rent-yielding industries has a chance to increase a region's domestic welfare, even though possibly at other regions' expense. Brander and Spencer (1985) build an oligopolistic competition model, in which a domestic firm and a foreign firm compete only in a third market (i.e., no consumption in the producing countries). Brander and Spencer show that if the domestic government provides a subsidy per unit of output in the oligopoly sector, both the output and the profit of the domestic firm will increase, while at the same time the output and the profit of the foreign firm will decrease. Importantly, they show that the gain in domestic welfare due to government subsidy could exceed the cost of the subsidy itself. In another research, Baldwin and Krugman (1988) propose a model in which a government subsidizes a new domestic firm to enter into an industry monopolized by only one foreign firm. They use this model to discuss about the welfare outcomes of European governments' support of Airbus to compete with the American aircraft firm Boeing. They underscore one important mechanism by which subsidizing domestic entry into a foreign-occupied monopolistic industry might be welfare-enhancing: the entry of the domestic new firm is likely to drive down the world price, and domestic consumers who used to pay high price to obtain those products would gain from the lower price.

Hypothesis 3: Policymakers launch industrial policies that target the rent-yielding industry categories.

3. Government as a Self-Interested Actor

Unlike supporters for targeted industrial policies, opponents of targeted industrial policies argue that the existence of market failure itself does not warrant government intervention, because governments may not be capable and benevolent enough to make the right decisions. This kind of idea is vividly illustrated by Milton Friedman' saying that "The government solution to a problem is usually as bad as the problem and very often makes the problem worse." (Friedman, 1975, page 6) Similar ideas have been emphasized in public choice theories that explain government behaviors by assuming governmental agencies pursue their self-interest rather than social welfare (Grand 1991).

Two self-interested motives of governments can potentially have great impact on government behaviors in industrial policymaking. The first motive is to obtain private gains by launching industrial policies that favor local special interest groups who actively participate in rent-seeking activities with government agencies. In this case I often say a government agency is "captured" by a local interest group. The second motive is to pursue job promotion or re-election within the governmental system. Now I will discuss the two types of government motives in detail and propose hypotheses based on them.

First, governments may intentionally support specific industry categories in a way that favor local interest groups who involve in rent-seeking with them. One common local interest groups that may exert great impact on governmental agencies is local large firms. In one study, Hellman, Jones, and Kaufmann (2003) examine state capture by firms in 22 transition economies worldwide based on data from the 1999 Business Environment and Enterprise Performance Survey. The authors find that large firms are the main receivers of private advantages in capture economies, while small firms are unlikely to engage in any form of interaction with the state. In another study, Aisbett and McAusland (2013) find similar results that large firms are more likely to be influential and to gain private advantage from subsidies and low tax constraints. Moreover, Rijkers, Freund, and Nucifora (2017) examine firm-level data in Tunisia and find the benefit of being politically connected is highest for large firms compared with other smaller firms. This result reconfirms the previous finding that large firms tend be more influential to government behaviors compared with smaller firms. Based on the above discussion, I propose the following hypothesis:

Hypothesis 4: Policymakers launch industrial policies that target industry categories which have more local large firms.

Another kind of local interest groups that potentially exert great impact on government agencies is state-owned enterprises. State-owned enterprises account for a large proportion of economy in many countries all over the world. In China, for example, more than 360000 firms are 100% state-owned, and the total capital of firms with some level of state ownership has reached 68% of total capital of all firms in Chinese economy in 2017. State-owned enterprises also play a big role in some European countries. Take Norway as am example, the state owns approximately 30 percent of the values in the Oslo Stock Exchange, and controls companies that account for more than half of the market value. I pay much attention to state-owned enterprises because this type of firms has a natural advantage in building connections with and obtaining private advantages from governments. For example, Aghion et al. (2015) find that Chinese state-owned enterprises enjoy higher level of subsidies from government than those received by private firms in China. They also find evidence that Chinese state-owned enterprises have access to bank loans with an interest rate only half of that faced by private firms. In the context of Russia, Libman, Stone, and Vinokurov (2022) find that state-owned enterprises and Russian government develop a reciprocal relationship with each other. State-owned enterprises align their interests with the country's foreign policy. In exchange, state-owned enterprises in Russia enjoy an information advantage compared with private enterprises, and they can leverage such information advantage to adjust their investment strategies. All these discussions show that state-owned enterprises do have closer relationship with the government and can possibly impact the latter's decision-making process.

Hypothesis 5: Policymakers launch industrial policies that target the industry categories which have larger share of output from state-owned enterprises.

Another self-interested motive of government agents is to get reelection or job promotion. Among all the factors that could influence politicians' likelihood to get reelected or promoted, local employment is among the most frequently mentioned ones in literature. Bisbee and You (2024) in their recent study shows that electorally insecure politicians tend to attract firms for job creation. They find that firms open subsidiaries in more election-competitive districts, suggesting that firms leverage local employment as a political strategy to build ties with vulnerable legislators. In another study, Coelho, Veiga, and Veiga (2006) examined employment data for Portuguese municipalities and find strong evidence that local employment increases shortly before elections through municipal expenditures that generate jobs in local firms. This results suggests that politicians care about local employment to improve their chances of reelection. In the context of China, Gong, He, and Zhang (2021) show that promotion incentives of Chinese local public officials help increase local employment rate. They find evidence that local public officials boost their performance in the political promotion period mainly by improving employment ratio of the secondary industry. Based on the aforementioned studies, I propose the following hypothesis:

Hypothesis 6: Policymakers launch industrial policies that target the industry categories which have large local employment.

In the context of China, subnational governments are faced with the so-called "GDP tournament" to get promoted. Subnational GDP tournament means that GDP growth rate is one of the most important indicators that are taken into consideration when select subnational public officials for promotion (Li and Zhou 2005; Xu 2011; Jia, Kudamatsu, and Seim 2015; Jiang 2018). In this study, I argue that subnational governments who are subject to GDP tournament tend to adopt an "output-oriented strategy" when selecting specific industry categories to support. An output-oriented strategy means that a government tends to selectively support industry categories that either 1) have already created large value-added output in its jurisdiction or 2) have already created large value-added output in all the other jurisdictions. On the one hand, public officials who want to maintain high GDP growth in its jurisdiction will try to preserve existing sources of GDP growth, and that's why it is important to support existing industry categories that have already created large value-added output locally. On the other hand, public officials would like to fast attract new sources of GDP growth in other jurisdictions, therefore they would prefer to support industry categories that have already created large output elsewhere.

Hypothesis 7: Policymakers launch industrial policies that target the industry categories which have already created large value-added output within their jurisdictions.

Hypothesis 8: Policymakers launch industrial policies that target the industry categories which have already created large value-added output in other jurisdictions.

4. Data and Method

I examined the above hypotheses in the context of provincial-level industrial policymaking in China. Following the idea of "developmental state" and inspired by the industrial policies adopted in other Asian countries like Japan and South Korea in last century, Chinese governments are eager to adopt supportive targeted industrial policies to boost domestic industries. This is not only true for Chinese central government, but also true for Chinese provincial governments as well. Altogether there are 31 provinces in mainland China. Provincial governments are directly under the control of Chinese central authority and are delegated much discretion in adopting particular targeted industrial policies within their jurisdictions. Moreover, Chinese provincial governments have a wealth of political and financial resources to draw upon. Therefore, it is both theoretically and practically important to understand how Chinese provincial governments selectively support particular industry categories in industrial policies they adopt.

4.1 Dependent Variable: Allocation of Attention among 146 Industry Categories

This study is based on an original dataset called "Chinese Industrial Policy Attention Dataset" (CIPAD). It contains 612 central-level and 1907 provincial-level targeted industrial policies launched between 2001 and 2019 in China. Since this study particularly focuses on "supportive" targeted industrial policies, I further chose 38 central-level (by State Council) and 1364 provincial-level supportive targeted industrial policies from the CIPAD dataset. A novel design of CIPAD is that the dataset transforms each industrial policy into a distribution-of-attention vector with 155 dimensions. Each vector dimension records the proportion of attention an industrial policy pays to one of the 155 finely segmented industry categories in the manufacturing sector, and the sum of all the dimensions in a vector is one. Industry categories are classified based on the 3-digit codes in the Chinese Industrial Classification for National Economic Activities (GB/T 4754-2002). Notably, in the data analysis below, I adjust the number of industry categories into 146, since some industry-level data after 2011 in based on the standard GB/T 4754-2011.

Based on CIPAD, I are able to get the proportion of attention that each industry category gets from an industrial policy. Then I can easily calculate the amount of attention that a provincial government pays to each industry category in each year based on the formula below:

$$GovAttention_{ijt} = \sum_{1}^{P_{it}} PolicyAttention_{p_{it}j}$$

Here, i denotes each province; j denotes each industry category; t denotes each year (2003 $\leqslant t \leqslant$2017). p_{it} denotes an industrial policy launched in province i in year t. P_{it} denotes the total number of supportive targeted industrial policies in province i in year t. $PolicyAttention_{p_{it}j}$ is the percentage of attention that a policy p_{it} pays to industry category j.

4.2 Examine Intention of Governments to Address Market Failure

According to hypothesis 1, A government tends to selectively support the industry categories in which its jurisdiction either has revealed comparative advantage or has latent comparative advantage. To measure whether a province has revealed or latent comparative advantage in an industry category, I follow the practice by Chen, Poncet, and Xiong (2017) and by Zhao and Chen (2019).

I judge whether a province has revealed comparative advantage in an industry category by calculating whether the value of the following formula is larger than 1:

$$LQ_{ijt} = \frac{output_{ijt}/output_{it}}{output_{jt}/output_{t}}$$

Here i denotes each province; j denotes each industry category; t denotes each year. $output_{ijt}$ is the total output of industry category j in province i in year t. Output data is from China Industrial Enterprise Database (CIED). It is worth noting that the data quality of CIED between the year of 2008-2010 are widely believed as suspect. Therefore, for the periods 2003-2007, 2008-2012, 2013-2017, I use the output data in year 2003, 2007, and 2013 respectively.

To calculate whether a province has latent comparative advantage in an industry category, I follow the practice in Chen, Poncet, and Xiong (2017). The authors measure a region's pre-existing productive capabilities and resources for each industry category by calculating the density of linkages between a targeted industry category and local productive structure. Local productive structure here is represented by local industry categories that already have revealed comparative advantage. Linkages between different industry categories are calculated based on Hidalgo et al. (2007).

Hypothesis 2 argues that governments tend to support the industry categories that create large inter-industry externalities. To measure inter-industry externalities, I follow Holz (2011) by calculating the forward linkages and backward linkages of each industry category. Forward linkage means the extent to which the outputs of an industry category are intermediate inputs to downstream industries. Backward linkage means the extent to which the inputs of an industry category are intermediate purchases from upstream industries. Data to calculate forward and backward linkages are from the input-output sheets provided by National Bureau of Statistics of China.

Hypothesis 3 argues that a government tends to selectively support the industry categories which are dominated by high-income countries. This is because industry categories dominated by high-income countries tend to be those that have imperfect competition and rents. To measure dominance of high-income countries, I follow Hausmann, Hwang, and Rodrik (2007) by calculating the income level of each industry category. The income level of each industry category is determined by the average income level of the nations that export products in that industry category weighted by the export amount of each nation. The higher the income level of an industry category, the more is it dominated by high-income countries. Export data is from BACI: International Trade Database at the Product-Level (Gaulier and Zignago, 2010).

4.3 Examine Government Failure

Hypothesis 4-6 argue that governments selectively support particular industry categories due to government failures. Specifically, governments may be captured by local interest groups, such as local large firms, state-owned enterprises, or by certain unions of local employees. Here, I measure the power of local large firms by calculating the total number of local firms whose annual output is larger than 1 billion RMB in 2003, 2 billion RMB in 2007, or 5 billion RMB in 2013. To measure the power of state-owned enterprises, I measure the ratio of the output by state-owned enterprises over total output by all the firms in each industry category. To measure the power of employees in each industry category, I calculate the total number of employees. Then I examine whether provincial governments in China tend to support industry categories that have more large firms, more output from state-owned enterprises, or more employees.

4.4 Examine “Output-Oriented Strategy” by Governments

Hypothesis 7 and 8 propose that Chinese provincial governments adopt an “output-oriented strategy” when they selectively support particular industry categories. This is shown by the tendency of provincial governments to selectively support the industry categories that have already created large value-added output in its own jurisdiction or in other jurisdictions. To measure value-added output by industry category, year, and province, I use data from China Industrial Enterprise Database (CIED). Value-added output does not directly given by CIED, so I calculate value-added output using the formula below:

$$Value\ Added = Output - Intermediate\ Input + Value\ Added\ Tax$$

4.5 Other Control Variables

Besides the above potential influencers, in this study I also control for the impact of Chinese central government on the behaviors of provincial governments. Specifically, I controlled for the amount of attention from the State Council to each industry category within the past year. This is calculated based on 38 supportive targeted industrial policies launched by the State Council between 2002-2016.

Summary statistics of all the previously mentioned variables is shown in table 19.

Table 19: Summary Statistics

Variable Name	Definition	Mean/ Proportion	Std. Dev.
GovAttention	The amount of attention that a provincial government pays to each industry category in each year.	0.0188	0.0735
Revealed Comparative Advantage	Dummy variable. Indicating whether a province has revealed comparative advantage in an industry category in a year.	0.2726	0.4453
Latent Comparative Advantage	Continuous Variable. Indicating extent to which a province has latent comparative advantage in an industry category in a year.	0.2714	0.1114
Forward Linkage	The extent to which the outputs of an industry category are intermediate inputs to downstream industries	0 .6223	0 .2688
Backward Linkage	The extent to which the inputs of an industry category are intermediate purchases from upstream industries	0 .7542	0.0826
Dominance of High-Income Nations	The extent to which the export of an industry category is dominated by high-income nations	19190.5	7434.061
Number of Big Firms	Number of big firms in an industry category, by province and year.	0.3411	1.5355
Ratio of Output by SOE	ratio of output by state-owned enterprises over total output by all the firms in an industry category, by province and year.	0.1069	0.2109

Employment	Total number of employees in an industry category, by province and year.	3805.017	10290.21
Value Added Within	Total value added output of an industry category within a province in a year.	24.0290	86.1904
Value Added Outside	Total value added output of an industry category in all other provinces in a year.	720.8698	1321.838
Central Attention	Amount of attention paid to an industry category by central government.	0.0166	0.0678

4.6 Research Design

In this study, I examine the underlying logic of Chinese provincial governments to selectively support particular industry categories in the following three subperiods respectively: 2003-2007, 2008-2012, and 2013-2017. I segment the time based on the change of leadership in China. The Politburo Standing Committee of the Chinese Communist Party consist of 7 members, and they are the top leadership in China. This Politburo Standing Committee gets re-elected every five years. In the past, Chinese Politburo Standing Committee got re-elected in the end of 2002, 2007, 2012, and 2017. Therefore, I believe it is reasonable to divide the time periods based on the turnover of top leadership in China. The observations are based on year*province*industry category. I focus on 30 mainland provinces in China (except Tibet) and 146 industry categories in manufacturing sector here. So, for each subperiod, there are 5*30*146=21900 observations. The dependent variable in our model is the amount of attention that a provincial government pays to each industry category in each year. I apply a two-way fixed effect model here by controlling for both province fixed effect and year fixed effect. Standard errors are clustered by each industry category.

5. Results

In table 20, I first examined whether “the output-oriented strategy” is influencing the behaviors of provincial governments in China. I controlled for central impact in this case. The results in table 20 below supports the hypotheses about the “output oriented strategy” taken by provincial governments in China: Provincial governments are more likely to support the industry categories which have already created large value-added outputs either 1) within the province itself or 2) in all the other provinces. As is shown by the table, in all three subperiods, i.e., 2003-2007, 2008-2012, and 2013-2017, both the coefficients of “Value-added Output within a Province” and “Value-added Output in Other Provinces” are positive and significant.

Table 20: Examine the Output-Oriented Strategy

	Dependent Variable: Government Attention to Each Industry Category, By Province & Year		
	(1)	(2)	(3)
VARIABLES	2003-2007	2008-2012	2013-2017
Output-Oriented Strategy			
Value-added Output within a Province	0.006*	0.010**	0.004**
	(0.003)	(0.003)	(0.001)
Value-added Output In Other Provinces	0.006***	0.013***	0.012***
	(0.001)	(0.004)	(0.003)
Impact of the Central Government			
Attention from State Council	0.010**	0.011***	0.027***
	(0.002)	(0.002)	(0.008)
Observations	21,900	21,900	21,900
R-squared	0.078	0.116	0.189

In table 21, I further add variables that test “market failure” hypotheses into the model. In the first three columns of table 21, I test “market failure” hypotheses while controlling for the impact of the State Council. In the last three columns of table 21, I further control for the existence of “output-oriented strategy” that could potentially impact the behaviors of provincial governments.

Table 21: Examine the Rationale to Address Market Failure

	Dependent Variable: Government Attention to Each Industry Category, by Province & Year					
VARIABLES	(1) 2003-2007	(2) 2008-2012	(3) 2013-2017	(4) 2003-2007	(5) 2008-2012	(6) 2013-2017
Rationale to Address Market Failure						
Revealed CA	0.004***	0.007***	0.004***	0.002***	0.004***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Latent CA	0.004	0.006	0.001	0.003	0.006	0.001
	(0.003)	(0.008)	(0.004)	(0.004)	(0.008)	(0.004)
Domination by	0.001	0.004**	0.004*	0.002	0.006***	0.006***
High-income Countries	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Forward Linkages	0.002*	0.000	0.001	0.001	-0.003	-0.001
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
Backward Linkages	-0.000	0.001	-0.000	-0.000	0.000	-0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Output-Oriented Strategy						
Value-added Output				0.005	0.008*	0.003*
within a Province				(0.003)	(0.003)	(0.001)
Value-added Output				0.006***	0.015***	0.013***
In Other Provinces				(0.001)	(0.004)	(0.003)
Impact of the Central Government						
State Council Impact	0.012**	0.014***	0.029***	0.010***	0.010***	0.026***
	(0.004)	(0.001)	(0.008)	(0.002)	(0.002)	(0.008)
Observations	21,900	21,900	21,900	21,900	21,900	21,900
R-squared	0.055	0.075	0.163	0.081	0.125	0.196

The first interesting result I obtain from table 21 is that provincial governments tend to support the industry categories that have already got revealed comparative advantage locally. This result still holds even after I control for both the “output-oriented strategy” and the impact of central government. However, there is no evidence that provincial governments are able to identity industry categories that have latent comparative advantage. Another result that I find interesting is that provincial governments tend to support industry categories that are dominated by high-income nations after 2008. As is shown by column 5 and 6, the coefficients of “Domination by High-income Countries” are significantly positive during the period of 2008-2012 and that of 2013-2017. This result may be explained by the fact that Chinese governments have always wanted to develop domestic high-tech industries, and this motive is even stronger after years of fast economic and industry development. In 2006, Chinese State Council issued The Outline of the National Medium- and Long-Term Science and Technology Development Program from 2006 to 2020. This policy, as is shown by its title, aims to boost Chinese science and technology in a way that matches those in western developed countries. Therefore, it is reasonable to see that Chinese provincial governments have begun to support industry categories dominated by high-income nations in the last two subperiods.

In table 22, I further test the hypotheses about the existence of government failures. To my surprise, as is shown by the last three columns in table 4, the coefficients of all the three variables under the hypotheses of government failures are not significant after controlling the impact of the State Council and the potential impact of “output-oriented strategy.” As is shown by the table, I find no evidence that the number of local large firms, output of state-owned enterprises, or large number of employees is associated with the willingness of provincial governments to support particular industry categories. It is also worth mentioning that the coefficients of “value-added output within a province” become no longer significant in column (4) and (5) after controlling for government failures. One potential reason is because there is high multicollinearity between “number of local large firms,” “number of employees,” and “value-added output within a province.” That said, the coefficients of “value-added output in other provinces” remain significantly positive in all six models of table 22. Therefore, it is quite safe to reach the conclusion that “output-oriented strategy,” especially the intention to support industry categories that have created large value-added output in other provinces, plays an important role in influencing Chinese provincial governments' preference in selectively supporting particular industry categories.

Table 22: Examine Existence of Government Failure

VARIABLES	(1) 2003- 2007	(2) 2008- 2012	(3) 2013- 2017	(4) 2003- 2007	(5) 2008- 2012	(6) 2013- 2017
Motive of Rent-Seeking						
Num. of Local large Firms	0.004**	0.011**	0.005	-0.004	-0.001	-0.003
	(0.002)	(0.004)	(0.003)	(0.004)	(0.003)	(0.002)
Ratio of State-owned Enterprises	0.001	0.002*	0.000	-0.000	-0.000	-0.002
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Motive of Job Promotion						
Number of Employees	0.003**	0.006*	0.004*	-0.002	-0.002	-0.003
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
Output-Oriented Strategy						
Value-added Output within a Province				0.010	0.012	0.008*
				(0.007)	(0.007)	(0.004)
Value-added Output in Other Provinces				0.006***	0.013***	0.013***
				(0.001)	(0.004)	(0.003)
Impact of the Central Government						
Attention of State Council	0.011***	0.013***	0.029***	0.010***	0.011***	0.027***
	(0.003)	(0.001)	(0.008)	(0.002)	(0.002)	(0.008)
Observations	21,900	21,900	21,900	21,900	21,900	21,900
R-squared	0.060	0.090	0.166	0.080	0.117	0.190

6. Conclusion

In this study, I examine the underlying logic of supportive targeted industrial policymaking by provincial governments in China. I propose two sets of hypotheses about how provincial governments selectively support particular industry categories by launching targeted industrial policies. The first set of hypotheses is based on the assumption that Chinese provincial governments are benevolent and omniscient policymakers. Therefore, provincial governments would support the industry categories which help address market failure. I examine three types of market failure here, which include 1) Intra-industry Coordination Failures, 2) Inter-industry Externalities, and 3) Imperfect Competition and Existence of Rents. The second set of hypotheses is based on the assumption that Chinese provincial governments are self-interested agents. I propose two main potential motives of government agents: 1) pursue private gains by colluding with firms; 2) pursue reelection or job promotion. I further discuss these motives in the institutional context of China. I argue that when faced with the GDP tournament, provincial leaders in China tend to adopt an "output-oriented strategy" when they select particular industry categories to support. That means they tend to support industry categories which either have created large value-added output within the jurisdiction or in other jurisdictions. I test the above hypotheses based on an original dataset called the "Chinese Industrial Policy Attention Dataset." Data analysis shows evidence that the output-oriented strategy is adopted by provincial governments. Provincial governments tend to support industry categories with revealed comparative advantage. Moreover, there is also evidence that after 2008, Chinese provincial governments began to support industry categories that are dominated by high-income nations. This study is among the first to provide a comprehensive analysis of the underlying logic of industrial policymaking across provincial governments in China. It shows that the motives of governments can be mixed and complicated during the industrial policymaking process. This study also suggests that how governments adopt certain industrial policies relies heavily on the institutional context in which they work.

7. References

Bisbee, James, and Hye Young You. 2024. "Political Geography and Firm Strategies: How Electoral Competition Influences Local Job Creation." *The Journal of Politics* 86(2): 687–703. doi:10.1086/726970.

Brander, James A. 1995. "Chapter 27 Strategic Trade Policy." In *Handbook of International Economics*, Elsevier, 1395–1455. doi:10.1016/S1573-4404(05)80007-3.

Brander, James A., and Barbara J. Spencer. 1985. "Export Subsidies and International Market Share Rivalry." *Journal of International Economics* 18(1): 83–100. doi:10.1016/0022-1996(85)90006-6.

Chen, Zhao, Sandra Poncet, and Ruixiang Xiong. 2017. "Inter-Industry Relatedness and Industrial-Policy Efficiency: Evidence from China's Export Processing Zones." *Journal of Comparative Economics* 45(4): 809–26. doi:10.1016/j.jce.2016.01.003.

Greenwald, Bruce, and Joseph E Stiglitz. 2006. "Helping Infant Economies Grow: Foundations of Trade Policies for Developing Countries." *American Economic Review* 96(2): 141–46. doi:10.1257/000282806777212206.

Harrison, Ann, and Andrés Rodríguez-Clare. 2010. "Trade, Foreign Investment, and Industrial Policy for Developing Countries." In *Handbook of Development Economics*, Elsevier, 4039–4214. doi:10.1016/B978-0-444-52944-2.00001-X.

Hausmann, Ricardo, Jason Hwang, and Dani Rodrik. 2007. "What You Export Matters." *Journal of Economic Growth* 12(1): 1–25. doi:10.1007/s10887-006-9009-4.

Hausmann, Ricardo, and Dani Rodrik. 2003. "Economic Development as Self-Discovery." *Journal of Development Economics* 72(2): 603–33. doi:10.1016/S0304-3878(03)00124-X.

Hernández, Iván, Nathalie Cely, Francisco González, Ernesto Muñoz, and Iván Prieto. 2010. "The Discovery of New Export Products in Ecuador." *SSRN Electronic Journal*. doi:10.2139/ssrn.1817280.

Hidalgo, C. A., B. Klinger, A.-L. Barabási, and R. Hausmann. 2007. "The Product Space Conditions the Development of Nations." *Science* 317(5837): 482–87. doi:10.1126/science.1144581.

Holz, Carsten A. 2011. "The Unbalanced Growth Hypothesis and the Role of the State: The Case of China's State-Owned Enterprises." *Journal of Development Economics* 96(2): 220–38. doi:10.1016/j.jdeveco.2010.10.007.

Irwin, Douglas A., and Peter J. Klenow. 1994. "Learning-by-Doing Spillovers in the Semiconductor Industry." *Journal of Political Economy* 102(6): 1200–1227.

Lin, Justin, and Ha-Joon Chang. 2009. "Should Industrial Policy in Developing Countries Conform to Comparative Advantage or Defy It? A Debate Between Justin Lin and Ha-Joon Chang." *Development Policy Review* 27(5): 483–502. doi:10.1111/j.1467-7679.2009.00456.x.

Lin, Justin Yifu. 2011. "New Structural Economics: A Framework for Rethinking Development1." *The World Bank Research Observer* 26(2): 193–221. doi:10.1093/wbro/lkr007.

Lucas, Robert E. 1988. "On the Mechanics of Economic Development." *Journal of Monetary Economics* 22(1): 3–42. doi:10.1016/0304-3932(88)90168-7.

Nemet, Gregory F. 2012. "Subsidies for New Technologies and Knowledge Spillovers from Learning by Doing." *Journal of Policy Analysis and Management* 31(3): 601–22. doi:10.1002/pam.21643.

Ngo, Tak-Wing. 2008. "Rent-Seeking and Economic Governance in the Structural Nexus of Corruption in China." *Crime, Law and Social Change* 49(1): 27–44. doi:10.1007/s10611-007-9089-x.

Stratford, Beth. 2022. "Rival Definitions of Economic Rent: Historical Origins and Normative Implications." *New Political Economy*: 1–16. doi:10.1080/13563467.2022.2109612.

Thompson, Peter. 2010. "Chapter 10 - Learning by Doing." In *Handbook of the Economics of Innovation*, Handbook of The Economics of Innovation, Vol. 1, eds. Bronwyn H. Hall and Nathan Rosenberg. North-Holland, 429–76. doi:10.1016/S0169-7218(10)01010-5.

Thornton, Rebecca Achee, and Peter Thompson. 2001. "Learning from Experience and Learning from Others: An Exploration of Learning and Spillovers in Wartime Shipbuilding." *American Economic Review* 91(5): 1350–68. doi:10.1257/aer.91.5.1350.

Wei, Shang-Jin, Jianhuan Xu, Ge Yin, and Xiaobo Zhang. 2023. "Mild Government Failure." doi:10.3386/w31178.

413 Maxwell Hall
Syracuse, NY, 13244-1020
Tel: +8617786446752
Email: sxiao11@syr.edu
Website: iamshiyangxiao.com

SHIYANG XIAO

RESEARCH INTERESTS

Public Administration, Policy Process, Intergovernmental Relations, Computational Social Science.

EDUCATION

Syracuse University, Maxwell School of Citizenship and Public Affairs — Syracuse, NY
Ph.D. in Social Science — 2017-2024 (expected)
Committee: Yilin Hou (chair), Mary Lovely, Alfonso Flores-Lagunes, Saba Siddiki, Junyan Jiang

Main Courses: Policy Analysis and Management, Intellectual History of Public Administration, Research Methods for Public Administration, Collaborative Governance, Public Financial Management, Econometrics I, III, Microeconomics I, II, Labor Economics, Education Economics, Survey & Experiment.

Syracuse University, Maxwell School of Citizenship and Public Affairs — Syracuse, NY
M.A. in Economics — 2018-2020

Tsinghua University, School of Public Policy & Management — Beijing
M.A. in Public Administration — 2015-2017

Peking University, Department of Philosophy — Beijing
B.A. in Philosophy — 2011-2015

Peking University, National School of Development — Beijing
B.A. in Economics (Double Major) — 2012-2015

PEER-REVIEWED PUBLICATION

[1] Chen, C., Xiao, S., & Zhao, B. (2023). Machine Learning Meets the Journal of Public Budgeting & Finance: Topics and Trends Over 40 Years. *Public Budgeting & Finance,* 43(4): 3-23.

[2] Xiao, S., & Zhu, X. (2022). Bureaucratic Control and Strategic Compliance: How Do Subnational Governments Implement Central Guidelines in China? *Journal of Public Administration Research and Theory*, *32*(2), 342-359.

[3] Ma, Y., & Xiao, S. (2021). Math and Science Identity Change and Paths into and out of STEM: Gender and Racial Disparities. *Socius*, 7.

[4] Xiao, S. (2020). Multi-Centre Collaborative Governance Network For Epidemic Prevention and Control. *China Public Administration Review "Frontline Observation on the Fight against Covid-19" Online Column*, https://mp.weixin.qq.com/s/rzdo1SI2SFQzqW9l0k0CfQ.

BOOK CHAPTER

[1] Zhang, F., & Xiao, S. (2016). The *U.S. Government Fiscal and Debt Crisis: Lessons for China.* Beijing: Peking University Press.

WORKING PAPER

[1] The Dilemma of Political Control: Top-Down Inspection and Its Impact on Bureaucrats' Use of Discretion in Policymaking (with Hou, Y. and Lovely, M.).

[2] The Transmission of Bureaucratic Control Measures in Multilevel Government (with Zhu, X.).

[3] Regime Change in Policy Convergence: Evidence from Chinese Industrial Policies 2006-2019 (with Hou, Y.)

WORK IN PROGRESS

[1] Market Failure, Government Failure, and Institutional Context: The Political Economy of Industrial Policymaking in China.

[2] Allocation of Responsibility in Hierarchical Organization and the Behaviors of Middle-Level Agencies: An Application of the Institutional Grammar Tool.

[3] Institutional Design of Collaborative Governance and Perceived Legitimacy among the Public.

[4] Perceived Value and Situation: Fostering Digital Co-Creation Amidst Crisis (with Zhang Y.)

[5] Skill-biased Technological Changes and State Government Financial Support for Higher Education.

[6] Authority Relations and the Problem of Shirking in Organizations.

CONFERENCES

[1] 2023, Seattle, U.S.: Public Choice Society Conference
Presentation on "The Political Economy of Subnational Industrial Policymaking in China."

[2] 2022, Singapore: Lien Development Conference
Presentation on "Regime Change in Policy Convergence: Evidence from Chinese Industrial Policies"

[3] 2021, Beijing, China: Summer Institute of Computational Social Science (SICSS)
Presentation on "Identify Industry Categories and Government Strategies in Policy Full Texts."

[4] 2020, Beijing, China: Annual Forum of Institutional Economics in China
Presentation on "The Top-Down Transmission of Hierarchical Governance Tools in China."

[5] 2019, Denver, U.S.: Association for Public Policy Analysis and Management Conference
Presentation on "Bureaucratic Control Dilemma: How Subnational Governments Comply with Central Guidelines in China."

[6] 2017, Singapore: Third International Conference on Public Policy
Presentation on "Bureaucratic Discretion and Behavioral Logics of Intermediate Agencies."

HONORS & AWARDS

[1] 2023, Student Fellow of the Public Choice Society
Public Choice Society

[2] 2022, Service Excellence Award
Chinese Policy Scholars Group (CPSG)

[3] 2017-2021, Syracuse University Fellowship
Syracuse University

[4] 2015-2016, Guanghua Scholarship
Tsinghua University

[5] 2013-2014, Feng Shenjun Scholarship
Peking University

[6] 2012-2013, Leadership Excellence Scholarship, Yang Qingqin Scholarship
Peking University

TEACHING EXPERIENCE

Teaching Assistant

[1] Summer 2019, Public Management, Policy, and Leadership, Teaching Assistant
Maxwell School of Citizenship and Public Affairs, Syracuse University

[2] Spring 2017, Development Strategy and Planning, Teaching Assistant
School of Public Policy & Management, Tsinghua University

Guest Lectures

[1] 2021, "Big Data Methods in Social Science Research"
Hamilton College

[2] 2021, Two-Day Lecture on "The Application of Big Data Methods in Social Science Research: Take Computational Text Analysis as an Example"
School of Public Policy & Management, Tsinghua University

PROFESSIONAL ACTIVITIES & SKILLS

[1] Referee Experience:
Public Administration Review; Governance; Humanities & Social Sciences Communications, Policy Studies Journal

[2] Service:
2021-2023, Student Representative, Chinese Policy Scholars Group (CPSG).
2015-2016, Volunteer in "A Better Community" (ABC) Consulting Agency
2016, Coordinator of "Think Tanks in Asia," co-sponsored by Tsinghua University and German Institute of Global and Area Studies.

[3] Skills:
Python, R, Stata.