NBER WORKING PAPER SERIES

DECODING CHINA'S INDUSTRIAL POLICIES

Hanming Fang
Ming Li
Guangli Lu

Working Paper 33814
http://www.nber.org/papers/w33814

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 2025

We thank Loren Brandt, Chang-Tai Hsieh, Ruixue Jia, Nathan Lane, Shanjun Li, Barry Naughton, Michael Zheng Song, Shaoda Wang, Shang-Jin Wei, Wei Xiong, Daniel Xu, David Yang, and conference/seminar participants in Chicago, CUFE, CUHK Shenzhen, Jinan, Lingnan, Macau, PKU HSBC Business School, UCSD, Virginia Darden School of Business, World Bank, ASSA (2025) and NBER Chinese Economy Working Group Meeting (Spring 2025) for useful comments. Li gratefully acknowledges the National Natural Science Foundation of China (Nos. 72403216 and 72192804), the Guangdong Province Natural Science Foundation (No. 2022B1515120060), and the Research Fund of the School of Management and Economics, Chinese University of Hong Kong, Shenzhen, for financial support. All remaining errors are our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Decoding China's Industrial Policies
Hanming Fang, Ming Li, and Guangli Lu
NBER Working Paper No. 33814
May 2025
JEL No. C55, L52, O25

ABSTRACT

We decode China's industrial policies from 2000 to 2022 by employing large language models (LLMs) to extract and analyze rich information from a comprehensive dataset of 3 million documents issued by central, provincial, and municipal governments. Through careful prompt engineering, multistage extraction and refinement, and rigorous verification, we use LLMs to classify the industrial policy documents and extract structured information on policy objectives, targeted industries, policy tones (supportive or regulatory/suppressive), policy tools, implementation mechanisms, and intergovernmental relationships, etc. Combining these newly constructed industrial policy data with micro-level firm data, we document four sets of facts about China's industrial policy that explore the following questions: What are the economic and political foundations of the targeted industries? What policy tools are deployed?How do policy tools vary across different levels of government and regions, as well as over the phases of an industry's development? What are the impacts of these policies on firm behavior, including entry, production, and productivity growth? We also explore the political economy of industrial policy, focusing on top-down transmission mechanisms, policy persistence, and policy diffusion across regions. Finally, we document spatial inefficiencies and industry-wide overcapacity as potential downsides of industrial policies.

Hanming Fang
University of Pennsylvania
Department of Economics
and NBER
hanming.fang@econ.upenn.edu

Ming Li
The Chinese University of Hong Kong,
Shenzhen (CUHK–SZ)
liming2020@cuhk.edu.cn

Guangli Lu
The Chinese University of Hong Kong,
Shenzhen (CUHK–SZ)
luguangli@cuhk.edu.cn

A data appendix is available at http://www.nber.org/data-appendix/w33814

1 Introduction

Industrial policy is experiencing a powerful resurgence around the world. From the CHIPS Act aimed at bolstering the semiconductor production in the US, to the European Green Deal prioritizing renewable energy, and India's "Atmanirbhar Bharat" for self-reliance, governments across the globe are launching initiatives to secure competitive advantages in critical sectors. Of course, China's industrial policy is often cited as a key reason for her structural transformation and transition up the global value chain. This surge of interest in industrial policy reflects a profound reevaluation of the role that governments can play in guiding economic growth and spurring innovation, especially in an interconnected but increasingly fragmented global economy.

There is also a revitalized academic interest in industrial policy. Early research on industrial policy often held a critical position, suggesting that government intervention could do more harm than good, with influential voices such as Krueger (1990) and Pack (2000), which underscored the inefficiencies from rent seeking that any industrial policy is bound to introduce. Recent studies, with refined identification methods and narrower scopes, have produced findings that are more favorable to industrial policy. Beyond the normative question of whether there should be industrial policy, positive – and possibly more important – questions include: What sectors are targeted? Which tool(s) are used for which industry and in what phase of the industry's development? How do governments experiment with and learn about the choice of sectors and policy tools? How do governments strike a delicate balance to boost entry and improve productivity while preventing excessive entries and potential overcapacity? What is the role of political incentives in shaping policy choices and outcomes? Echoing Rodrik (2004, 2009), the more relevant question about industrial policy is not whether it should be practiced, but *how*. Despite the fundamental importance of these questions, we face a striking scarcity of basic facts and systematic data on industrial policy practices. Juhász et al. (2022) made an important attempt to address this gap by examining *national*-level policies in a number of countries, but research focusing on the internal dynamics and regional variation of industrial policy *within* a single country remains scarce. This is the literature gap that our study seeks to fill, using a detailed and large-scale analysis of industrial policy documents in China's hierarchical government structure.

China presents a unique laboratory for investigating the above questions. First, China's extensive use of industry policies to shape its sectoral development and technological capabilities makes it especially valuable to investigate the role of industry policies in its substantial structural transformation and technological upgrading (Naughton, 2021; Naughton, Xiao, and Xu, 2023). Second, China's hierarchical government structure, where central authorities establish strategic guidelines while local governments exercise discretion over policy adoption, experimentation, and implementation, yields rich variations in local policies. Local governments, heterogeneous in their economic fundamentals, administrative and fiscal capacity, and political incentives, vary significantly in both their policy choices and tool selections, thus allowing researchers to examine the determinants and the effectiveness of industrial policies. Importantly, unlike cross-country comparisons, where varied institutional and economic contexts complicate analysis, China's unified political and legal framework across regions allows for clearer insight into the determinants and effects of industrial policies. Third, China's institutional arrangement and regional heterogeneity also facilitate rich policy experimentation and policy learning across administrative units, enabling researchers to examine these dynamics. Fourth, the discretion afforded to local governments, combined with their distinct incentives and capabilities, provides a window into studying the challenges in policy coordination and the implications of possible coordination failures. It is not an exaggeration to say that understanding China's industrial policy is the key to understanding both the success and the pitfalls of the Chinese economy in the past two decades.

Despite the importance of studying China's industrial policy, significant gaps remain in the literature, mainly due to data constraints. Scholars have limited access to detailed and systematic information on the implementation of these policies, particularly at the *local* level. This knowledge gap underscores the need for a big-data approach to advance the study of China's industrial policy. To address this, we leverage a vast dataset of government documents that spans the past 20 years, covering all levels of government from the central to the city level. With the help of LLMs, we systematically analyze the near universe of publicly released government policy documents to build a structured data set that encompasses a wide range of dimensions within China's industrial policy framework. This data set enables us to decode the intricacies of policy formulation, implementation, and diffusion across various levels of government. In addition, we integrate these newly constructed policy data with various micro-level firm data sets not only to analyze the relationship between policies as documented and those implemented, but also to explore how the complex industrial policies interlink to influence firm entry and subsequent performance.

More specifically, our sample starts with a comprehensive dataset of more than 3 millions of *unstructured* policy texts issued by governments of all levels in China from 2000 to 2022. The LLMs are used to systematically classify whether a government document is an industrial policy document and if so, extract *structured* information about the issuing government; list of targeted industries; policy objectives; policy tone (supportive or regulatory/suppressive); policy tools; measures of policy strength; policy conditionality; references to other governments; citations of other policies; policy dates; measures to monitor, evaluate, and incentivize lower-level governments; measures that grant discretion and promote policy innovation and learning; local adaptation of policies, among others. The richness of the resulting policy dataset allows us to move beyond a simplistic, binary view of industrial policy. As Rodrik (2004, 2009) rightly emphasized, industrial policy is not merely a question of whether or not it should exist; rather, the key to understanding its impact lies in the nuanced details of its implementation. Although such information is embedded within the voluminous government policy documents, we can extract such detailed multidimensional data on China's industrial policy in a structured form only with the advent of LLMs. To our knowledge, we are the first to assemble this comprehensive dataset of China's industrial policy at this granular level, which allows us to answer many questions that could not be addressed in the previous literature (see Section 2.1).

LLMs, while increasingly popular as a powerful research aid in social science studies, are particularly challenging to use in our context, where they are tasked with analyzing long documents and answering complex questions. The risk of LLM hallucination—the tendency for the LLMs to give inaccurate responses—increases significantly with the length of texts and prompts. We propose multiple novel strategies, which we refer to as *hallucination-robust LLM*, to address this issue. Our strategies include: decomposing complex questions into subquestions to guide the LLM to analyze the policy document thoroughly and step by step; providing clear definitions and guidance with counterexamples to reduce ambiguity; requiring the LLM to respond with all relevant texts, reasoning, and confidence level to force it to answer with valid reasoning; separating the tasks into text extraction tasks and classification tasks based on the relevant text to reduce unwarranted claims; verifying response validity based on whether the extracted text appears in policy texts post LLM queries. Importantly, based on the literature that integrating responses from multiple LLMs can significantly reduce hallucination (Li et al., 2024), we integrate responses from *multiple* LLMs for critical tasks such as the identification of industrial policy documents, the mapping of each policy to the standardized industry codes it targets, and the classification of policy tools. Lastly, we assess the validity of our approach using word clouds, as well as conducting manual verification of random policies. We also cross-validate our data using time series of industrial policies in the electric vehicle (EV) industry by demonstrating that the distribution of policies aligned well with known policy milestones and dynamics.

Overall, our procedure first successfully identifies about 0.77 million industrial policies from all government policy documents, and then labels and extracts all the detailed information about the industrial policies mentioned above. The large volumes of documents identified by LLM as industrial policies reveal their importance in China. Over time, we see a continuous increase in the number of industrial policies, an increasing proportion of which have a supportive tone. Spatially, we find more industrial policies in more developed regions, consistent with Juhász et al. (2022)'s finding that at the country level, the use of industrial policy also skews heavily towards rich countries. In terms of policy objectives, the promotion of strategic industries is the most common, mentioned in 22% of the policy documents. Across sectors, manufacturing and production-related services are the target of, respectively, 29% and 40% of all policies, reflecting the focus of the Chinese government on these sectors. Over time, while the proportion of industrial policies targeting the manufacturing sector may have slightly declined, within the manufacturing sector, the proportions of industrial policies targeting high-skilled and emerging manufacturing have both increased steadily, consistent with the country's emphasis on technological upgrading. In terms of policy tools, we follow the literature and guide the LLM to classify them into 21 tools. Although fiscal subsidy is the most common policy tool that appeared in 41% of the policies, more than half of the policies do not employ fiscal subsidy, suggesting the potential bias of the existing measures of industrial policy based on the amount of government subsidies. The choices of tools are always in bundles and exhibit substantial variations across regions and sectors, suggesting the potential bias from studying any single policy tool in isolation. Interestingly, we find that the industrial policy tools deployed over the phase of a sector's development evolve, from entry subsidies to R&D to supply chain clustering, for example, which is a feature that will be missed using the existing measures of industrial policy in the literature. Regarding conditionality for policy eligibility, regional focus and firm sizes are the most common forms. Regarding the central-local relationship, we confirm from policy citation information the hierarchical structure where lower-level governments rely on guidance from the higher-level governments. In terms of policy implementation, the setting of targets and coordination between government entities are most common, appearing in 48% and 65% of the policies, respectively, reflecting the strong position of the government in policy implementation. In addition, we find that local adaptation is prominent at the city level (51%). Lastly, around 21% of the policies encourage piloting.

We then document four sets of facts on China's industrial policy. These facts provide a rich account of the economic and political foundations of local governments' choice of targeted industries, the variation in the use of policy tools across different regions and industries, the dynamic evolution of policy tools and implementation methods over the industry's development stages, the diffusion across regions of the target sectors and policy tools, and how these policies affect firm entry, financing, and productivity. Our findings reveal not only the successes of China's industrial policies but also the inefficiencies and unintended consequences such as local protectionism and overcapacity.

The first set of empirical facts examines the economic and political determinants of the local governments' choice of targeted sectors. We find that economic rationale, political incentives, and the administrative and fiscal capacity of local governments all play an important role in the choice of targeted sectors, which is consistent with the model of Juhász, Lane, and Rodrik (2023). On the economic foundation front, we show that, consistent with what is suggested by the theory, regions tend to target industries with a revealed comparative advantage (RCA), and more developed regions with stronger administrative and fiscal capacities are better at such targeting (Fact 1a). On the political determinants of policy formation and pass-through, we show that city-level governments follow the upper-level governments in their choice of target sectors, and the top-down pass-through is stronger for less developed regions and cities with fewer connections with the upper-level government, and when the city chiefs face more fierce political competition (Fact 1b). Examining the time trend of the top-down policy pass-through rates, we find that 2013 is a turning point when the top-down pass-through rates reversed the previous declining trend and started to get stronger with the new wave of political re-centralization (Fact 1c). In addition, we find that the choices of target sectors in a city exhibit a certain degree of persistence over time; but interestingly, we find that the target sectors in a city are more likely to shift when there is a change of local politicians and tend to mimic previous policies of the new politician in the city he/she previously served (Fact 1d), which confirms that the rotation of politicians is an important mechanism for the learning and diffusion of industrial policies in China.

The second set of facts focuses on the policy tools, which is a critical aspect of industrial policy that is feasible only in our LLM-analyzed granular policy data. We find that local governments in more developed regions are early users of new policy tools, which are later spread throughout the country and adopted by higher-level governments (Facts 2a and 2b). That is, even though local governments tend to follow upper governments in sector choices, they nevertheless have flexibilities in policy implementation; it is the local governments, who have more information on the ground, that are the main agents in policy tool experimentation. Moreover, consistent with the importance of administrative capacity, more developed regions conduct more experimentation, and the gradual adoption of such policy tools by other governments reveals both the effectiveness and the learning externality of such experimentation. In addition, we find that policy tools vary systematically across industries, with skill-intensive manufacturing industries using new policy tools more frequently compared to other traditional industries (Fact 2c). Interestingly, consistent with the idea of industry policies as customized public services (Juhász, Lane, and Rodrik, 2023), we find that within each industry, local governments adjust their industrial policy tools and implementation methods over time to accommodate the development phase of the industry. The bundles of policy tools evolve from those aimed at boosting entries, e.g., entry subsidies and encouragement of entrepreneurship, to those aimed at promoting industry upgrading, e.g., R&D, and supply chain enhancement (Fact 2d). The policy implementation starts with local governments' emphasis on strict enforcement combined with local adaptation, to encouraging policy innovation and learning with more concrete and comprehensive organizational support (Fact 2e).

In the third set of facts, we examine the diffusion of policies across regions. We show a trend of increasing interregional policy similarity in the choice of the target sectors, and that the level of policy similarity among cities in the same province is strongly correlated with local protectionism in intercity trade (Fact 3a). We also provide empirical evidence that imitating the sectors supported by pioneering cities is often ineffective or even counterproductive (Fact 3b). Further examining the mechanism behind the ineffectiveness of policy diffusion, we find that as policies diffuse across regions, policy followers are less savvy in the choice of the target industry, policy tools, and implementation methods, and more likely to follow the upper-level government's practice (Fact 3c). This suggests that industrial policy is far more complex than just a matter of copying successful models—it requires careful adaptation to local conditions as well as administrative and fiscal capacity. In addition, the third set of facts highlights the challenges in coordinating policies to incentivize local governments to boost firm entries to a target sector, and at the same time to avoid protectionism and overcapacity from overly similar policies and excessive entries.

In the fourth set of empirical facts, we combine industrial policy information with various firm datasets to evaluate the effectiveness of industrial policies. We find that industrial policies are effective in providing firms in the targeted industries with extra monetary benefits, such as fiscal subsidies, tax deductions, and access to financing, etc. (Fact 4a), and thus significantly boost entry (Fact 4b), but the association between industrial policy and firm productivity is rather mixed and tenuous (Fact 4c). The effectiveness also varies significantly with the policy tools being used.

Related Literature. This paper contributes to the growing literature on industrial policy (see (Juhász, Lane, and Rodrik, 2023) for a comprehensive review). There is a large theoretical literature on industrial policy (e.g. Baldwin, 1969; Krueger, 1990; Krugman, 1992; Harrison and Rodríguez-Clare, 2010; Lin, Monga, and Stiglitz, 2013; Itskhoki and Moll, 2019). The earlier empirical literature on industrial policy focuses mainly on describing what happens to policy-targeted industries, most of which find that industrial policies have generally been ineffective or counterproductive (Baldwin and Krugman, 1986; Head, 1994; Luzio and Greenstein, 1995; Irwin, 2000; Hansen, Jensen, and Madsen, 2003). More recent literature zooms into specific settings with a careful identification design to assess whether industrial policy elicited the desired responses from firms in the target sectors (e.g. Lane, 2022, 2020; Juhász, 2018; Choi and Levchenko, 2021). These studies produce results that are much more favorable to industrial policies.

Our research advances the study of industrial policy on three fronts. First, the existing literature often examines industrial policy within a specific context, which can contribute to mixed findings on its effectiveness. By applying LLMs to one of the largest collections of government documents ever analyzed, we provide a more holistic view of China's industrial policy landscape across multiple regions and over an extended period of time, with the potential to reconcile and synthesize previous debates in the literature. This approach reveals not only the effectiveness but also the potential pitfalls of industrial policies.

Second, we demonstrate the potential for using LLMs to decode complex policy documents with granular information. We show that industrial policy is multifaceted. Elements such as policy initiation, policy tools, top-down pass-through, and cross-regional learning and diffusion, all contribute to our understanding of the effectiveness of industrial policies. The data set created through our analysis can serve as a basis for future research on the optimal design of industrial policies and offer insights that can be applied beyond China. As global interest in industrial policy continues to grow, understanding the nuances of policy implementation and adaptation at both the central and the local levels will be crucial to assess the impact of these policies.

Third, our paper also contributes to the literature on China's industrial policy. Naughton (2021) provides a detailed overview of the evolution of China's industrial policy over the past 20 years. DiPippo et al. (2022) provide an estimate of Chinese industrial policy spending as of 2019. Aghion et al. (2015) use firm-level data and find that subsidies and tax holidays promote productivity when directed at more competitive industries; tariffs and loans do not. Barwick, Kalouptsidi, and Zahur (2023) use a dynamic equilibrium structural model of the shipbuilding industry to structurally recover different types of unobserved government subsidies to Chinese shipyards, and then use the estimated model to assess the welfare consequences of alternative subsidy policies. Branstetter, Li, and Ren (2023) document negative impact of government subsidies on firms' ex-post productivity growth.[1] Liu (2019) demonstrates the importance of taking into account the input-output linkages in the optimal choice of the sector to be targeted by industrial policy. Our research offers by far the most comprehensive description of China's industrial policy landscape, spanning over 20 years and granular at the city level, as previous research has generally been limited to national or provincial analyses relying on specific policy documents, e.g., the Five-Year Plans. We provide new insights into the political economy of industrial policies by documenting interactions between central and local governments in policy formation and implementation, and by examining the role of local politicians in policy formulation and diffusion. We offer a deeper understanding of how China's politically centralized and economically decentralized system influences policy transmission and adaptation (Xu, 2011), and the inefficiencies such as local protectionism and overcapacity that can arise when regions replicate each other's policies. Our findings thus provide a balanced perspective on China's industrial policy, highlighting both its benefits and the potential risks.

Methodologically, we contribute to the fast-growing literature in economics and finance that uses big text data (Gentzkow, Kelly, and Taddy, 2019; Goldstein, Spatt, and Ye, 2021), especially those that employ LLM to analyze text data (e.g. Li et al., 2025; Lopez-Lira and Tang, 2023; Li, Tu, and Zhou, 2024; Kim, Muhn, and Nikolaev, 2024; Bai et al., 2023; Bybee, 2023; Jha et al., 2024). For example, Korinek (2023) introduces LLMs and their potential applications in various research tasks. Eisfeldt, Schubert, and Zhang (2023) measure the exposure of each occupation to generative AI based on the analysis of the task statement

[1] See Branstetter and Li (2023) for a comprehensive review on studies of China's industrial policies.

of the occupation by LLM. Jha et al. (2024) use LLM to create a firm-level investment score from conference calls. Chen et al. (2024) apply LLM to measure match quality in the labor market. Li et al. (2025) use LLM to measure corporate culture, as well as its determinants and consequences, from analyst reports.

In this paper, we apply LLMs for complicated information extraction rather than text classification or prediction tasks. We demonstrate the capabilities of LLMs to perform multiple complex tasks in extended texts, where hallucination—a pervasive problem with LLMs, where models can generate plausible, yet inaccurate responses—becomes more pronounced. We introduce several novel strategies to address these hallucination issues. Specifically, we highlight the effectiveness of integrating multiple LLMs to mitigate hallucinations (Li et al., 2024). In addition, we extract all the relevant text to the response to improve response quality, enhance transparency, and facilitate further improvement. This method effectively reduces hallucination by encouraging the model to refer to specific phrases, ensuring that responses are closely aligned with the actual content of the documents. To improve prompt clarity, we employ LLMs to systematically search for counterexamples and decompose complex questions into simpler steps. These methodological innovations provide a robust framework for applying LLMs to other economic contexts involving intricate text-based data, enhancing the reliability of AI-generated outputs in capturing multidimensional policy information. We also systematically compare the performance of LLMs with an alternative keyword search approach.

The remainder of the paper is organized as follows. In Section 2 we review the existing measures of industrial policies, discuss the advantages of LLM in analyzing industrial policies, and provide details on applying LLM in analyzing policy documents; in Section 3 we present a detailed description of the industrial policy data we extracted using LLM; in Section 4 we describe several additional data sets of firms and Chinese politicians that we will use in combination with the industrial policy data set; in Section 5 we document a set of facts about China's industrial policy over the past two decades; finally in Section 6 we conclude.

2 Measuring Industrial Policy

2.1 Existing Measurement of Industrial Policy

Several approaches have been adopted in the existing literature to measure industrial policies. These approaches primarily rely on either structured policy documents, e.g., national or provincial Five-Year Plans, or specific policy announcements, or *de facto* measures based on government subsidies received by firms. There is also a more recent attempt to apply text-based methods to official government documents to code industrial policies. Below, we group existing measures into three broad categories.

The first group of studies relies on structured policy documents or specific policy shocks. For studies on China, Five-Year Plans issued by the national or provincial governments, which list the "pillar" or "encouraged" industries that are prioritized for development, have long been used as a source for measuring industrial policy. For example, Barwick, Kalouptsidi, and Zahur (2023) analyze the provincial-level Five-Year Plans, identifying the supported industries through keyword searches for terms such as "pillar industry." Cen, Fos, and Jiang (2024) focus on national Five-Year Plans, identifying "encouraged industries" at the four-digit industry level using keyword searches and linking these industries with government subsidies after the plan issuance. Chen, Li, and Xin (2017) also explore the role of national Five-Year Plans, using keyword searches to identify specific industrial policy initiatives. Other studies leverage specific policy announcements to measure industrial policy. For example, Wei et al. (2023) examine the impact of a national innovation policy, InnoCom, implemented in 2008, which aimed to stimulate indigenous technological innovation. Branstetter and Li (2022) analyze the "Made in China 2025" initiative, a policy document aimed at upgrading China's manufacturing capabilities, as an industrial policy shock. Scholars have similarly relied on various historical episodes to proxy for industrial policy shocks in other economies. For example, Juhász (2018) evaluates the "infant industry" argument using the disruptions to trade that resulted from a blockade against Britain in the 19th century during the Napoleonic Wars (1803-1815); Lane (2022) evaluates the impact of industrial policy on industrial development by studying South Korea's heavy and chemical industry (HCI) drive in the 1970s.

The second group of studies employs a data-driven approach using firm-level data to measure the intensity of industrial policy. For example, Aghion et al. (2015) use China's Annual Survey of Industrial Firms (ASIF) data set to construct policy support intensity measures at the city-industry level by aggregating firm-level information on subsidies, tax holidays, interest payments, and tariffs. Similarly, Branstetter and Li (2023) analyze the total subsidies received by public firms using data from the China Stock Market & Accounting Research (CSMAR) Database to assess the impact of government subsidies on firm performance. DiPippo et al. (2022) compare industrial policy expenditures across countries and use firm-level data to measure policy interventions. Compared to the first approach, this approach only focuses on the industries or firms that actually receive government subsidies; thus, it may fail to capture industrial policies that mainly use other tools, which we will highlight later, such as land and labor inputs, consumer subsidy, government procurement, government equity fund, etc.

The third group of studies uses government documents as a source for policy analysis. For example, Sinclair and Zhang (2023) scrape 444 official policy documents issued by China's State Council after 2008 and focus on those relevant to industry-specific policies. Their analysis attempts to identify policies using keywords such as "promote" and "develop." Recent advances in text-based methods have enabled the analysis of industrial policy using machine learning techniques. For example, Juhász et al. (2022) use the Global Trade Alert (GTA) database to analyze industrial policies across countries and industries and over time. They manually classify a subset of industrial policies and then apply the BERT model to classify the entire dataset, covering a total of 28,000 policy observations. Goldberg et al. (2024) also utilize a subset of the GTA data, focusing specifically on the chip industry. Evenett et al. (2024) develop the New Industrial Policy Observatory (NIPO) database to track recent industrial policies around the world. Compared with the previous literature, the text-based method is able to provide a more comprehensive coverage of industrial policies. However, the method relies on significant manual work; the GTA database is manually collected and labeled by a team of observers in each country, and Juhász et al. (2022) further labeled the documents with a refined definition of industrial policies. This makes the method infeasible for studies at a more granular level, which may involve a larger volume of longer and possibly unstructured documents.

The existing measures of industrial policy have two important limitations. First, they focus primarily on identifying the targeted industries, but do not measure critical details about industrial policy, such as implementation tools, eligibility conditions, the government's objectives or rationale for targeting particular industries, etc. Second, existing measures focus predominantly on national or provincial-level industrial policies; however, in a large economy such as China, it is essential to measure industrial policy at the more granular city level, where many details of the policy are formulated and implemented. In addition, understanding the dynamics of policy pass-through from the central government to the local governments, along with the patterns of policy learning and experimentation, also requires detailed local-level measures of industrial policies. New methods enabled by LLMs, which allow the analysis of complex, unstructured text data, thus offer the potential to overcome these limitations.

2.2 Government Policy Documents

We start with the near universe of official government documents issued by the central and local governments of China during the period of 2000 and 2022. The core component of our data set comes from PKULaw.com, an authoritative online platform hosted by the Peking University Law School. It includes a wide array of policy-related documents, such as regulatory guidelines, policy announcements, and official statements from various levels of government. To ensure exhaustive coverage and capture the most recent policy developments, we supplement this data set with continuous web scraping. This process involved systematically collecting data from official websites at all levels of government, including central, provincial, and municipal administrations. The scraping effort targeted websites of key ministries, departments, and other government entities, ensuring a diverse and up-to-date representation of policy documents.

We identify and remove duplicate documents based on the title of the document, the issuing entity, and the publication date. After deduplication, the final data set contains 3 million unique policy documents for the years 2000-2022.

2.3 Classifying and Coding Policy Documents Using LLMs

The government documents provide a wealth of information on policy. In this section, we outline how we use LLMs to systematically classify whether a policy document is an industrial policy, and if so, extract and organize the multidimensional aspects of the policy.

2.3.1 Overview: What Can We Learn from Policy Documents

First, we identify industrial policies from the near universe of government policy documents described above, according to a clear and consistent definition (see below). Second, we determine the tone of each policy document (e.g., supportive or regulatory/suppressive) and classify the governments' stated objective of each policy. Third, we identify the specific industries targeted by each policy, and map them to China's standard industry code. Fourth, we identify 20 policy tools used to implement the policy, which can be broadly categorized in 5 groups: fiscal and financial incentives; entry and regulation tools; input policy tools; demand-side tools; and tools to foster supply chains. Fifth, we zoom in on more policy details contained in the policy document, such as the date of issuance, the eligibility criteria for firms to receive policy support, and the specific mechanisms and organizational arrangements for implementation. Lastly, we learn about the intergovernmental relationships in policy setting, which explores how the policy aligns with or deviates from upper-level government directives. Specifically, we seek to understand whether the policy follows a top-down directive from the central government, aligns with provincial goals, or represents local adaptation or innovation.

Using these six categories, we guide LLMs to process the unstructured text in the policy documents and to systematically structure it into a well-organized data frame (see Appendix A for details of the LLM implementation). By prompting the LLM to follow this line of thinking, we transform the lengthy raw policy texts into a manageable data set that allows detailed empirical analysis in Section 5. Thus, each policy document is broken down into these core components, allowing us to capture the complexity of the design, implementation, and intergovernmental coordination of industrial policies in China. We now describe the details of each of the tasks.

Defining Industrial Policy. As the first step of the process, we must be clear about the definition of industrial policy for LLM to identify them from the universe of government policy documents. There are extensive discussions about the exact definition of what constitutes an industrial policy among scholars and practitioners. Naughton (2021), in his comprehensive review of China's industrial policy practice, defines industrial policy as "any type of *selective and targeted* government intervention that attempts to alter the sectoral structure of production toward sectors that are expected to offer better growth than would occur in the (non-interventionist) market equilibrium." In a similar vein, in trying to identify industrial policies from the Global Trade Alert database, Juhász et al. (2022) apply a similarly narrow definition as policies with: 1) a stated goal of changing relative prices across sectors or directing resources towards certain selectively targeted activities and purpose of shifting the long-run composition of economic activity; 2) specific actions to be taken and financed by a national or extra-national government.

We follow Naughton (2021) and Juhász et al. (2022) to use a relatively narrow definition of industrial policy. Specifically, industrial policy refers to government policy measures directed at changing the long-term structure of the local economy; the government influences the relative prices of various sectors in the economy (e.g., providing subsidies or tax incentives) or uses other means to guide the allocation of resources it can influence or control. Industrial policy can target specific industries or specific economic activities within certain industries, such as exports, innovation, digitalization, or green transformation.

More precisely, to determine whether some document qualifies as industrial policy, we apply the following criteria:

1. The subject of industrial policy must be the government, including various levels of government and subordinate departments. If the text only involves company or nongovernmental entities, it is not an industrial policy.

2. Industrial policy must involve specific government policy measures. If the text merely reports economic progress or general aspiration, or describes government activities such as government relocation or recruitment, it is not an industrial policy.

3. Industrial policy must be directly biased towards a specific industry or economic activity within certain industries. General policies that do not target specific industries or activities are not industrial policies. Policies that aim to boost long-term economic growth without a biased target on a specific industry, e.g., China's reform and opening up policy, are not counted as industrial policies.

4. Industrial policy aims to affect the long-term structure of the economy. Policies that address short-term economic shocks, such as responses to the COVID-19 pandemic or a downturn in the business cycle, do not qualify as an industrial policy.

Remark 1 A general policy may turn out to be biased towards certain sectors. For example, *Hukou* reforms that relax labor mobility restrictions may benefit labor-intensive industries more; joining the World Trade Organization (WTO) may benefit export-oriented industries more; a carbon tax will foster the development of the green sector. In our study, we do not consider these general policies as industrial policies.

Remark 2 The potential benefit of an alternative broader definition of industrial policy is that it might help us to systematically identify and contrast some common features across different countries. For example, Knight (2014) uses a broad definition of industrial policy that depends on whether there is the presence of an overarching national economic development goal, as well as an incentive structure that rewards government officials for their pursuit of growth. This broad definition of industrial policy allows the authors to draw out the commonalities between several East Asian economies. A broad definition also allows researchers to include regulation, fiscal and monetary policy, innovation policy, and human resource policy as part of industrial policies. Brandt and Rawski (2019) also use a broad definition to bring multiple perspectives to bear on the electrical sector, among others, showing the complex relations between regulation, competition policy, and direct sectoral intervention.

However, defining industrial policy too broadly risks conflating sector-neutral policies with targeted interventions aimed at structurally transforming the economy. Such a broad definition would dilute the focus of the analysis, making it harder to identify the unique mechanisms and impacts of policies explicitly designed to promote specific sectors or activities. By narrowing the scope to targeted policies, we aim to provide a clearer understanding of the tools, objectives, and outcomes associated with industrial policy and to distinguish it from broader economic reforms or general public policies that indirectly affect certain industries more. In addition, this also minimizes the risk of conjecture with LLMs, which is a common source of hallucinations.

Policy Tone. An industrial policy can support, regulate, or suppress the target industry, which we refer to as the "policy tone." Notice that even according to our narrow definition of industrial policy, it does not have to be supportive of an industry or a sector. Supportive policies aim to advance sectors through initiatives such as promoting technological innovation, industrial upgrading, attracting and training labor, improving the business environment, coordinating regional development, infrastructure investment, encouraging openness to foreign investment, and lowering entry barriers. Regulatory policies, while potentially beneficial in the long term, are more focused on immediate controls that aim to regulate industry behavior and establish standards, e.g., setting industry standards, enforcing environmental regulations, market regulation, corporate oversight, ensuring production safety, etc. Suppressive policies seek to limit or phase out certain sectors, for example, restricting overproduction, eliminating outdated production capacity, controlling real estate speculation, or limiting energy-intensive industries.[2]

Policy Objectives. Economists view industrial policy as potentially justifiable only if it helps correct some market failures, including positive social externality, coordination failure, among others. Ironically, in a second-best world, some of the distortions can, in fact, result from other government policies or bureaucratic failure. We task our LLMs with extracting information from policy documents on the stated objectives of industrial policies. Some of the most commonly stated goals include promoting certain types of important industries such as strategic industries, pillar industries, emerging new industries, traditional industries, etc., promoting technological innovation or technology adoption, as well as social goals such as employment, equity, or urbanization, etc. These policy objectives do not directly inform us about the distortions that the industrial policies aim to address, but they do reflect the strategic and social priorities of the government, thus providing some insight into the rationale behind each policy and the broader goals that the government hopes to achieve.

Target Industry/Sector. Because we require an industrial policy to target specific industries, we can identify the industries targeted in each industrial policy document. We identify the industry at the most granular 4-digit industry level. Note that we distinguish the industries that are being directly targeted versus the industries that are mentioned without strong intention for support and the industries that may enjoy the spillover effect of the policy target. For example, an industrial policy promoting the long-run growth of electronic vehicles may also benefit battery manufacturers; we do not include battery manufacturing in the definition of "directly targeted industry" unless the document specifically mentions policies for the battery

[2]Environmental policies can fall into either supportive or suppressive categories depending on their emphasis: if they are focused on pollution control, they are regulatory/suppressive; if they are focused on promoting green development, then they are supportive.

industry.

Policy Implementation Tools. One of the most critical pieces of information we task the LLMs to extract from the industrial policy documents is the identification and categorization of the implementation tools. However, there is no agreed-upon framework to categorize these tools. For example, the Multi-Agency Support Team (MAST) of the United Nations Conference on Trade and Development (UNCTAD) has developed a coding system for *trade*-related policy measures that includes 12 categories, ranging from capital control, subsidies, tariffs, to migration measures, and others. Similarly, Juhász et al. (2022) used the more detailed taxonomy used by the Global Trade Alert (GTA) project to track various policy interventions around the world. These approaches, while comprehensive for measures related to imports and exports, are designed to focus on trade-related interventions, which by nature are predominantly national-level policies.

We extend the existing framework to account for the unique characteristics of domestic industrial policy, especially at the local government level. We retain several categories of policy tools relevant to trade and international competitiveness, such as entry subsidies, import/export controls, financing tools, tax incentives, and fiscal subsidies, as they remain relevant within China's broader industrial strategy. However, to accurately reflect the distinctive features of China's domestic industrial policies, we incorporate additional policy tools that local governments frequently use. These include labor policies, preferential land allocation, infrastructure investment, industrial funds, and policies that promote industrial clusters, among others, which are tools more tailored to regional economic development and reflect the decentralized economic governance structure of China.

More explicitly, we classify industrial policy implementation tools into the following five broad categories:

1. **Fiscal and Financial Tools.** The first category is a group of traditional financial measures that align with existing frameworks, which include credit and finance provisions, tax incentives, equity support, and fiscal subsidies.

2. **Entry and Regulation Tools.** The second category is a set of tools that are directly aimed at promoting market entry and regulating competition. They include industrial funds that offer venture capital support, policies that promote entrepreneurship, and policies to attract investment; they also include regulatory mechanisms to improve the business environment, market access regulations, and trade protection instruments (e.g., import/export controls and possible non-tariff barriers).[3]

3. **Input Policy Tools.** The third category includes tools that affect the prices of various critical inputs in different stages of industrial development. They include labor policy (such as training programs and wage subsidies), preferential land supply (such as reduced land costs for industrial use), infrastructure investments (including transportation and energy infrastructure), policies to promote R&D and technology adoption, as well as environmental policies (e.g., green credit and subsidies for sustainable practices to encourage environmental protection).

4. **Demand Side Tools.** The fourth category covers tools that aim to stimulate demand and ensure that firms can access large and stable markets. They include demand stimulation through consumer subsidies, government procurement, and industrial promotion policies (e.g., public exhibitions and trade shows to increase product visibility and market access).

5. **Supply Chain Tools.** The fifth category focuses on supply chain-related policies that promote industrial clusters and localization policies that support local supply chains. Industrial cluster policies,

[3] Regulatory mechanisms manifest in both supportive and regulatory policies; a policy becomes supportive when it eases existing regulations or simplifies administrative processes.

for example, aim to create economic zones where firms can benefit from proximity to suppliers and customers. Localization policies further ensure that industries use local labor and suppliers, which are aimed at strengthening local economies but may also lead to local protectionism.

By organizing industrial policy tools into these five categories, we advance the existing literature by capturing the comprehensive tool kits of China's industrial policies both at the national and local level. Such a granular industrial policy dataset allows us to systematically assess the range of tools used by governments to achieve their policy objectives, while also revealing key differences in the approaches taken by various levels of government, be it central, provincial, or local; moreover, it highlights the flexibility of the Chinese policy environment, where different tools are employed depending on regional needs, industry characteristics, and the development stage of the supported industries.

Conditionality of Policy Support. Industrial policy documents often specify the requirements or conditions that firms must meet in order to qualify for policy support, which we refer to as *conditionality of policy support*. These criteria serve as filters through which governments target specific types of firms, ensuring that the policy benefits are allocated according to the intended objectives. The common conditions found in Chinese industrial policies can usually be categorized by the following dimensions: firm location, firm scale, firm age, R&D investment or specific technological qualifications (e.g., patents, R&D platforms, or high-tech capabilities), ownership structure (state-owned, private, foreign-invested enterprises, etc.), sometimes even designated specific firms, or others.

Organizational Arrangements for Policy Implementation. Besides policy implementation tools, another important component of the *how* of industrial policies is the organizational arrangement of the government agencies that are responsible for implementing the policy. Specifically, we task the LLMs to evaluate the following four aspects regarding organizational arrangements:

1. **Incentive Schemes for Government Officials.** Policy documents often specify how government agencies, lower-level governments, and their officials will be evaluated for how well they implement industrial policies. This includes specifying performance metrics, setting targets, designating key performance indicators (KPIs), articulating supervision and inspection, specifying potential punishments for underperformance, and/or incentive measures aimed at rewarding successful implementation. By understanding these measures, we can gauge the level of accountability and motivation built into the policy framework.

2. **Experimentation and Learning.** Many policy documents highlight how lower-level governments, government agencies, and their officials are encouraged to engage in policy innovation. This reflects the government's willingness to allow local experimentation and adaptation to achieve policy goals. We can track how and to what extent lower-level actors are given the freedom or incentives to innovate within the policy framework.

3. **Adaptation to Local Conditions.** Policy documents often reflect how a policy has been adapted to the specific local conditions of the region. This adaptation could involve tailoring goals to local economic strengths, adjusting implementation timelines, or accommodating specific regional challenges. By identifying these local adaptations, we can better understand the flexibility and responsiveness of the policy to the unique local needs and conditions.

4. **Organizational Support.** Policy documents may also contain specific measures or arrangements designed to advance the implementation of the policy. This can include task forces, cross-departmental

collaborations, targeted funding support, or other arrangements to streamline execution. These details give us insight into the actual machinery behind policy implementation and how governments mobilize resources to achieve policy goals.

Intergovernmental Relationship. We also extract valuable information on intergovernmental relationships by examining how different levels of government—central, provincial, and local—interact within the policy-making process. This analysis involves two major dimensions: the policy citation network and direct references to upper or lower government levels. These references help us understand how policies are transmitted, coordinated, aligned, or adapted across different levels of government.

First, we extract information on the citation of policies within the documents, revealing how policies influence and evolve across different government levels.[4] Citations can be categorized into several types. "Forwarding and issuance" citation refers to distributing the policy to other government levels or departments for implementation; "implementation" citation involves citing policies as the basis for specific actions, highlighting their continued influence; "basis for policy" citation occurs when a policy is formulated based on higher-level laws or frameworks; "policy continuation or abolition" citation captures whether a policy continues or replaces (or abolishes) a previous one; lastly, "policy coordination" citation reflects how the current policy aligns with existing ones to ensure consistency and avoid conflicts.

Second, references to higher or lower government bodies can be categorized according to their purpose. Mentions of upper-level government often relate to implementing higher-level policies, citing higher-level laws or policies as a basis, executing specific requirements, forwarding central policies for local action, responding to national initiatives, receiving technical guidance, or seeking approval or authorization from upper authorities. In contrast, references to lower government typically involve directing policy implementation, directing lower government coordination, designating pilot programs, promoting successful policy experiences, defining where the policy is applicable, recognizing commendation or rewards for effective implementation, or issuing criticisms and punishments for non-compliance. In addition, there are miscellaneous mentions of lower government relevant to policy enforcement and governance.

Identifying these relationships enables a deeper understanding of how national strategies trickle down to local levels and how local governments align their strategies with those of upper-level authorities. This analysis also highlights the interconnected nature of policy making in China, where both central directives and local innovations contribute to the broader industrial policy landscape.

2.4 LLM Approach vs. Keyword Search Approach

Although we leave the details of the implementation of LLM for the policy documents to Appendix A, it is useful to assess the efficacy of our LLM approach, and we compare it with a hypothetical scenario in which a researcher relies on *keyword searches.*

We should first note that certain textual analyses performed by the LLMs are inherently infeasible using keyword-based methods. For example, identifying the main target industry names from the plethora of names mentioned in each policy document requires a contextual understanding of the prominence of each name and a nuanced interpretation of the wording: distinguishing whether an industry is merely mentioned in passing, or identified as one of the policy targets, or discussed with details such as local industry conditions, key enterprises, and detailed policy measures. Furthermore, mapping these major target industry names to the 432 unique standardized industry names presents significant challenges to the traditional approach.

[4] Note that some policies may be cited in abbreviated forms, such as "xx Five-Year Plan," "xx Five-Year Planning," "**th Plenary Session," "Report of the *th National Congress of the Communist Party of China," "Made in China 2025" government policy; these also count as cited policies.

The sheer number of potential combinations between names extracted from policy texts and standardized industry classifications renders the task computationally overwhelming, and fuzzy matching techniques are impractical. For example, keywords such as “new energy,” “clean technology,” “intelligent,” “digital,” “power battery,” and “energy savings,” which capture the characteristics or directions of China’s electric vehicle industry, do not directly correspond to the industry classification of “electric vehicle manufacturing” and require interpretation based on context.

In light of these challenges, we focus on comparing the LLM approach and the keyword search approach in their performance of identifying industrial policy documents from the universe of all government documents, which is a critical component of our data construction, where a keyword approach might be potentially feasible. To implement the keyword search approach, we first need to come up with a “*bag of keywords*.” We begin by selecting informative keywords from both the policy titles and the full policy texts. An option is to define the bag of keywords as the keywords that appeared with sufficient frequency, say at least 100 times, in the titles or full texts of policy documents *judged by our LLM as industrial policy documents*. However, such an approach would result in a vast number of such keywords, in total 12,002 unique keywords from policy titles and 141,199 from full texts, which makes it challenging to thoroughly verify their informativeness manually within a reasonable timeframe. We choose an alternative option. We define and rank the informativeness of each keyword by the proportion of policy titles (respectively, full texts) that our LLM approach identifies as industrial policies among all the titles (full texts, respectively) that contain the keyword. We then select keywords based on the rankings. The approach is justified as long as our LLM approach can reasonably classify industrial policy, even with some noise. In Table A4, we present the top 20 keywords by their frequency in titles and full texts, respectively. All of them are arguably related to industrial policies.

In Table 1, we present the number of unique keywords based on policy title and full text, respectively, under different informativeness thresholds, as well as the number of policy documents that contain at least one title (full text, respectively) keyword above the threshold. The results involve many keywords to identify a decent number of industrial policies. For example, there are 239 (651, respectively) unique title (full text, respectively) keywords whose informativeness measure exceeds the threshold 80%, that is, at least 80% of the appearances of these keywords are from industrial policy document titles (full text, respectively) identified by our LLM approach. Using this bag of keywords, only 168,309 (116,057, respectively) policies at least contain one such keyword in their title (full text, respectively), much smaller than the 768,387 industrial policies that we identify from the LLM approach. Lowering the informativeness threshold to 70% for a word to be included in the bag of keywords would result in 518 (3,602, respectively) unique title (full text, respectively) keywords. The high numbers of unique keywords imply that a substantial amount of effort is required to manually identify them, especially when it comes to full text. The length of the full texts, with a median length of 1,160 words, further adds to the challenge. However, even with this informativeness threshold of 70%, only 328,495 unique policies are identified as industrial policy documents based on the title keywords, and the number of policies identified by the full-text keywords is less than the number from the LLM approach as well.

[Table 1 about here]

We compare the accuracy of the two keyword-based approaches with that of the LLM approach. We find that while the policies identified by the keyword methods contain informative keywords by construction, closer examination reveals that they often pertain to topics such as the reporting of exemplary cases, social and public affairs, public projects, universities, approvals from securities exchanges, poverty alleviation measures, responses to proposals, proposals by the Chinese People’s Political Consultative Conference, and internal government governance, which would not have met our definition of industrial policy.

In contrast, even though the industrial policies identified by our LLMs do not *always* contain the aforementioned high-frequency informative keywords by design, the LLMs nonetheless identify them as industrial policy through the contextual understanding of the entire document. Some policies that are judged by LLMs as industrial policies are not captured by keyword approaches because of unique phrasing.[5] The LLM approach successfully identifies such policies as industrial policies, but they will be overlooked in keyword searches. These findings underscore the importance of contextual understanding and confirm the advantages of the LLM approach.[6]

3 Description of Industrial Policies

In this section, we present an exploratory description of industrial policies in China over the past two decades based on data constructed using LLMs. We first provide an overview of the temporal and regional distribution and then provide a detailed description of the industrial policy data, classified by key thematic dimensions, such as government objectives, targeted industries, policy tools, implementation details, and intergovernmental relationships.

3.1 Overview

Table 2 presents the distribution of industrial policies by the issuing government level, where each level of government includes all affiliated government departments and entities at the same level. It shows that upper-level governments issue a larger proportion of industrial policies. At the central level, 30.9% of government documents are industrial policies; at the provincial and city levels, 26.8% and 23.5%, respectively, of the government documents are identified as industrial policies. The central, provincial, and city governments represented, respectively, 13.2%, 44.8%, and 38.5% of all industrial policies identified in our LLM approach. It is also interesting to note that, first, industry policy documents issued by the central government include significantly more than Five-Year Plans that were often used in the existing literature; second, the industrial policy documents issued by the central government only account for 13.2% of all industrial policy documents, suggesting the importance of the provincial and city-level policies in China's overall industrial policy landscape. Due to the significantly smaller volume of government policies at the county or township level, our analysis below focuses only on the central, provincial, and city-level industrial policies, resulting in a total of 741,269 policy documents.

[Table 2 about here]

Figure 1 presents the temporal distribution of policy documents. Panel A shows the number of total government documents issued (solid line, left scale), the subset of documents classified by the LLMs as industrial policies (dashed line, left scale), and the proportion of industrial policies as a percentage of all documents (dotted line, right scale). From 2000 to 2022, there is a noticeable upward trend in the overall number of government documents, which is mirrored by a rise in the number of industrial policy documents. It shows that while the total number of industrial policy documents steadily increased over time,

[5]For example, the unique keyword"Xiufeng Residents Tour" refers to a local tourism program, which will not be included as a high-frequency keyword for industrial policy, but the document in question is clearly an industrial policy document that supports the local tourism industry.

[6]Table A5 lists ten randomly selected policy titles that contain at least one title or full text keyword with informativeness greater than or equal to 70%, along with the corresponding keywords. In contrast, Table A6 presents ten randomly selected policy titles that the LLM identifies as industrial policies, but that do not contain any title or full-text keywords that meet the informativeness threshold.

its proportion among all government documents fluctuated until around 2018; Since 2018, there has been a significant surge, suggesting a greater governmental focus on industrial policy as a key tool for shaping economic development. Panel B breaks down the proportion of industrial policies among all government policy documents, by government level. The central government consistently shows a higher proportion of industrial policy documents compared to provincial and city governments, although all exhibit a surge in recent years.

[Figure 1 about here]

Figure 2 presents a geographic overview of the distribution of industrial policies across China. The map highlights significant regional variations in the number of industrial policies issued, with a clear concentration in wealthier and more industrialized regions in South and East China. Coastal provinces such as Guangdong, Jiangsu, and Zhejiang exhibit a much denser concentration of industrial policies. In contrast, the economically less developed Central and Western regions show a lower frequency of industrial policies. This geographic disparity in policy issuance underscores the role of regional economic disparities in shaping China's industrial policy priorities, with wealthier regions deploying more targeted interventions aimed at fostering innovation, upgrading industries and driving economic growth. This finding is consistent with Juhász et al. (2022)'s finding that, at the country level, industrial policy is also unevenly used and skews heavily towards rich countries.

[Figure 2 about here]

3.2 Policy Tones

Table 3 presents the distribution of the tones of industrial policy (supportive, suppressive, and regulatory) by the level of the issuing government entity. Overall 69.6% of all industrial policy documents have supportive tones, 28.9% have regulatory tones, and about 1.5% have suppressive tones. Breaking down by government level, 56.5% (respectively, 69.3% and 74.4%) of the industrial policy documents issued by the central government (respectively, the provincial and city-level governments) support the target industry, while 40.4% (respectively, 29.6% and 24.2%) of the industrial policy documents issued by the central government (respectively, the provincial and city-level governments) aim to regulate the target industry. A small fraction of the industrial policy documents at each government level have a suppressive tone. The fact that a significant fraction of industrial policies have regulatory tones, and some small percentage even have suppressive tones, suggests that focusing only on supportive policies such as subsidies, as is the standard practice in the existing literature, is likely to paint an incomplete picture of China's industrial policy landscape. Indeed, to the extent that industrial policies are aimed at affecting the long-term structure of the economy (see our definition of industrial policy in Section 2.3.1), both supportive and regulatory/suppressive tools should be part of the policy mix.

[Table 3 about here]

Figure A5 plots the evolution over time of the fraction of industrial policy documents with supportive tones by the level of the issuing government entity. It highlights the growing prominence of supportive industrial policies at all levels of government.

3.3 Policy Objectives

Table 4 tabulates the objectives of industrial policies as described in the policy documents, broken down by government level. We group various policy objectives into three broad categories: promoting key industries, fostering innovation, and improving social welfare. Each cell contains the fraction of industrial policy documents issued by the governments in the column heading that contain the objective listed in the row.[7]

The first panel presents the share of industrial policy documents that list objectives related to promoting and supporting key industries. Promoting strategic industries is by far the most common objective, mentioned in 22% of all policy documents. The focus on strategic industries is consistent across government levels. The city-level governments place greater emphasis on the promotion of emerging industries (13%) compared to other levels, reflecting the focus of the local governments on the promotion of new economic sectors, possibly to improve regional competitiveness. Policies aimed at upgrading traditional industries are also prevalent, particularly at the city level (14%), indicating local efforts to modernize established sectors.

[Table 4 about here]

The second and third panels present the share of industrial policy documents that list objectives related to innovation and social welfare. Consistent with the significant proportion of industrial policy tools to encourage innovation and R&D, promoting innovation and new technology adoption remains a key focus at all government levels, with roughly 17% of policies dedicated to innovation and 8% to technology adoption. The social equity and welfare objectives are present in 26% of all documents, and city governments place higher weights on this objective (29%) than the central government (19%). Meanwhile, city governments place more emphasis on stimulating employment (15%) and urbanization (7%), reflecting local concerns about job creation and regional development. These patterns demonstrate the varying focus across government levels, with the central government focusing on strategic industries and innovation, while local governments have a slightly more balanced objective in promoting emerging industries, employment, and urbanization.

Even though the industrial policy documents do not explicitly articulate the relevant market failures or distortions that motivate the industrial policy, it is plausible to conjecture that the government supports key industries because it perceives the social value, which includes the strategic importance, of the key industries to be higher than their private values to firms; or it helps firms overcome large fixed costs; or to overcome existing distortions due to underdeveloped financial markets that favor the SOEs, etc.

3.4 Distribution of Target Industries

The LLM-analyzed data enables us to systematically identify the specific industries targeted by various industrial policies. We analyze how policies have evolved to target different sectors over time and across regions, highlighting the gradual shifts in government priorities and an uneven geographical focus.

Table 5 provides a breakdown of the target sectors of industrial policies for the 2-digit industry code and some key 3-digit sub-industries, by government level.[8] Manufacturing and production-related services receive the highest overall focus, being the target of 29% and 40% of all policies, suggesting a close link between traditional manufacturing and the services that support production processes. In particular, the central government emphasizes manufacturing even more, with 35% of its policies targeting this sector. The focus of the central government on manufacturing highlights the national strategy to strengthen industrial

[7] Since multiple policy objectives can be listed in a document, the sum in each column can exceed 1.

[8] See https://www.stats.gov.cn/sj/tjbz/gmjjhyfl/202501/P020250116506795831658.pdf

production and competitiveness. In the service sector, technology-related services, high-skill services, and lifestyle services also receive significant attention at all government levels, representing the target sector of 20%, 18%, and 29% of all industrial policy documents, respectively. This indicates that China is increasingly targeting these sectors, aligning with the national drive toward technological innovation and structural transformation toward more service-oriented economic development. Interestingly, the agriculture industry, while primarily rooted in traditional sectors, also draws substantial attention from all levels of government, accounting for about 17% of the overall industrial policy documents.

[Table 5 about here]

In the manufacturing sector, the emerging manufacturing and high-skill manufacturing sectors represent the target of a smaller proportion of industrial policies overall (5% and 11%, respectively). However, Figure 3 shows that, while the proportion of industrial policies targeting the manufacturing sector may have slightly declined over time, within the manufacturing sector, the proportions of industrial policies targeting high-skilled and emerging manufacturing have both increased steadily, reflecting China's growing emphasis on technological upgrading and innovation within its industrial policy framework.[9]

[Figure 3 about here]

Figure 4 shows that there are significant regional disparities in the industries targeted in their industrial policies. Panels A and B compare the geographical distribution of policies that target agriculture with those that target manufacturing. Agriculture policies are more concentrated in less developed inland regions, especially in the northern and western provinces; on the contrary, manufacturing policies are heavily concentrated in central and coastal regions, particularly in provinces such as Guangdong, Zhejiang, Shanxi, and Jiangsu, underscoring their roles as key industrial hubs. Panel C shows that high-skill manufacturing policies are predominantly concentrated in economically strong eastern and central regions, aligning with China's strategic focus on technological advancement and industrial upgrading in these areas. Panel D suggests that emerging manufacturing industries, which often involve new technologies and sectors driven by innovation, are geared towards wealthier coastal regions, especially the south and east regions. Lastly, Panels E and F plot the regional distribution of the service sector. Interestingly, the geographical distribution of technology-related services (Panel E), such as the software and Internet industries, aligns closely with the regional distribution of high-skill manufacturing (Panel C). This suggests that advanced manufacturing and technology services receive coordinated policy support. Production-related services (Panel F) are more closely related to the manufacturing industries in general (Panel B), further strengthening the alignment between the manufacturing sectors and their complementary services. These maps reveal not only the uneven regional distribution of industrial policies, but also a degree of policy coordination.

[Figure 4 about here]

3.5 Policy Implementation Tools

As we mentioned in Section 2.3.1, we broadly group industrial policy implementation tools into five categories: Fiscal and Financial Tools; Entry and Regulation Tools; Input Policy Tools; Demand Side Tools; and Supply Chain Tools. Multiple implementation tools can be deployed in a single industrial policy

[9] Figure A6 further presents a breakdown of the targeted industry at the 3-digit level for the most frequently targeted within the manufacturing and service sector.

document. Table 6 reports the share of usage (defined as the percentage of policy documents that include the implementation tool) for each industrial policy tool, with a breakdown by different government levels. There are several industrial policy tools widely used by all levels of government. The most common implementation tool is *fiscal subsidies*, used in 41% of all industrial policy documents. On the one hand, this is consistent with the common belief that industrial policies are usually carried out with government subsidies; on the other hand, this also means that more than half of the industrial policies do not use fiscal subsidies as an implementation tool, which suggests that the existing data-driven method using ex post government subsidies to quantify industrial policies is likely to result in significant measurement error and bias. Table 6 shows that, following fiscal subsidies, market access and regulation (35%), technology R&D and adoption (24%), labor policy (22%) and tax incentives (20%) are tools that are commonly used in general.

[Table 6 about here]

Although there are shared characteristics in the choice of implementation tools at various government levels, there are also significant differences. The central government predominantly employs market access and regulation as industrial policy tools (42%), followed by fiscal subsidies (25%), technology R&D and adoption (21%), tax incentives (20%), and trade protection (19%). At the city level, fiscal subsidies (48%), market access and regulation (34%), labor policy (27%), and technology R&D and adoption (27%) are the most widely utilized tools. The provincial governments' choices lie between those of central and city-level governments, resembling more closely the latter.

The stark difference between central and local governments reflects their different roles in China's industrial policy landscape: The central government's emphasis on market access and regulation highlights its pivotal role in managing entry into crucial sectors and establishing regulatory standards, while local governments focus on offering financial and nonfinancial incentives to support local businesses, especially amid intense regional competition for attracting investment and encouraging entrepreneurship in key industries. In addition, the proactive participation of local governments in supporting specific industries with specific tools is evident in their more pronounced use of labor policies (27% at the city level versus 16% at the central level), infrastructure investment (23% at the city level compared to 11% at the central level), and the encouragement of industrial clusters (18% at the city level compared to 8% at the central level).

Panel A of Figure 5 shows the time trends for the five broad categories of industrial policy implementation tools over the past two decades. First, the use of fiscal and financial tools, such as subsidies and tax incentives, has remained relatively stable over the observed period, suggesting the continued importance of financial interventions as a key element in industrial policies at different levels of government. Second, tools aimed at promoting or regulating market entry have been in gradual decline, indicating a shift in policy focus away from entry regulation toward more open market practices. Third, input-related tools, such as labor policies, infrastructure investment, and R&D support, have seen a slight increase over time. This reflects a growing focus on supporting firms during the production phase, particularly through investments in skilled labor and technological development. Fourth, supply chain tools, including policies that promote industrial clusters and localization, and demand side tools, such as government procurement and demand stimulation, have nearly doubled in use, growing from around 10% to 20% over the observed period, suggesting the shift of focus from single-sector targeting to supply chain management.

[Figure 5 about here]

For some of the empirical analysis in Section 5.2 below, it is useful to categorize policy tools according to their initial usage and growth patterns into five distinct groups:

- **New tools (rapid growth):** Tools that started with low usage but grew rapidly over time, including "industrial funds," "promote industrial cluster," "environmental policy," and "promote entrepreneurship." All of these tools show a strong upward trend in their usage, indicating increasing policy focus on fostering innovation, encouraging entrepreneurial activity, nurturing local supply chain, and addressing environmental concerns.
- **New tools (moderate growth):** Tools that started with low usage but experienced relatively moderate growth, including "government procurement," "localization policy," "equity support," and "demand stimulation." While these tools have not grown as rapidly as those in the first group, they reflect the expanding role of government intervention in areas such as local sourcing and targeted demand side measures.
- **Traditional tools (strong):** Tools that have been traditionally popular and have seen steady growth over time, including "infrastructure investment," "labor policy," "technology R&D and adoption," and "fiscal subsidies."
- **Traditional tools (stable):** Tools that have retained stable usage over time, including "credit and finance," "preferential land supply," "investment policy," and "improving business environment."
- **Traditional tools (declining):** Tools that have experienced a significant decline in usage over time, including "market access and regulation," "tax incentives," and "trade protection."

Panel B of Figure 5 shows the average usage pattern of these five groups of implementation tools over time in China by all levels of government.[10]

3.6 Conditionality of Policy Support

Table 7 categorizes the requirements that firms must meet to be eligible for the support specified in the industrial policy documents, with a breakdown by government levels. It shows that 44% of all industrial policies have a regional focus by specifying the location of the firm as an eligibility criterion, with a slightly higher emphasis on this condition at the city level (47%) compared to the province level (45%) and the central government (32%). This reflects the importance of geographically targeted policies, particularly at the local level, where regional development is a priority. The firm scale is also frequently mentioned (33%), with city-level policies placing the greatest emphasis on this criterion (38%).[11] About 11% of policies include R&D and technological investment as eligibility conditions, with a slightly higher focus at the city level (12%). Central government policies focus more on designating a specific set of firms (19% compared to 15% for city-level policies) and on the type of firm ownership (17% compared to 12% for city-level policies), likely reflecting national-level priorities to support certain types of enterprise (e.g. state-owned enterprises).

[Table 7 about here]

3.7 Organizational Arrangement for Policy Implementation

An essential feature of China's industrial policies is the intergovernmental coordination between the central, provincial, and local governments. The LLM analysis allows us to explore these vertical relationships and examine how policies cascade from the central government and how local governments tailor these policies

[10] Appendix Figures A7 and A8 further present a breakdown of the time trend of each tool within each category.

[11] The scale requirement can be either targeting only the large and leading firms, or specifically targeting the small-and-medium enterprises.

to regional contexts. Furthermore, the data provide information on how local governments experiment with policies, both in the choice of sectors and the choice of implementation methods, reflecting the dynamic nature of the formulation and implementation of industrial policies in China.

Table 8 presents the summary statistics on what we refer to as the "organizational arrangement" for policy implementation, including the role of political incentives, experimentation and learning, adaptation to local conditions, and organizational support in the implementation of industrial policy, with a breakdown at different levels of government.

[Table 8 about here]

The first panel reports the summary statistics of the measures of the government's incentive scheme. Target-setting is prevalent at all government levels, appearing in 48% of policies, reflecting the widespread reliance on explicit targets as a core implementation strategy to establish clear goals for various sectors. The central government is relatively less specific in target-setting than the provincial and city governments. All levels of government emphasize the importance of supervision and inspection. Political Key Performance Indicators (KPIs) are mentioned in a small portion of policies (13%), with a higher emphasis at the city level (18%). Although positive incentives (e.g. rewards) are used in 13% of policies overall, negative incentives (e.g. penalties for non-compliance) are more common (30%), with all levels of government employing negative incentives much more frequently than positive incentives.

The second panel then looks at the incentives and mechanisms for policy experimentation and innovation. Approximately 21% of policies across all levels encourage pilot program and the demonstration effect of the pilots. This dynamic policy formulation process fosters an interactive feedback loop between central and local governments, where local experimentation informs national policy refinement (Wang and Yang, 2025). 6% of the policy documents encourage local policy innovation and only 2% explicitly mention mechanisms that allow mistakes in the policy experimentation process. On the other hand, 13% of the policies emphasize the participation of local governments and 15% of the policies encourage the learning from existing experiences.

The third panel shows that, although the central government sets broad strategic priorities, local governments customize these to fit regional economic conditions and industry strengths. This flexibility allows local governments to align with national goals while fostering local adaptation. Local adaptation is particularly prominent at the city level (51%) compared to the central government (24%), indicating the local awareness in tailoring policies to their specific contexts. In terms of the consideration of local advantages, 12% of the policies emphasize local industry advantage, and 8% emphasize local input (e.g., supply chain) advantage, and both measures show significant variations across government levels.

The fourth panel examines measures of organizational support. 45% of the policies emphasize strict enforcement. Coordination between government entities is another important aspect (65%), particularly at the city government level (71%), underscoring the need for inter-agency collaboration in the process of policy implementation. 43% of the policies mention the government's funding support, and local governments emphasize much more (50%) on this aspect compared to the central government (28%).

3.8 Central-Local Relationship

We further explore the central-local dynamics through the lens of policy citation networks. Frequently, policies refer to other policies, either to signal adherence to a hierarchical governmental strategy or for other reasons. For instance, a lower-level governmental policy might cite a higher-tier government's policy to illustrate a top-down policy transmission, enabling the adoption and execution of the higher-tier government's directives with more specific implementation tactics or to leverage them to enhance the policy's authority.

Policies that refer to other government departments of the same hierarchical level often aim at coordination, focusing on department-specific implementation details. As an example, a city-level fiscal department might refer to an industrial policy issued by the city's industry department to elaborate on fiscal-subsidy arrangements.

Figure A9 shows the rate of policy citation over time for industrial policies at different levels of government. Specifically, Panel A of shows the percentage of city-level policies citing provincial government policies, the percentage of provincial policies citing central government policies, and the percentage of city-level policies citing central government policies. There are three notable patterns. First, from 2000 to 2012, both the city and the provincial governments showed a gradual decline in citing central government policies. This trend suggests that during this period, local governments were exercising more autonomy in policy formulation, relying less on central directives and perhaps focusing more on region-specific challenges. Second, during the same period, there was a steady increase in city-level policies citing provincial government policies, reflecting a stronger vertical integration within sub-national levels of governance. Third, after 2013, there is a noticeable reversal in the previous trends. Both the city and the provincial governments began to cite central government policies more frequently, indicating a return to top-down imposition in the wake of a national move toward re-centralization. In addition, the increase in city governments that cite provincial policies accelerates during this period. However, after 2018, a slight reversal of these trends is observed, possibly reflecting a return to more localized policy experimentation or flexibility.

Panel B of Figure A9 illustrates the rate of citation within the same level of government over time. This is a useful indicator of intra-government coordination across different departments within the same government tier. Two interesting patterns emerge. First, both provincial and city governments show a steady increase in self-citation rates over time, indicating improved coordination between departments within the provincial and city governments. By citing policies from the same level of government, local governments demonstrate a growing reliance on internally consistent policy frameworks, reinforcing coordination between different agencies or sectors at the local level. Second, the central government consistently exhibits the highest self-citation rate, reflecting its role in setting comprehensive national strategies, which are likely coordinated across multiple ministries.

3.9 Case Studies: Semiconductors, EVs, and Solar Energy

In Appendix C we take a deeper dive into three industries that have been hotly discussed in recent years, semiconductors (chips), electric vehicles (EVs), and solar energy, and present insights into the industrial policies at various levels of government to support the development of these three sectors. It shows that the support is much more than the subsidies that have been the focus of the existing literature.

4 Other Data Sets

In the rest of the paper, we will combine the industrial policy data set with rich firm-level data to investigate the effect of industrial policies in promoting entry, competition, and growth of the targeted industries, and we will also use a comprehensive data set of Chinese politicians at the provincial and city levels to offer insights into the role of political-economic influence on the choice and effects of industrial policies in China.

4.1 Firm Data Sets

Firm Registration Data. Our first firm-level data set is the firm registration database released by the Chinese State Administration for Market Regulation. This data set covers the universe of all firms, more than 200 million in total, that were ever registered in China. It contains detailed information about a firm's location, the year of its establishment and exit (if any), the value of its registered capital, its investment history, its initial main shareholders, and the records of any subsequent changes in the main shareholders, etc. With the comprehensive firm registration data, we construct the city-industry-year level measures of firm entry and exit, as well as the overall stock of registered capital in each industry.

Administrative Tax Records. To enrich our measure of firm performance, we also use the administrative enterprise income tax records from the Chinese State Administration of Tax (SAT) for the years 2008-2020, covering a representative sample of more than 1 million firms from stratified sampling.[12] For tax collection and audit purposes, SAT collects firm-level records of tax payments, as well as other financial statement information used in tax-related calculations. The advantages of tax data are two-fold. First, it is representative with wide coverage. As administrative data, it is not subject to the potential measurement error problem of self-reported data. Second, it contains detailed historical information on a wide array of tax-related information about the firms, including their total production, sales, inputs, employment, etc. This allows us to examine the firms' performance in multiple dimensions. Table A9 reports the summary statistics for key variables.

Value-Added Tax Data. The last firm-level data set is a unique dataset from the SAT that catalogs all Value-Added Tax (VAT) invoices issued by firms in mainland China from 2014 through 2018. It encompasses over 16.1 billion transactions among 18 million entities, providing a granular view of commercial exchanges within the Chinese market. It includes detailed information on each transaction, such as the identity, registration location, and industry classification of buyer and seller firms, the tax levied, and transaction values. VAT filing is required for all transactions to claim input tax credits, and failures to comply are strictly punishable by law.[13] In Section 5 we use this data set to construct city-to-city trade flows to measure the extent of local protectionism and analyze its relationship with industrial policies.

4.2 Politicians Data Set

To facilitate the understanding of the political economy behind industrial policies in China, we further enrich our data set with a manually collected data set on all provincial and prefectural city leaders, encompassing both party secretaries and governors/mayors, who held office between January 2003 and December 2019.

For each city party secretary and mayor, we collected key personal attributes such as age, gender, place of birth, educational background, work experience, and factional ties. By incorporating this detailed information on politicians, our dataset enables a more nuanced analysis of the role that political leadership plays in shaping industrial policy decisions across different regions and administrative levels in China, as well as how individual politician's characteristics and networks might influence the formulation and implementation

[12] China's SAT is the equivalent of the Internal Revenue Service (IRS) in the US.

[13] It's important to note that there are certain exceptions to transactions that fall outside the purview of the VAT invoice policy. For example, special invoices cannot be issued for transactions exempt from VAT, sales to consumers, and several other specified conditions. It supports small businesses by providing VAT exemptions based on sales thresholds while ensuring that larger enterprises engage in compliant invoicing practices.

of industrial policies at the local level. Table A10 reports the summary statistics for key variables based on the politician data.

5 Facts of China's Industrial Policies

In this section, we document a set of facts about China's industrial policy over the past two decades. Our findings are organized into four themes: the economic and political determinants of local governments' choices of policy-targeted sectors; the choice of policy tools across levels of government, regions, and industries, and the dynamic evolution of policy tools and implementation methods; the spatial diffusion of policies and the inefficiencies that emerge from regional competitions; and lastly, the effect of these policies and tools on firm entry and performance. The first two sets of empirical patterns mainly employ LLM-analyzed policy data; the third set combines the LLM-analyzed policy data with city-level aggregated data on firms; and the fourth set merges policy data with various micro-level firm data sources. By examining these themes, we shed light on the mechanisms that shape China's industrial policy and its broader economic impact, providing insight into the complex interactions between central directives and local adaptations.

We emphasize at the outset that the "facts" of China's industrial policies in this section are only descriptive, because we do not address the endogeneity of the policies. We believe that these descriptive facts nonetheless provide new insights into the multidimensionality, successes, and pitfalls of China's practice of industrial policies in the last 20 years.

5.1 Political-Economic Determinants of Targeted Industries

As shown in Section 3.4, industrial policies in China show clear regional differences in sectoral focus. This suggests that sectoral priorities are not only shaped by national strategies, but also reflect local conditions and the specific economic strengths of each region. The local government's choice of the policy target reflects an intricate balance of the top-down policy transmission and local adaptations. Both mechanisms are deeply ingrained in China's political framework. As Xu (2011) convincingly argues, China's economic success is founded on a system, referred to as *Regionally Decentralized Authoritarianism*, that is characterized by centralization of political authority and decentralization of administrative and economic powers. The centralized political structure incentivizes the transmission of policies from the central government to provincial governments, then further onto the local governments, while the decentralized economic powers, coupled with competition among local officials for promotions, encourages and fosters experimentation at the local level. Furthermore, the relative strengths of the two mechanisms are not static. It has shifted over time depending on the central government's main focus, which has oscillated between economic growth and political stability. Understanding this interplay between central directives and local adaptation is key to analyzing the political-economic determinants of China's industrial policies. We first examine the economic rationality of the choice of targeted industry/sectors by China's local governments (Fact 1a). We then combine the industrial policy data with the politician data set to explore the political-economic underpinnings of these policies, where we begin by investigating the top-down policy transmission mechanism (Fact 1b), followed by an analysis of how this transmission has evolved over time (Fact 1c). Finally, we explore the regional diffusion of industrial policies and the role of politicians' career mobility in the diffusion of industrial policies across regions (Fact 1d).

Fact 1a: *Cities' choices of targeted industries are positively correlated with both their capital-based revealed comparative advantage (RCA) and absolute advantage (AA).*

Scholars of industrial policy debate on the "comparative advantage-following" versus the "comparative advantage-defying" strategies when choosing the target sectors of industrial policies (Wade, 2015; Rodriguez-Clare, 2007). Lin and Chang (2009) and Lin (2015) assert that government efforts should remain within the existing comparative advantage of the economy, because firms operating within the existing comparative advantage are more likely to attain and/or sustain profitability. In sharp contrast, the "infant industry argument" argues that industrial policy should support sectors in which they currently lack a comparative advantage, but may acquire such an advantage in the future as a result of the potential productivity growth induced by the industrial policy (e.g. Redding, 1999; Melitz, 2005; Greenwald and Stiglitz, 2006). However, recent empirical evidence on international comparisons consistently finds that, in the recent wave of industrial policies, countries tend to support industries with revealed comparative advantage (Juhász et al., 2022; Evenett et al., 2024).

To examine whether China's industrial policies at the local level align with economic theory and the current country-level evidence, we use the city-level industrial policies identified by the LLM, and focus on the period between 2001 and 2020. We examine the city government's choice of policy-targeted sectors and its relationship with the cities' capital-based RCA and AA.

We begin by collapsing the policy data into city-(4-digit) industry-year cells. For each city-industry-year combination, we create a policy indicator, which is coded as "1" if at least one industrial policy document targets the specific industry in the given city and year, and "0" otherwise.[14] This binary variable serves as the dependent variable in our empirical analysis, allowing us to test the factors that affect the local governments' choice of the targeted industries. Local governments' choice of the targeted industry is selective; on average only 7% of industries in each city-year cell are targeted by industrial policies.

We construct measures of a city's advantage from firm registration data based on cumulative registered capital of firms registered in the city in each industry; two of the measures proxy the city's RCA and a third measure proxy the city's AA. Specifically, for city c (in province p), industry s, and year t, the three measures are calculated as follows:

$$RCA^p_{cst} = \frac{Capital_{cst}}{\sum_s Capital_{cst}} \bigg/ \frac{\sum_{c' \in p(c)} Capital_{c'st}}{\sum_s \sum_{c' \in p(c)} Capital_{c'st}} \tag{1}$$

$$RCA^n_{cst} = \frac{Capital_{cst}}{\sum_s Capital_{cst}} \bigg/ \frac{\sum_{c'} Capital_{c'st}}{\sum_s \sum_{c'} Capital_{c'st}} \tag{2}$$

$$AA_{cst} = \frac{Capital_{cst}}{\sum_s Capital_{cst}} \tag{3}$$

The two RCA measures, RCA^p_{cst} and RCA^n_{cst}, are constructed in the spirit of Balassa (1965), with slight modifications, to measure the relative importance of industry s within city c, as proxied by the cumulative registered capital, compared to its overall importance of the industry in the province p and in the nation overall, respectively; it captures whether a city is more specialized in a particular industry than other cities in the province or in the nation overall.[15] The AA measure, AA_{cst}, on the other hand, reflects the absolute importance of industry s in city c, and is proxied by the cumulative registered capital of firms registered in the city-industry-year cell. Table 9 reports the summary statistics for key measures based on firm registration

[14] We tried different specifications for robustness. For example, whether the industry has been targeted in at least three city-level government documents; or whether the industry has been targeted at least once in a narrowly-targeted policy document (a policy document mentioning no more than five 4-digit industries); or the number of documents targeting the industry. Our results remain robust with different measures of policies.

[15] Balassa (1965)'s original RCA index is concerned with assessing a country's comparative advantage in global exports, whereas our modified measure intends to evaluate a city's relative strength in domestic production.

data for the period 2001-2020.

[Table 9 about here]

We estimate the following Poisson pseudo-maximum likelihood (PPML) estimator (Silva and Tenreyro, 2006; Silva and Winkelmann, 2024), which accounts for the large share of zeros in the dependent variable:

$$Policy_{cst} = \exp\left[\lambda_1 L.RCA^n_{cst} + \lambda_2 L.RCA^p_{cst} + \lambda_3 L.AA_{cst} + \delta_c + \eta_s + \gamma_t\right] + \epsilon_{cst}, \tag{4}$$

where the outcome variable $Policy_{cst}$ is an indicator for whether there is an industry policy issued by city government c, for industry s, in year t; the key explanatory variables are the one-year lagged measures of RCA^p_{cst}, RCA^n_{cst} and AA_{cst}, δ_c, η_s, γ_t represent city, industry, and year fixed effects, and ϵ_{cst} is the error term. We use the lagged terms on the right-hand side to avoid a mechanical correlation with the policy dummy because industrial policy may induce more new firm entries in the targeted industries.

[Table 10 about here]

Table 10 reports the regression results. Column (1) shows that there is a positive and statistically significant relationship between the national RCA measure and the likelihood of policy targeting. Specifically, one standard deviation increase in RCA^n_{cst} is associated with 1.2% (=0.00078*14.5) increase in the probability of the industry being targeted by some industrial policy in the city. Similarly, Column (2) suggests that the RCA within the province, RCA^p_{cst}, is also positively associated with policy targeting, and with a larger magnitude: when RCA^p_{cst} increases by one standard deviation, the chance that the industry being targeted by some industrial policy in the city increases by 5.9%(=0.0089*9.7). Column (3) examines the correlation between the industry's absolute advantage in the city and the probability of that industry being targeted, and it shows that AA is also a strong predictor of policy targeting: when AA_{cst} increases by one standard deviation, the probability that the industry being targeted increases by 4.5%(=3.46*0.013). Cities are more likely to target industries with a larger presence, which may reflect the desire to support key local industries with established economic importance. It is worth noting that the average probability that an industry being targeted in a city a year is around 7%, suggesting that the magnitudes of the effects of RCA and AA are significant. In Column (4), we run a horse race between the three variables. The findings indicate that while the coefficients for the RCA within the province and the AA remain relatively stable, the coefficient for the national RCA notably decreases, which implies that cities are more responsive to competitions within the same province than to those from cities from different provinces.

Remark 3 *One potential concern is that the policies are serially correlated, and previous policies enhance the subsequent local RCA. In such a scenario, the observed link between policy target and RCA could be attributed to this endogenously developed advantage rather than the deliberate strategies of the local government. To differentiate between these factors, we analyze the initial year in which each industry was targeted in each city, examining the relationship between policy targeting and the local comparative advantage measures constructed from the year prior to the initial target year. Table A11 reports the regression results. It shows that the correlations between the target industry and local RCA and AA remain robust.*

In Column (5), we interact the RCA and AA measures with the log of the city's GDP to test whether the impact of comparative and absolute advantages on the choice of target sectors varies with the city's economic development level. Column (5) highlights that cities with higher GDP tend to focus on industries possessing a revealed comparative advantage, whereas those with lower GDP tend to focus on industries with an absolute advantage. To the extent that more developed regions have stronger administrative and fiscal capacity, the results highlight the importance of such capacity in making an appropriate policy choice. Failing to target industries with comparative advantage may hurt the growth potential of less developed regions and exacerbate regional disparities.

Remark 4 *The capital-based AA measure we constructed can also proxy for the political influence of the industry in the city. The idea is that sectors that account for a larger share of the city's total firm capital may have stronger influence in the policymaking of the city government. Thus the finding in Column (5) that less developed regions are more likely to targeted the industries with absolute advantage could be suggestive of political capture. In contrast, the RCA measures are less likely to reflect local capture.*

Fact 1b: *City-level governments follow upper-level governments in the choice of target industries in their industrial policies, but the pass-through is heterogeneous with city characteristics.*

We now delve into the political-economic factors that can also affect local governments' industrial policy choices; in particular, we examine the "pass-through" effects that capture how city-level governments align their industrial policy sectoral choices with those of both the provincial government and the central government.

We estimate the relationship between the target sectors at the city-level industrial policies and those targeted by provincial and central industrial policies, where we include the forward and lag terms of the 6 year window to allow for intertemporal correlations in the pass-throughs:

$$Policy_{cst} = \exp\left[\sum_{t'=-6}^{6} \beta^p_{t'} Policy^{p(c)}_{st'} + \sum_{t'=-6}^{6} \beta^n_{t'} Policy^n_{st'} + \delta_c + \eta_s + \gamma_t\right] + \epsilon_{cst}, \tag{5}$$

where the dependent variable $Policy_{cst}$ is the binary indicator for whether city c has industrial policies targeting sector s in year t as previously defined, and the key independent variables $Policy^{p(c)}_{st}$ and $Policy^n_{st}$ are the binary indicators for whether there are policies targeting sector s at year t at the provincial (province $p(c)$ where city c belongs) and central levels, respectively. The regression controls for city, industry, and year fixed effects. Similarly, we also test how provincial policies respond to central policies by running the following analogous regression:

$$Policy^p_{st} = \exp\left[\sum_{t'=-6}^{6} \gamma^n_{t'} Policy^n_{st'} + \delta_p + \eta_s + \gamma_t\right] + \epsilon_{pst} \tag{6}$$

Figure 6 plots the estimated coefficients from the regression equations (5)-(6), showing the local response to the upper-level government policies with different leads and lags. The x-axis represents the event time which ranges from six years before to six years after the issuance of upper-level policies, and the y-axis shows the magnitude of the response. The red and blue dots respectively represent the policy pass-through from provincial governments and from the central government to city governments, estimated from Eq. (5), while the green triangles plot the policy pass-through from the central government to provincial governments estimated from Eq. (6). They show that the same-year correlation between the target sectors for city and provincial industrial policies is the strongest, but there are also some weak serial correlations for proximate leads and lags. The alignment between provincial policies and central policies shows similar patterns with the strongest same-year correlation and weaker serial correlation over time. On the other hand, the response of city policies to central policies is generally weaker than their response to provincial policies, and is also weaker than the response of provincial policies to central policies. This is consistent with China's one-level-up political system, which implies that provincial governments are more directly accountable to central authorities than city governments.

[Figure 6 about here]

Having established that the contemporaneous correlation between different levels of government is the strongest, we next examine the heterogeneity in policy pass-through by interacting the policy indicators with city characteristics:

$$Policy_{cst} = \exp\left[\beta_1 Policy_{st}^{p(c)} + \beta_2 Policy_{st}^{p(c)} \times X_{ct} + \beta_3 Policy_{st}^{n} + \beta_4 Policy_{st}^{n} \times X_{ct} + \beta_5 X_{ct} + \delta_c + \eta_s + \gamma_t\right] + \epsilon_{cst}, \tag{7}$$

where X_{ct} is one of the following: 1) GDP (log transformed), to proxy the city's development level; 2) number of cities in the province (log transformed), to proxy the intensity of political promotion competition within the province;[16] 3) the city secretary or mayor's political connection with the provincial government.

Table 11 presents the regression results. Column (1) shows the baseline result without any X_{ct} where we find that city governments tend to follow the target industries of the industrial policies issued by the central and provincial governments, with a stronger correlation observed between city and provincial policies compared to city and central government policies. Column (2) reports the results with the log of the city's GDP as the interacting variable, and it shows that more developed cities exhibit weaker pass-through from provincial and central policies. This could be driven by the fact that more developed cities have greater capacity to make more independent industrial policy decisions that possibly better reflect their local relative comparative advantage, as suggested by the result in Table 10. In Column (3) we further include the interactions with the number of cities in the province. The regression results indicate that cities in more competitive political environments show stronger policy alignment with provincial and central directives, due to their stronger need to demonstrate political loyalty or to secure more support from higher level government for promotions. Column (4) reports the result interacting the policy indicators with local politicians' political connection indicators. It shows that the pass-through effect is weaker when local officials have strong personal connections with higher-level officials. These connections, measured by overlapping hometowns, colleges, or previous workplaces, can give local officials more latitude to diverge from centrally established policies. The personal relationships provide local leaders with informal political capital, enabling them to implement policies more suited to their local circumstances.

[Table 11 about here]

Fact 1c: *The extent of top-down policy pass-through is linked to the degree of political centralization; and there has been a resurgence of top-down pass-through since 2013.*

Policy pass-through measures the extent to which local governments are following the upper-level government directives as opposed to local initiatives. The existing literature documents a reversal towards centralization since 2013 (Fang et al., 2022; Zhou et al., 2021; Bo, 2020; Lee, 2017). We examine the time pattern in the estimated degree of top-down policy pass-through with a special focus on whether the trend

[16] The measure is used in Lü and Landry (2014) in the analysis of the effect of political competition on the local government's taxation. The idea is that the greater the number of officials accountable to the same principal, the more intense political competition is.

is consistent with the received wisdom of China's political centralization cycle. The regression equation used to estimate the time-varying policy pass-through is:

$$Policy_{cst} = \exp\left[\sum_{t'=2001}^{2020} \beta_{1t'} Policy_{st'}^{p(c)} + \sum_{t'=2001}^{2020} \beta_{2t'} Policy_{st'}^{n} + \delta_c + \eta_s + \gamma_t\right] + \epsilon_{cst}. \tag{8}$$

The two panels in Figure 7 plot the estimated coefficients, $\hat{\beta}_{1t}$ and $\hat{\beta}_{2t}$, over time, representing the degree of pass-through from provincial and national governments to city level, respectively. It shows that the pass-through of the targeted sectors from the central and provincial governments to the city governments exhibits notable changes over time, and the results underscore 2013 as a pivotal year. Panel A shows the time-varying response of city-level industrial policies to the provincial policies, where the downward trend from year 2005 illustrates a decline in the province-to-city pass-through, but there has been a resurgence after 2013. Panel B depicts the policy pass-through from the central to city-level governments. The correlation between city and central policy choices of targeted sectors was largely insignificant before 2013, suggesting a period of relative local autonomy in policy formulation. This is consistent with the common belief of China's one-level-up political system and the corresponding incentive scheme of the local bureaucracies. Post-2013, however, the correlation became significantly positive, marking a clear shift towards stronger alignment with central government directives. This shift after 2013 can be attributed to various factors, including a political reorientation towards centralization, stronger monitoring mechanisms, and perhaps the changing national priorities that required a more coordinated policy framework across all levels of governments.

[Figure 7 about here]

Fact 1d: *The choices of targeted sectors tend to be persistent, and local politician's career relocation contributes to both the shifts in the targeted sectors and to the policy diffusion across regions.*

We then explore the concept of policy persistence in China's industrial policy landscape. On the one hand, policy persistence can create a stable environment, allowing firms to form consistent expectations and plan for the long term, which is particularly beneficial for industrial sectors that require continuous investment and stable regulatory frameworks. On the other hand, the persistence of poorly designed or ineffective policies can be detrimental, as local governments may face difficulties in correcting course due to path dependence, institutional inertia, or political pressures.

Given these considerations, understanding the patterns of policy persistence, as well as the factors that influence changes in these patterns, is crucial. One key factor we examine is the impact of the changes, due to rotation or replacement, of local politicians on policy continuity. When local leaders rotate or are replaced, the alignment of local policies with upper-level government directives may shift, and policies that were previously in place may be altered.

We begin by examining the degree to which the targeted sectors of local industrial policies persist over time, and whether this persistence is interrupted by changes in local politicians. The regression equation is:

$$\begin{aligned} Policy_{cst} = \exp\Big[&\beta_1 Policy_{st}^{p(c)} + \beta_2 Policy_{st}^{n} + \beta_3 Policy_{cs,t-1} + \beta_4 Policy_{st}^{p(c)} \times Change_{ct} \\ &+ \beta_5 Policy_{st}^{n} \times Change_{ct} + \beta_6 Policy_{cs,t-1} \times Change_{ct} + \beta_7 Change_{ct} + \delta_c + \eta_s + \gamma_t\Big] + \epsilon_{cst} \end{aligned} \tag{9}$$

where $Change_{ct}$ is an indicator which takes value 1 if the city's party secretary or mayor differed from that in the previous year, and other variables are as previously defined. We include the interaction terms between the indicators for the targeted sectors—particularly the city's targeted sector indicators in the previous year—and the indicators for the local politician change to examine how local political turnovers affect the persistence of city-level industrial policies.

Table 12 reports the regression results. Column (1) shows that the sectors targeted by local industrial policies exhibit a significant degree of persistence with a first-order autoregressive coefficient of 0.37; Column (2) shows, however, that the persistence is partially disrupted when the city experiences a turnover in its leaders. The negative and statistically significant coefficient estimate on the interaction term $Policy_{cs,t-1} \times Change_{ct}$ suggests that local politician turnover disrupts the continuity of previous local policies; our results also show that in the year of a change in local leadership, local policies tend to align more closely with upper-level government directives, which may suggest that the new local leaders have a stronger incentive to show political loyalty at the beginning of their term.

[Table 12 about here]

To further examine the role of politician mobility on policy diffusion, we identify a subsample of politicians who experienced lateral moves across cities, namely the newly appointed party secretary or mayor who has served as either the party secretary or the mayor of another city in the previous year. We examine the policy choice of the city and decompose its persistence into the correlation with the city's policy choice in the previous year and the correlation with the local politician's policy choice in his/her previous jurisdiction in the previous year, i.e., the persistence by location and the persistence by politician.

Columns (3)-(4) of Table 12 report the regression results. Column (3) shows that, when there is a turnover of local politicians, the correlation with the previous year's policy drops to 0.28. Interestingly, there is a positive correlation between the sectors targeted in the new city and those targeted in the previous jurisdiction of the politicians, as the coefficient estimate of the term *L.Policy (same politician)* is 0.09 and statistically significant at the 1% level. To address the concern that the positive correlation with *L.Policy (Same Politician)* follows from the fact that the previous and current cities of the politician are in the same province, we construct a measure of the average lagged policy indicator for all the other cities in the province, which we denote by *L.Policy (Neighobor Cities)*, and include it in the regression. Column (4) shows that the coefficient estimate of *L.Policy (Same Politician)* remains positive and statistically significant, with a somewhat larger magnitude, while the coefficient estimate for the placebo control, the neighbor's average policy, is small (0.04) and not statistically significant.

This analysis sheds light on the role of politicians' career dynamics in shaping the continuity and shifting of industrial policies at the local level, and our results also demonstrate that the rotation of politicians is an important mechanism for policy diffusion.

5.2 Policy Tools: Regional and Sectoral Variations and Dynamic Evolution

We now turn our attention to the choice of policy implementation tools. In Section 3.5, we observe a notable increase in the variety of policy tools over time and a more balanced use of the traditional tools and the new tools. In this subsection, we explore the choice of implementation tools used in industrial policies across different dimensions. Specifically, we focus on three aspects: How does the choice of policy tools vary across different levels of government (Fact 2a), across regions (Fact 2b), across industries (Fact 2c), and over an industry's development stages (Fact 2d and Fact 2e)? These questions shed light on the processes by which industrial policies are carried out in China.

Fact 2a: *Local governments are earlier adopters of new policy tools, while the central government is heavier user of traditional tools and provincial governments are somewhere in between.*

We first explore how city, provincial, and central governments differ in their use of policy tools, particularly the new and traditional tools, over time. We estimate the following regression:

$$\mathbb{1}(Tool_{ikgst}) = \exp\left[\sum_{t'=2001}^{2020} \beta^{n}_{k,t'}\, \text{Year}_{t'} \times \mathbb{1}\{g=n\} + \sum_{t'=2001}^{2020} \beta^{p}_{k,t'}\, \text{Year}_{t'} \times \mathbb{1}\{g=p\} + \delta_s + \gamma_t\right] \times \epsilon_{ikgst}, \quad (10)$$

where $\mathbb{1}(Tool_{ikgst})$ is a binary variable that takes value 1 if a specific tool type k is used in industrial policy i for industry s, by government level g, in year t; $\mathbb{1}\{g=n\}$ is an indicator for central-level policy, and $\mathbb{1}\{g=p\}$ is an indicator for provincial-level policy; $Year_t$ are year indicators, and δ_s and γ_t are industry and year fixed effects. Note that city-level policy is used as the default group, whose tendency to use the type k policy is absorbed in the year fixed effect γ_t. Because the focus of the analysis is the dynamics in the choice of policy tool over time, to sharpen the contrast, we categorize them into five distinct groups based on their initial usage and growth patterns as described in Section 3.5. Specifically, k can represent one of these categories: rapidly growing new tool, moderately growing new tool, stable traditional tool, strong traditional tool, or declining traditional tool.

Figure 8 illustrates the trend in tool usage across government levels over time. Panels A and B plot $\hat{\beta}^{n}_{k,t}$—the coefficients estimated for the central government, and Panels C and D plot $\hat{\beta}^{p}_{k,t}$—the coefficients estimated for the provincial governments—relative to the city-level government in tool usage.

Panels A and C show that city-level governments tend to be earlier adopters of new tools, followed by provincial governments, with the central government adopting new tools more conservatively. Panels B and D demonstrate that the central government maintains a stronger preference for traditional tools such as market regulation and trade protection, followed by provincial governments. In general, city-level governments are more entrepreneurial in experimenting with new tools, reflecting their flexibility in adjusting policies to local needs and innovation, while the central government remains more consistent in its use of traditional tools. Moreover, these trends suggest a convergence over time, with all levels of government increasingly adopting new tools.

[Figure 8 about here]

Fact 2b: *More developed regions are earlier adopters of new policy tools, and new tools gradually diffuse to less developed regions. More developed regions are consistently heavier users of the fiscally costly tools.*

Local governments' fiscal resources and administrative capabilities play crucial roles in determining which policy tools they choose to implement the industrial policies. It can be expected that cities with stronger finances may employ more extensive fiscal subsidies for their industrial policies.

We employ the sample of city-level industrial policies and follow the empirical specification as in Equation (10). We control for industry-by-year fixed effect to focus on the within-industry cross-region variations in the choice of policy tool. Specifically, we estimate the following regression at policy level:

$$\mathbb{1}(Tool_{ikcst}) = \exp\left[\sum_{t'=2001}^{2020} \beta_{k,t'}\, \text{Year}_{t'} \times \log(GDP_{ct'}) + \gamma_{st}\right] + \epsilon_{ikcst}, \quad (11)$$

where $\log(GDP_{ct})$ represents the GDP of city c in year t, serving as a proxy for the level of economic development, $Year_t$ are year indicators, γ_{st} are industry-by-year fixed effects, and ϵ_{ikcst} is the error term.

Figure 9 plots the estimated coefficients $\hat{\beta}_{k,t}$ to illustrate how the use of different policy tools interacts with the level of the city's economic development. As seen in Panel A, more developed cities are earlier adopters of new policy tools like industrial fund, industrial promotion, and demand stimulation, etc. However, there is a significant converging trend over time. Panel B shows that the more developed regions also rely much more heavily on traditional tools like tax deduction and trade protection; wealthier regions have better fiscal conditions and thus are more able to afford lower effective tax rates to attract investment; and they also have more interactions with the international market. Less developed regions rely more on traditional tools, such as preferential land supply because fiscal constraints limit the adoption of more expensive policy tools.

[Figure 9 about here]

Fact 2c: *The choice of policy tools vary across the targeted industry.*

We now examine how the choice of industrial policy tools varies across different industries. We again use the sample of city-level policies, but now focus on the within-city across-industry variations. The regression equation is specified as:

$$\mathbb{1}(Tool_{ikcst}) = \exp\left[\sum_{t'=2001}^{2020} \beta_{k,t'}\, Year_{t'} \times Industry_s + \gamma_{ct}\right] + \epsilon_{ikcst}, \tag{12}$$

where $Industry_s$ are indicators for industry type—we first compare manufacturing industry versus other industries (i.e. $Industry_s = 1$ for manufacturing industry and 0 for others), and we also focus on the subsample of policies targeting the manufacturing sector and compare between skill-intensive versus other traditional manufacturing industries (i.e. $Industry_s = 1$ for skill-intensive manufacturing industry and 0 for other manufacturing industries). γ_{ct} are city-by-year fixed effects, and ϵ_{ikcst} is the error term.

Panels A and B of Figure 10 plot the estimated coefficients, $\hat{\beta}_{k,t}$, when we compare the policy tool choices for industrial policies targeting manufacturing industry with those targeting other industries. Panel A suggests that the fast growing new tools such as industrial fund, promoting industrial cluster, and encouraging entrepreneurship are more prevalently used in supporting the manufacturing sector. Panel B indicates that manufacturing sectors more frequently use traditional market protection tools while rely less on other traditional tools, such as fiscal subsidy or other financial support.

[Figure 10 about here]

Panels C and D compare the policy tool choices supporting skill-intensive and other manufacturing industries. Panel C suggests that governments more frequently use the moderately growing new tools such as demand stimulation, including consumer subsidy and government procurement, and localization policy, etc. to support skill-intensive manufacturing industries; Panel D suggests that monetary incentives (fiscal and finance) are used more prevalently to support the skill-intensive manufacturing industries, while traditional market protection methods are used less frequently.

Fact 2d: *For a given industry over its development phases, the choice of tools evolves over time from entry promotion to industry upgrading.*

We now examine how, within each industry, the industrial policy tools and implementation methods used by local governments evolve over the industry's developmental phase. Specifically, for a given industry, how do the tools and implementation methods employed during its early development phase differ from those utilized when the industry reaches a more mature stage?

In order to understand the local government's dynamic decision based on local conditions, we focus on the within-city-industry variations. We identify the first year when each industry is targeted in each city, and then calculate for each industry, each year, and in each city, the number of years from the industry first being targeted by the city's industrial policies. This is crucial as the same industry might be well-established in some cities, but remain emerging in other cities. We then estimate the following model at the policy level:

$$\mathbb{1}(Tool_{ikcst}) = \exp\left[\beta^k Duration_{cst} + \delta_t + \gamma_{cs}\right] + \epsilon_{ikcst}, \tag{13}$$

where $\mathbb{1}(Tool_{ikcst})$ is a binary variable indicating the use of a specific tool k by policy i for industry s in city c during year t, $Duration_{cst}$ is the number of years since first being targeted, and δ_t and γ_{cs} are respectively the year and the city-by-industry fixed effects. It is worthwhile to note that by controlling the city-by-industry fixed effect, we are able to distinguish whether within the same city and the same industry, the local government uses different tools depending on the industry's development stage (as proxied by $Duration_{cst}$).

Panel A of Figure 11 plots the estimated coefficients, $\hat{\beta}^k$, for various tools, where a positive coefficient indicates an increasing likelihood of tool utilization as the industry matures (more years from the initial target year in the city). The results show that, initially, the policy focus is on boosting firm entry and government-led demand stimulation. The commonly used tools are those targeting the firms' entry stage and attempting to lower firms' fixed costs and entry barriers, for example, fiscal subsidies, favorable land allocation, industrial funds, market access and regulation, and entrepreneurship encouragement. On the demand side, government procurement is used more often in the initial development stage. Over time, the focus gradually shifts to industrial upgrading, market-based selection mechanism, and consumer-based demand stimulation. The policy tools that are used more often are technology R&D, labor and talent development, environmental protection, promoting industrial cluster, etc. Compared to entry promotion, these tools focus more on facilitating firms' production and industrial upgrading. On the demand side, policy tools increasingly rely on industrial promotion and consumer-based demand stimulation. While government procurement relies on the government's ability to pick the winners, consumer subsidies and trade fairs foster market transactions and allow the market to pick the winners. Overall, the results suggest that local governments are not only choosing different tools for different industries, but also dynamically changing the tools according to the industry's development stage.

[Figure 11 about here]

Fact 2e: *For a given industry over its development phase, the choice of the organizational arrangement for policy implementation evolves over time.*

With the same empirical setting, we then examine the local governments' dynamic choice of the organizational arrangement for policy implementation over an industry's development phase. Panel B of Figure 11 plots the estimated coefficients, $\hat{\beta}^k$, for various organizational arrangements, where a positive coefficient indicates an increasing likelihood of utilization as the industry matures. The results depict the dynamic evolution of the organizational arrangements—specifically, the political incentive scheme for policy implementation (blue triangles), the promotion of policy experimentation and innovation (purple triangles), the government's organizational support (red triangles), and the considerations of local conditions in policy implementation (orange triangles)—over time.

First, in terms of the political incentive scheme, the results suggest that, over the industry's development phase, the local governments are more specific in setting targets for the implementation of the policies and take a stronger position in conducting supervision and inspection, and by including the results in the local bureaucrats' political KPI. Despite the increased emphasis on the results, more positive incentives are used and fewer negative incentives are used, reflecting a change of the incentive mechanism from top-down enforcement to local dynamism. Second, we examine measures of policy experimentation and innovation. The results suggest that as the industry matures, there is an increasing emphasis on policy innovation, learning from experiences, and the demonstration effect of pilot programs, and a decreasing need to require lower-level government departments' participation. Third, we examine measures of the local government's organizational support for policy implementation. There is a significant decrease in emphasis on "strict enforcement," which reflects the local government's gradual shift away from top-down enforcement as the industry becomes more mature and market mechanism starts to weigh more heavily. On the other hand, there is a slightly elevated emphasis on providing institutional support and facilitating coordination among different government departments, reflecting a more comprehensive institutional support over time. Lastly, as for the measures of local considerations, there is a high emphasis on local adaptation and differentiation in the initial stage of development of an industry; as the industry matures with a gradually established local advantage in the industry and the supply chain, the policies emphasize more on exploiting the local advantages.

5.3 Spatial Diffusion and Potential Inefficiency of Industrial Policies

We now turn attention to the spatial diffusion of the choices of target sectors by local governments. We first examine the regional similarity of policy choices and its implication on regional trade (Fact 3a); we then take a dynamic perspective and investigate the efficiency implications of policy diffusion (Fact 3b); finally, we examine the local governments' use of policy tools and implementation methods as industrial policies diffuse across different cities (Fact 3c).

Fact 3a: *Increasing inter-regional policy similarity is positively correlated with local protectionism.*

From the perspective of traditional trade theory, regions should ideally focus on industries where they have a comparative advantage, achieve agglomeration, and engage in inter-regional trade to optimize economic outcomes. This would allow each region to specialize in industries that best suit their natural resources, workforce, and infrastructure, resulting in efficient regional allocations. However, with strong top-down policy pass-through in China, regional policy choices are becoming increasingly similar, which can lead to overly homogeneous industrial structures.[17] The result can be local economies that are too similar to one another, fostering competition rather than complementarity between regions, which can lead to heightened local protectionism, where cities and regions attempt to shield their own firms from external competition to maximize local tax revenue. Local protectionism, which often involves policies aimed at protecting local industries from competition within the same country, has been a prevalent issue in China, driven by both fiscal incentives and political motives (Fang, Li, and Wu, 2022; Young, 2000).

We examine the spatial similarity of policy sector choices across cities to assess the degree of policy similarity. For each city in each year, we construct an industrial policy vector consisting of the 0/1 indicators for whether each industry is supported or not by an industrial policy. We then calculate the *cosine similarity* of the policy vectors between each city pair in the same province, from which we calculate the city-year level policy similarity index as the average of the cosine similarity measure for the city with all the other cities in the *same province*. Figure 12 plots the over-time and geographical distribution of policy similarity, revealing

[17] See https://m.thepaper.cn/newsDetail_forward_28084984 for anecdotal evidence.

a significant increase in policy similarity over time, as well as great regional variations.[18]

[Figure 12 about here]

To investigate the possible connections between policy similarity and local protectionism, we turn to the VAT data set with firm IDs matched to the firm registration data (which allows us to know the city where the firm is registered). Recall that the VAT data set records transactions at firm pair level. We first aggregate the firm-pair transactions to city-pair level, we calculate, for each city, the total value of trade of firms within the same city, which we refer to as intra-city trade, as well as the total trade of the city's firms with other firms in the same province, which we refer to as intra-province trade. As a proxy for the level of local protectionism, we construct two measures. In the first, we divide a city's total intra-city trade by the city's total trade nationwide; in the second measure, we divide a city's total intra-city trade by the city's total intra-province trade.

Figure 13 presents the bin-scatter plot for the city's within-province policy similarity index and the two intra-city trade shares we created. On the x-axis, Panel A uses the share of intra-city trade in the city's total trade volume, and Panel B uses the share of intra-city trade in the city's total intra-province trade. The figures show a positive correlation between policy similarity and the percentage of intra-city trade, and the effect is stronger for city pairs within the same province. Thus, more similar industrial policy choices may lead to similar economic structures across regions and thus reduce the incentive for inter-regional trade, potentially contributing to elevated local protectionism which can harm overall economic efficiency.

[Figure 13 about here]

Despite the costs of policy similarity, why are local governments pursuing more similar policies? There are several possible explanations for the similarities in local governments' policy choices. First, as we documented in Section 5.1, the local government's choice of the targeted sector is significantly shaped by the top-down policy directive. This will naturally generate correlations among the choices of local governments as they follow the same upper-level policies.

In addition to the influence of top-down directives, another significant factor driving policy similarity is regional competition. Local governments often compete fiercely for key industries—particularly those that are critical to the supply chains. By attracting and retaining critical industries within their jurisdictions, regions aim to capture the entire supply chain, foster localized economic growth, and secure fiscal revenues.

Local protectionism is therefore reinforced by both fiscal and political imperatives. From a fiscal point of view, local governments are incentivized to protect and nurture local industries to secure tax revenues and create jobs. Politically, local officials are evaluated based on their city's economic performance relative to their peer cities in the same province, which motivates them to adopt policies that favor local industry retention and growth. This protectionism can manifest itself as barriers to inter-regional trade and duplication of industrial efforts across cities, contributing to inefficiency in resource allocation on the national scale.

The third contributing factor to policy similarity is learning, where cities imitate successful industrial policies from other cities. This effect is especially pronounced in high-growth sectors such as high-tech and renewable energy, where regional officials may see the success of other cities as a blueprint to follow. However, this imitation can dilute regional specialization, as cities pursue the same industries rather than capitalizing on their local relative comparative advantages (see Fact 3b below).

Fact 3b: *As policies diffuse across regions, their effectiveness diminishes.*

[18] For example, areas such as Inner Mongolia and the coastal regions exhibit higher levels of policy similarity, while other regions, such as parts of the northwest, show lower similarity in policy choices.

We now explore the effectiveness of industrial policies as they diffuse across regions. As previously discussed, the competitive and learning incentives often push local governments to replicate successful policies implemented by pioneering cities. This dynamic creates a diffusion process where cities tend to promote the same industries over time. However, this diffusion can lead to inefficiencies, particularly in terms of overcapacity when too many cities target the same industries.

We analyze how the sequence of cities targeting a particular industry affects the policy effectiveness on the new firm entry, firm's capital investment, and performance. Specifically, for each industry, we define the order in which cities start to support it, allowing us to differentiate between early (pioneers) and late adopters (followers). We estimate the following regression at the city-industry-year level:

$$Y_{sct} = \beta_1 Policy_{sct} + \beta_2 Policy_{sct} \times Order_{sc} + \delta_{sc} + \gamma_t + \epsilon_{sct} \tag{14}$$

where Y_{sct} is the outcome variable (e.g., log number of new firm entries, log value of new registered capital, or log value of average new registered capital) in industry s, city c, and year t; $Policy_{sct}$ is a dummy variable indicating whether city c implements an industrial policy targeting industry s in year t; $Order_{cs}$ represents the order in which city c first adopts a policy for industry s. We normalize the measure by the total number of cities—330— with lower values indicating earlier adoption. We include the interaction between the policy variable and the order of adoption ($Policy_{sct} \times Order_{cs}$) to capture how the timing of policy adoption affects the outcomes of interest. δ_{sc} and γ_t are the city-by-industry and the year fixed effects, respectively, and ϵ_{sct} is the error term. We control for the city-by-industry fixed effect to tease out the region-industry specific shocks, such as the region's comparative advantage in the industry, to focus on the heterogeneous policy effect driven by the sequence of policy entry.

Table 13 reports the regression results. Column (1) reports the result with the log of the number of new firm entries in city c, industry s, and year t, as the dependent variable. The coefficient for *Policy* is positive and significant, indicating that cities that support the industry experience an increase in the entry of new firms. The coefficient for the interaction term (*Policy* $\times$ *Order*) is negative, although statistically insignificant, which means that policy followers may see smaller increases in firm entry compared to pioneers. Column (2) reports the result for the log of the value of new capital, and shows a similar pattern. The effect of *Policy* is again positive, showing that cities that adopt policies attract more capital investment. However, the coefficient for the interaction term (*Policy* $\times$ *Order*) is negative and statistically significant at 5% level, suggesting that although policy pioneers benefit from increased capital formation, this effect notably decreases for cities that follow. This may be due to overcapacity, as more cities vie for identical industries, leading follower cities to attract firms of smaller sizes. Column (3) reports the results for log of the value of average new capital per firm. Similarly, the coefficient for *Policy* is positive, but that for the interaction term is negative and statistically significant at 1% level.

[Table 13 about here]

At the firm level, we further assess the impact of policy diffusion on firm performance using the same specification as (14), but at the firm level:

$$Y_{fsct} = \beta_1 Policy_{sct} + \beta_2 Policy_{sct} \times Order_{cs} + \delta_f + \gamma_t + \eta_s + \epsilon_{fsct} \tag{15}$$

where Y_{fsct} represents firm performance measures such as revenue, profit, or productivity, δ_f is the firm fixed effect to control for time-invariant firm characteristics, and all other terms are defined as above.

Table 14 shows the firm-level effects. Firms in policy pioneer cities benefit from the industrial policy in achieving higher firm revenues and profits, but as more cities target the same industry, firms in the policy follower cities experience lower or even negative revenue and profit gain. Columns (1) and (3) control for city, industry, and year fixed effects, while columns (2) and (4) further control for firm fixed effect. The larger magnitude of the negative effect of the interaction term in columns (1) and (3) further supports the conclusion that new entrants in follower cities are of inferior quality.

[Table 14 about here]

We advance two possible reasons for the diminishing effectiveness of industrial policy in the follower cities. The first is overcapacity, as a result of excessive entry under government support. As more cities adopt similar industrial policies, it leads to excessive entry of firms into the same industries, ultimately creating overcapacity. With too many firms competing in the same market, resources such as labor, capital, and upper-level government support become stretched, reducing efficiency and productivity for all firms.

The second possible reason for the diminishing effectiveness for industrial policy in follower cities is the low learning quality in policy implementation: Policy followers may not have as much capacity as the policy pioneers in choosing the target sector and in executing policies with the same level of complexity. In particular, followers may be less likely to target industries where they have a comparative advantage, focusing instead on industries that other cities have already established comparative advantages. Moreover, they may be less savvy in grasping the intricate combinations of policy tools and implementation strategies that lead to success, or may have fewer fiscal resources in the choice of policy tools and implementation methods.

Fact 3c: *As policies diffuse across regions, policy followers are less savvy in the choice of the target industry, policy tools, and implementation methods.*

To empirically ascertain these hypotheses, we first examine the choice of the target industry by running the following PPML estimation at city-industry-year level:

$$Policy_{cst} = \exp\left[\beta_1 \cdot RCA_{cst} + \beta_2 \cdot Order_{cs} + \beta_3 \cdot RCA_{cst} \times Order_{cs} + \delta_{sc} + \gamma_t\right] + \epsilon_{cst}, \tag{16}$$

The sign of the coefficient estimate of interest, $\hat{\beta}_3$, informs us about whether follower cities are more or less likely to target sectors where they have a revealed comparative advantage.

Table 15 reports the estimation results. The results indicate that policy pioneers tend to choose industries more aligned with their RCA, while followers often fail to do so, leading to inefficient policy targeting. This pattern reflects the tendency of follower regions to mimic successful policies elsewhere and not fully take advantage of their own local conditions.

[Table 15 about here]

Second, we examine the choices of policy tools for the pioneers and the followers. In particular, we ask whether the followers show more or less savvy in the choice of policy tool. We utilize the policy-level data and examine the correlation between tool choice and the order in which each local government entered each city. The regression equation is specified as follows:

$$\mathbb{1}(Tool_{ikcst}) = \exp\left[\beta_k \cdot Policy_{icst} \times Order_{cs} + \gamma_{ct}\right] + \epsilon_{ikcst}, \tag{17}$$

where $\mathbb{1}(Tool_{ikcst})$ is a binary variable indicating the use of a specific tool k by policy i for industry s in city c during year t, and $Order_{cs}$ is as defined previously.

In Panel A of Figure 14 we plot the coefficient estimates $\hat{\beta}_k$, from Eq. (17), for each policy tool k, representing how the timing of policy adoption influences the selection of policy tools. It indicates that policy follower cities are more likely to rely on simple and less selective tools like fiscal subsidies, financing, promoting entrepreneurship, or preferential land supply, etc. In contrast, more complex tools such as demand-based interventions, promoting industrial cluster, or R&D subsidy, etc. are less likely to be implemented by followers. This pattern of using less complex policy tools by follower cities may explain why the industrial policies by follower cities are less effective than those by pioneer cities.[19]

[Figure 14 about here]

Third, with the same empirical specification, we also examine the differences between pioneer and follower cities in their choices of policy implementation methods. In Panel B of Figure 14 we plot the coefficients estimated for each implementation method. It shows that, in general, policy follower cities show less local dynamism in their choice of policy implementation methods: they are less likely to set specific targets, use more negative incentives and fewer positive incentive schemes; they are less likely to encourage policy innovation and, accordingly, are less tolerant of mistakes in policy implementation; they emphasize more on top-down strict policy enforcement, while providing less funding; and they significantly emphasize less on local advantages, which is consistent with the previous fact that they are less likely to target industries with local comparative advantage.

Now we take a different perspective and examine to what extent the local governments, especially those of the policy follower cities, adopt the policy tool bundles as specified in the upper-level government policies. Specifically, within each city-industry-year cell, we construct a tool vector representing each government's choice of policy tools— the k-th element of the vector takes the value 1 if the government uses type k tool for this industry in this year. We then calculate the cosine similarity between the tool vector of each city government and the provincial government (or central government) in each industry each year. Figure 15 presents the bin-scatter plot of the tool similarity index with the order of policy adoption on the horizontal axis. The figure shows a strong correlation between the order and the similarity index, indicating that follower cities follow the upper-level government in the choice of policy tools with less local experimentation and adaptation.

[Figure 15 about here]

5.4 Effects of Industrial Policies on Firm Performance

The success of industrial policies hinges not only on the choice of the targeted industry but also, and probably more importantly, on how these policies are implemented using various policy tools. We now combine LLM-analyzed industrial policy data with micro-level firm data to investigate the impact of policy on firm performance. First, we investigate whether firms in targeted industries receive actual policy benefits, such as subsidies or tax deductions, and how these benefits are distributed across firms of different sizes (Fact 4a); second, we examine whether industrial policies lead to an increase in firm entry and whether different policy tools have heterogeneous impacts on new firm formation (Fact 4b); third, we assess whether industrial policies enhance firm productivity and analyze the differential effectiveness of various policy tools (Fact 4c).

Fact 4a: *Supportive industrial policies are effective in reducing tax rates, providing subsidies, and increasing firms' access to borrowing, and the effect is heterogeneous with respect to firm size.*

[19] The follower cities' reluctance to use demand-based interventions is partly because broad consumer subsidies are more likely to benefit firms in policy pioneer cities because of their leading position.

First, we employ the administrative tax records of firms to determine whether those in sectors targeted by industrial policies actually receive government support, such as tax breaks, subsidies, or better financing options, by regressing various measures of firm outcomes on the policy dummies. This analysis ensures that the allocation of policy supports aligns with their intended goals.

To capture the differential effects of policies with different tones, we separately include indicators for whether the city has supportive policies, denoted by $Policy^{+}_{sct}$, or regulatory/suppressive policies, denoted by $Policy^{-}_{sct}$, for industry s in year t. The regression equation is:

$$Y_{fsct} = \beta^{+} \times Policy^{+}_{sct} + \beta^{-} \times Policy^{-}_{sct} + \delta_{sc}(+\delta_f) + \gamma_t + \epsilon_{fsct}, \tag{18}$$

where the dependent variables, Y_{fsct}, measure various aspects of firm-level financial conditions, including: (1) tax deduction rate defined as the ratio of total tax exemption to the pre-tax revenue; (2) log of the total amount of subsidies received by a firm; (3) a binary indicator for whether a firm has long-term debt, which can reflect the firm's ability to secure bank loans or other long-term financing. We include either the industry-by-city fixed effects δ_{sc} or the firm fixed effects δ_f, and year fixed effects γ_t.[20]

Table 16 presents the regression results. In Columns (1), (3) and (5), we control for the industry-by-city and year fixed effects to estimate the effect of industrial policy on the *average* firms in the targeted industries; and in Columns (2), (4) and (6), we control for the firm fixed effects, which allows us to estimate the effect of industrial policy on the *existing* firms in the targeted industry (which captures the intensive margin). Columns (1) and (2) find that supportive industry policy is associated with a 6% industry-wide average increase in firm subsidy, and the effect drops to 1.8% on the intensive margin among existing firms after controlling for the firm fixed effects. Columns (3) and (4) suggest that firms in targeted industries with supportive industrial policy, on average, enjoy a 5 percentage points lower effective tax rate, and the effect turns null after controlling for the firm fixed effect. Columns (5) and (6) present the results of firms' long-term debt, and they show a significant industry-wide effect of policy support on firms' financing condition: the probability of acquiring long-term debt increases by 2.3 percentage points under policy support. The magnitude of the effect decreases to 1.1 percentage points on the existing firms when we control for the firm fixed effects.

[Table 16 about here]

Comparing the coefficients for the supportive policies and regulatory/suppressive policies reveals an interesting pattern worth further investigation—both types of policies show positive correlations with firm benefits such as subsidies and enhanced financing conditions. There are two potential explanations for the positive contemporaneous correlation observed between firm performance and industrial policy indicators. First, it may stem from endogenous targeting: regulatory/suppressive policies frequently target industries that have already overheated due to prior industrial support. As a result, the regulatory/suppressive policy indicator is positively correlated with benefits accrued to firms from prior supportive policies. Second, the policies themselves might directly contribute to increased firm benefits.

To disentangle these two channels, we examine the dynamic responses of firm outcomes to supportive and regulatory/suppressive policies. Specifically, we include both forward and lag terms of policy issuance

[20] The newly entered firms would be excluded when we control for firm fixed effects, but will be included when we control for industry by city fixed effects.

to capture the temporal relationships between policies and firm outcomes.

$$Y_{fsct} = \beta_0 + \sum_{l=-2}^{2} \beta_l^+ \times Policy^+_{sc(t-l)} + \sum_{l=-2}^{2} \beta_l^- \times Policy^-_{sc(t-l)} + \delta_{sc}(+\delta_f) + \gamma_t + \epsilon_{fsct} \tag{19}$$

where $Policy^+_{sc(t-l)}$ and $Policy^-_{sc(t-l)}$ are the lag (forward for negative values of l) terms of supportive and regulatory/suppressive policy indicators, and β_l^+ and β_l^- measure the l-period lag responses of firm performance to supportive and regulatory/suppressive policies, respectively. All other terms are defined similarly to those for Eq. (18).

The results are reported in Panel A of Figure 16. It unveils the different mechanisms that drive the positive contemporaneous correlation between policy indicators and firm outcomes for supportive policies and regulatory/suppressive policies. Forward terms of regulatory/suppressive policies, indicating future policy targeting, are positively correlated with firm subsidies and financing conditions, while lagged terms are either negatively correlated or statistically insignificant. This temporal pattern supports the endogenous targeting channel, where regulatory/suppressive policies aim to regulate/suppress previously heavily subsidized industries. In contrast, supportive policies exhibit an opposite dynamic: their lagged terms are positively correlated with firm benefits, suggesting that these policies directly contribute to increased subsidies, tax deductions, and financing opportunities for firms over time. The results show similar patterns when controlling for the city-by-industry fixed effects and for the firm fixed effects, although the magnitudes are less pronounced when controlling for the firm fixed effects.

[Figure 16 about here]

Some policies may favor smaller, younger firms, while others may benefit larger firms. Lastly, we explore the heterogeneities in policy support across firms of different sizes by interacting the policy dummies with the firm's log of registered capital. Panel B of Figure 16 reports the regression results. It suggests that, on average, larger firms benefit more from industrial policies.

Fact 4b: *Supportive industrial policies are effective in increasing new firm entry, and the effect varies by the policy implementation tools used.*

Reassured that the industrial policies indeed provide benefits to the targeted industries, we proceed to analyze how these policies influence firm behavior, both on the extensive margin, which pertains to the entry decision, and the intensive margin, which involves investment and productivity growth.

First, we investigate the impact of industrial policies on encouraging the entry of firms. Our analysis utilizes the firm registration dataset, which provides comprehensive details on all registered firms in China. We aggregate the firm registration data into city-industry-year cells to determine the count of new firms and the stock of existing firms for each city-by-(4-digit) industry and year. The regression is at city-industry-year level.

$$Y_{sct} = \sum_{l=-6}^{6} \beta_t^+ \times Policy^+_{sc(t-l)} + \sum_{l=-6}^{6} \beta_t^- \times Policy^-_{sc(t-l)} + \delta_{sc} + \gamma_t + \epsilon_{sct}, \tag{20}$$

The dependent variable Y_{sct} is the city-industry-year level entry rate defined as the number of new entries divided by the stock of existing firms in each year t. We include the industry-by-city fixed effect δ_{sc} and year fixed effect γ_t. All other terms are as previously defined.

Figure 17 plots the estimated coefficients, $\hat{\beta}_t^+$s and $\hat{\beta}_t^-$s. It indicates that supportive policy is associated with positive firm entry rate, and regulatory/suppressive policy is associated with negative firm entry rate.

Further examining the intertemporal correlation indicates that the positive firm entry rate leads supportive policies by one period, suggesting a potential anticipation effect. On the other hand, the negative response to regulatory/suppressive policies takes 2 years to prevail.

[Figure 17 about here]

Lastly, we focus on supportive policies only and investigate how different policy tools vary in their effectiveness in promoting firm entry. The regression equation is specified as follows:

$$Y_{sct} = \sum_{k} \beta_k \times Policy_{ksct} + \delta_{sc} + \gamma_t + \epsilon_{sct} \tag{21}$$

Figure 18 plots the estimated coefficients for each tool $\hat{\beta}_k$s. It shows large variations across policy tools on new firm entry. Fiscal subsidies, labor policies, preferential land supply, industrial promotion are the most effective tools to increase the entry of new firms, followed by tools to promote entrepreneurship, market access and regulation methods, and infrastructure investment. These tools provide direct benefits, and thus lower entry barriers for new firms. Access to credit and finance, tax deduction, demand stimulation, promoting industrial clusters, and industrial fund have relatively mild effects on attracting new firms. Tax incentive, technology R&D and adoption, investment policy, equity support, and improving the business environment show a null effect on the entry of new firms. It may be because these tools mainly benefit the incumbent firms. In sharp contrast, environmental policies, trade protection, and government procurement policies have significantly negative effects on new firm entry. Environmental policy deters new firm entry because of the elevated environmental standards and compliance costs. Trade protection may protect domestic or local firms, but can come at the cost of deterring the entry of foreign firms and firms from other cities. Government procurements are usually biased toward larger or state-owned enterprises and thus may lead to more concentrated market power and deter the entry of smaller new firms.

[Figure 18 about here]

Fact 4c: *Supportive industrial policies have a positive but short-lasting effect on firm productivity, and the effect varies by the policy implementation tools.*

Lastly, we examine whether and how industrial policies affect firms' productivity. The impact of industrial policy on firm productivity may be ambiguous ex ante. Several mechanisms can operate simultaneously under industrial policies, particularly when different policy tools are employed. For example, entry subsidies and low-cost land allocations promote new firm entry, fostering market competition; demand stimulation policies not only increase firm revenues, but also potentially enhance productivity through market selection, where more productive firms capture a larger share of the increased demand; tools to foster industrial cluster can generate economies of scale, leading to productivity gains. However, there can also be countervailing forces. Policies that encourage the entry of new firms can lower the threshold for market participation, allowing less productive firms to enter, which can dilute overall productivity. In addition, excessive entry could lead to overcapacity and resource crowding out, even for high-performing firms. Labor subsidies reduce labor costs and may encourage firms to adopt more labor-intensive production technologies, thus lowering productivity.

While it is beyond the scope of this paper to decompose the effect of different policy tools and separate the possible mechanisms, we attempt to provide evidence on the rich variations in policy effect on different dimensions of firm behavior. In particular, we use the firm-level administrative tax data and follow the same firm-level specification as in Equation (19) to examine the policy impact on firms' productivity, revenue, employment, intermediate input, and capital formation.

Figure 19 presents the results of the impact of industrial policy on firm productivity (measured by revenue-based TFP). Overall, the results suggest a positive but short-lasting impact of supportive policies and a negative impact of regulatory policies. The results further inform us on the selection pattern of supportive policies versus regulatory/suppressive policies—the forward terms of regulatory policies are positively correlated with firm TFP and that of supportive policies are negative, suggesting that regulatory/suppressive policies more often target high-TFP industries and supportive policies target low-TFP industries.

[Figure 19 about here]

Figure 19 suggests a one-period lag in the firm's productivity response to supportive industrial policies. To further decompose policy effects into different policy tools, we examine the correlation between firms' productivity and the one-period lag terms of the policy tools focusing only on supportive policies using the following specification:

$$Y_{fsct} = \sum_k \beta_k \times Policy_{ksc,t-1} + \delta_{sc} + (\delta_f) + \gamma_t + \epsilon_{fsct} \tag{22}$$

Figure 20 reports the results on the correlation between policy tools and firm TFP (revenue-based), controlling for city-by-industry and year fixed effects. It shows large variations across policy tools on firm productivity. First, R&D policy contributes the most to firm TFP growth. Second, policy tools that encourage capital investment, such as equity support, investment policy, and better access to credit and finance, significantly contribute to firm TFP, suggesting that these policy tools relax firms' financial constraints and allow firms to invest in long-term growth. In contrast, the policy tool that promotes labor input is negatively correlated with firm TFP. This is consistent with Imbert et al. (2022)'s finding that relaxing labor mobility constraints encourages firms to become more labor-intensive and productivity declines. Third, policy tools to promote firm entry, such as promoting entrepreneurship and providing market access and regulation, have a consistent negative effect on firm productivity, possibly reflecting the fact that the entry of less productive and smaller firms dilutes the incumbent firms' access to resources, thus lowering overall productivity. In contrast, trade protection tools, by deterring firm entry and protecting incumbent firms, contribute positively to firm TFP. Fourth, fiscal subsidies directly increase firm revenue and are thus positively correlated with firm productivity. Moreover, policy tools that aim to foster supply chains, including promoting industrial clusters and industrial promotion, are all effective in increasing firm productivity, suggesting the importance of reducing supply chain frictions. Lastly, the remaining policy tools, such as preferential land supply, demand stimulation, localization policy, tax incentives, infrastructure investment, improving the business environment, industrial fund, and government procurement, are insignificantly correlated with firm TFP. This is likely due to a combination of different mechanisms, such as increased market competition, weakened entry screening, higher market demand, better access to inputs, and so on.

[Figure 20 about here]

6 Conclusion

We decode China's industrial policies from 2000 to 2022 by employing large language models to extract and analyze rich information from a comprehensive dataset of 3 million documents issued by central, provincial, and municipal governments. Through careful prompt engineering, multistage extraction and refinement, and rigorous verification, we use LLMs to classify the industrial policy documents and extract structured information on policy objectives, targeted industries, policy tones (supportive, regulatory, or suppressive), policy tools, implementation mechanisms, and intergovernmental relationships, etc. To the best of our knowledge, we are the first to compile a dataset of China's industrial policies at such granular levels, both in the details of the policies and the hierarchical levels of governments, for such an extended time period.

Combining these newly constructed industrial policy data with micro-level firm data, we document four sets of facts about China's industrial policy that explore the following questions: What are the economic and political foundations of the targeted industries? What policy tools are deployed? How do policy tools vary across different levels of government and regions, as well as over the phases of an industry's development? What are the impacts of these policies on firm behavior, including entry, production, and productivity growth? We also explore the political economy of industrial policy, focusing on top-down transmission mechanisms, policy persistence, and policy diffusion across regions. Finally, we document spatial inefficiencies and industry-wide overcapacity as potential downsides of industrial policies.

We find that economic rationale, political incentives, and the administrative and fiscal capacity of local governments all play an important role in the choice of targeted sectors. On the economic foundation front, we find that regions tend to target industries with a revealed comparative advantage, and more developed regions with stronger administrative and fiscal capacities are better at such targeting; on the political determinants of policy formation and pass-through, we show that city-level governments follow the upper-level governments in their choice of target sectors, and the top-down pass-through is stronger for less developed regions and cities with fewer connections with the upper-level government, and when the city chiefs face more fierce political competition.

We find that local governments in China vary significantly in the choice of policy tools to implement their industrial policies, and governments in the more developed regions tend to be early users of new policy tools, which are later spread throughout the country and adopted by higher-level governments. We also find that policy tools vary systematically across industries, with skill-intensive manufacturing industries using new policy tools more frequently compared to other traditional industries. Importantly, we find that within each industry, local governments adjust their industrial policy tools and implementation methods over time to accommodate the development phase of the industry. The bundles of policy tools evolve from those aimed at boosting entries, e.g., entry subsidies and encouragement of entrepreneurship, to those aimed at promoting industry upgrading, e.g., R&D, and supply chain enhancement.

We show a trend of increasing interregional policy similarity in the choice of the target sectors, and that the level of policy similarity among cities in the same province is strongly correlated with local protectionism in intercity trade. We also provide empirical evidence that imitating the sectors supported by pioneering cities is often ineffective or even counterproductive, and may contribute to the overcapacity in China's industrial production.

Finally, we find that industrial policies are effective in providing firms in the targeted industries with extra monetary benefits, such as fiscal subsidies, tax deductions, and access to financing, etc., and thus significantly boost entry; but the association between industrial policy and firm productivity is rather mixed and tenuous. The effectiveness also varies significantly with the policy tools being used.

Although our paper provides new insights into the multidimensionality, successes, and pitfalls of China's practice of industrial policies in the last 20 years, our newly constructed granular industrial policy database opens up several avenues for future research. First, in this paper we documented the heterogeneous effects of different policy tools, but a careful structural model is needed to understand the precise mechanisms through which these tools jointly influence firm behavior. For example, disentangling the relative importance of competition effects, agglomeration, and innovation spillovers in driving productivity growth is a promising avenue for further research. Second, our findings highlight the role of policy diffusion and inter-regional similarities in policy choices in local protectionism and potential overcapacity. In future research, it is important to explore the political-economic barriers against the process of merge and acquisition (M & A) and bankruptcy that contributes to the overcapacity problem in China. It is also important to further investigate the multiple driving forces of policy diffusion, including top-down directive, regional competition, and policy learning.

References

Aghion, Philippe, Jing Cai, Mathias Dewatripont, Luosha Du, Ann Harrison, and Patrick Legros. 2015. "Industrial Policy and Competition." *American Economic Journal: Macroeconomics* 7 (4):1–32.

Bai, John Jianqiu, Nicole M Boyson, Yi Cao, Miao Liu, and Chi Wan. 2023. "Executives vs. Chatbots: Unmasking Insights through Human-AI Differences in Earnings Conference Q&A." *Northeastern U. D'Amore-McKim School of Business Research Paper 4480056* .

Balassa, Bela. 1965. "Trade Liberalisation and "Revealed" Comparative Advantage." *The Manchester School* 33 (2):99–123.

Baldwin, Richard and Paul R Krugman. 1986. "Market Access and International Competition: a Simulation Study of 16k Random Access Memories."

Baldwin, Robert E. 1969. "The Case Against Infant-industry Tariff Protection." *Journal of Political Economy* 77 (3):295–305.

Barwick, Panle Jia, Myrto Kalouptsidi, and Nahim Bin Zahur. 2023. "Industrial Policy Implementation: Empirical Evidence From China's Shipbuilding Industry." *Review of Economic Studies* forthcoming.

Bo, Shiyu. 2020. "Centralization and Regional Development: Evidence From a Political Hierarchy Reform to Create Cities in China." *Journal of Urban Economics* 115:103182.

Brandt, Loren and Thomas G Rawski. 2019. *Policy, Regulation and Innovation in China's Electricity and Telecom Industries*. Cambridge University Press.

Branstetter, Lee G and Guangwei Li. 2022. "Does" Made in China 2025" Work for China? Evidence From Chinese Listed Firms." *NBER Working Paper No. 30676* .

———. 2023. "The Challenges of Chinese Industrial Policy." *NBER Working Paper No. 14871* .

Branstetter, Lee G, Guangwei Li, and Mengjia Ren. 2023. "Picking Winners? Government Subsidies and Firm Productivity in China." *Journal of Comparative Economics* 51 (4):1186–1199.

Bybee, J Leland. 2023. "The Ghost in the Machine: Generating Beliefs with Large Language Models." *arXiv preprint arXiv:2305.02823* .

Cen, Xiao, Vyacheslav Fos, and Wei Jiang. 2024. "How Do Us Firms Withstand Foreign Industrial Policies?" *NBER Working Paper No. 32411* .

Chen, Donghua, Oliver Zhen Li, and Fu Xin. 2017. "Five-year Plans, China Finance and Their Consequences." *China Journal of Accounting Research* 10 (3):189–230.

Chen, Yi, Hanming Fang, Yi Zhao, and Zibo Zhao. 2024. "Recovering Overlooked Information in Categorical Variables with LLMs: An Application to Labor Market Mismatch." *NBER Working Paper No. 32327* .

Choi, Jaedo and Andrei A Levchenko. 2021. "The Long-term Effects of Industrial Policy." *NBER Working Paper No. 29263* .

DiPippo, Gerard, Ilaria Mazzocco, Scott Kennedy, and Matthew P Goodman. 2022. "Red Ink: Estimating Chinese Industrial Policy Spending in Comparative Perspective." *Center for Strategic & International Studies (CSIS). May* .

Eisfeldt, Andrea L, Gregor Schubert, and Miao Ben Zhang. 2023. "Generative AI and Firm Values." *NBER Working Paper No. 31222* .

Evenett, Simon, Adam Jakubik, Fernando Martín, and Michele Ruta. 2024. "The Return of Industrial Policy in Data." *The World Economy* 47 (7):2762–2788.

Fang, Hanming, Ming Li, and Zenan Wu. 2022. "Tournament-style Political Competition and Local Protectionism: Theory and Evidence From China." *NBER Working Paper No. 30780* .

Fang, Hanming, Jing Wu, Rongjie Zhang, and Li-An Zhou. 2022. "Understanding the Resurgence of the SOEs in China: Evidence From the Real Estate Sector." *NBER Working Paper No. 29688* .

Gentzkow, Matthew, Bryan Kelly, and Matt Taddy. 2019. "Text as Data." *Journal of Economic Literature* 57 (3):535–574.

Goldberg, Pinelopi K, Réka Juhász, Nathan J Lane, Giulia Lo Forte, and Jeff Thurk. 2024. "Industrial Policy in the Global Semiconductor Sector." *NBER Working Paper No. 32651* .

Goldstein, Itay, Chester S Spatt, and Mao Ye. 2021. "Big Data in Finance." *Review of Financial Studies* 34 (7):3213–3225.

Greenwald, Bruce and Joseph E Stiglitz. 2006. "Helping Infant Economies Grow: Foundations of Trade Policies for Developing Countries." *American Economic Review* 96 (2):141–146.

Hansen, Jørgen Drud, Camilla Jensen, and Erik Strøjer Madsen. 2003. "The Establishment of the Danish Windmill Industry—was It Worthwhile?" *Review of World Economics* 139:324–347.

Harrison, Ann and Andrés Rodríguez-Clare. 2010. "Trade, Foreign Investment, and Industrial Policy for Developing Countries." *Handbook of Development Economics* 5:4039–4214.

Head, Keith. 1994. "Infant Industry Protection in the Steel Rail Industry." *Journal of International Economics* 37 (3-4):141–165.

Imbert, Clement, Marlon Seror, Yifan Zhang, and Yanos Zylberberg. 2022. "Migrants and firms: Evidence from china." *American Economic Review* 112 (6):1885–1914.

Irwin, Douglas A. 2000. "Could the United States Iron Industry Have Survived Free Trade After the Civil War?" *Explorations in Economic History* 37 (3):278–299.

Itskhoki, Oleg and Benjamin Moll. 2019. "Optimal Development Policies with Financial Frictions." *Econometrica* 87 (1):139–173.

Jha, Manish, Jialin Qian, Michael Weber, and Baozhong Yang. 2024. "Chatgpt and Corporate Policies." *NBER Working Paper No. 32161* .

Juhász, Réka. 2018. "Temporary Protection and Technology Adoption: Evidence From the Napoleonic Blockade." *American Economic Review* 108 (11):3339–3376.

Juhász, Réka, Nathan Lane, Emily Oehlsen, and Verónica C Pérez. 2022. "The Who, What, When, and How of Industrial Policy: A Text-based Approach." *Available at SSRN: https://ssrn.com/abstract=4198209* .

Juhász, Réka, Nathan J Lane, and Dani Rodrik. 2023. "The New Economics of Industrial Policy." *NBER Working Paper No. 31538* .

Kim, Alex, Maximilian Muhn, and Valeri V Nikolaev. 2024. "Bloated Disclosures: Can Chatgpt Help Investors Process Information?" *Chicago Booth Research Paper 23-07* :2023–59.

Knight, John B. 2014. "China as a Developmental State." *The World Economy* 37 (10):1335–1347.

Korinek, Anton. 2023. "Generative AI for Economic Research: Use Cases and Implications for Economists." *Journal of Economic Literature* 61 (4):1281–1317.

Krueger, Anne O. 1990. "Government Failures in Development." *Journal of Economic Perspectives* 4 (3):9–23.

Krugman, Paul. 1992. *Geography and Trade*. MIT press.

Lane, Nathan. 2022. "Manufacturing Revolutions: Industrial Policy and Industrialization in South Korea." *Available at SSRN 3890311* .

Lane, Nathaniel. 2020. "The New Empirics of Industrial Policy." *Journal of Industry, Competition and Trade* 20:209–234.

Lee, Sangkuk. 2017. "An Institutional Analysis of Xi Jinping's Centralization of Power." *Journal of Contemporary China* 26 (105):325–336.

Li, Edward Xuejun, Zhiyuan Tu, and Dexin Zhou. 2024. "The Promise and Peril of Generative AI: Evidence From Chatgpt as Sell-side Analysts." *Available at SSRN 4480947* .

Li, Junyou, Qin Zhang, Yangbin Yu, Qiang Fu, and Deheng Ye. 2024. "More Agents Is All You Need." *arXiv preprint: arXiv:2402.05120* .

Li, Kai, Feng Mai, Rui Shen, Chelsea Yang, and Tengfei Zhang. 2025. "Dissecting Corporate Culture Using Generative AI–insights From Analyst Reports." *Available at SSRN 4558295* .

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. 2015. *The Quest for Prosperity: How Developing Economies Can Take Off*. Princeton University Press.

Lin, JY, C Monga, and JE Stiglitz. 2013. "The Rejuvenation of Industrial Policy." *Policy Research Working Paper 6628* .

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

Lopez-Lira, Alejandro and Yuehua Tang. 2023. "Can Chat GPT Forecast Stock Price Movements? Return Predictability and Large Language Models." *arXiv preprint arXiv:2304.07619* .

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):706–722.

Luzio, Eduardo and Shane Greenstein. 1995. "Measuring the Performance of a Protected Infant Industry: the Case of Brazilian Microcomputers." *Review of Economics and Statistics* :622–633.

Melitz, Marc J. 2005. "When and How Should Infant Industries Be Protected?" *Journal of International Economics* 66 (1):177–196.

Naughton, Barry. 2021. *The Rise of China's Industrial Policy, 1978 to 2020*. Universidad Nacional Autónomica de México, Facultad de Economía México.

Naughton, Barry, Siwen Xiao, and Yaosheng Xu. 2023. "The Trajectory of China's Industrial Policies." *IGCC Working Paper No 6., escholarship.org/uc/item/28f568zv* .

Pack, Howard. 2000. "Industrial Policy: Growth Elixir or Poison?" *The World Bank Research Observer* 15 (1):47–67.

Redding, Stephen. 1999. "Dynamic Comparative Advantage and the Welfare Effects of Trade." *Oxford Economic Papers* 51 (1):15–39.

Rodriguez-Clare, Andres. 2007. "Clusters and Comparative Advantage: Implications for Industrial Policy." *Journal of Development Economics* 82 (1):43–57.

Rodrik, Dani. 2004. "Industrial Policy for the Twenty-first Century." *CEPR Discussion Papers 4767* .

———. 2009. "Industrial Policy: Don't Ask Why, Ask How." *Middle East Development Journal* 1 (1):1–29.

Silva, JMC Santos and Silvana Tenreyro. 2006. "The log of gravity." *The Review of Economics and statistics* 88 (4):641–658.

Silva, JMC Santos and Rainer Winkelmann. 2024. "Misspecified exponential regressions: Estimation, interpretation, and average marginal effects." *Review of Economics and Statistics* :1–25.

Sinclair, Andrew J. and Chuyi Zhang. 2023. "Discounting Industrial Policy." *Working Paper* .

Wade, Robert. 2015. "The Role of Industrial Policy in Developing Countries." *Rethinking development strategies after the financial crisis* 1:67–78.

Wang, Shaoda and David Yang. 2025. "Policy Experimentation in China: The Political Economy of Policy Eearning." *Journal of Political Economy* 133 (7).

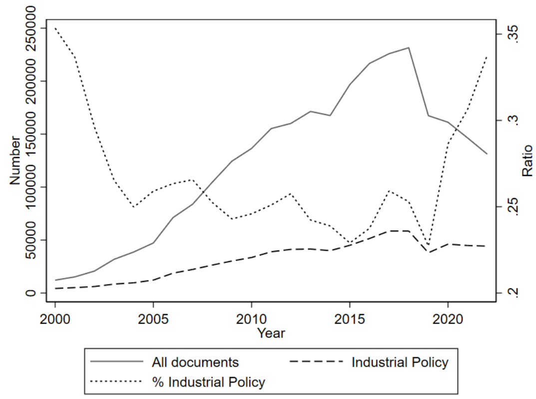
Wei, Shang-Jin, Jianhuan Xu, Ge Yin, and Xiaobo Zhang. 2023. "Mild Government Failure." *NBER Working Paper No. 31178* .

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

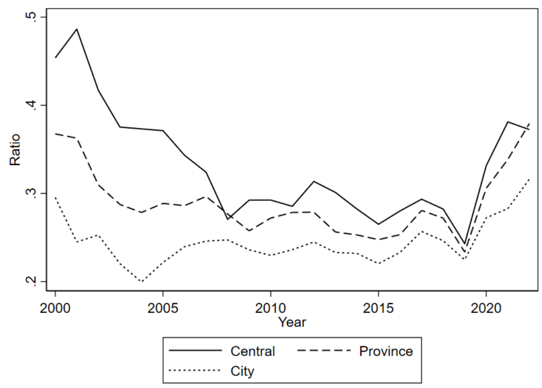
Young, Alwyn. 2000. "The Razor's Edge: Distortions and Incremental Reform in the People's Republic of China." *Quarterly Journal of Economics* 115 (4):1091–1135.

Zhou, Hui, Junqiang Liu, Jiang He, and Jianxin Cheng. 2021. "Conditional Justice: Evaluating the Judicial Centralization Reform in China." *Journal of Contemporary China* 30 (129):434–450.

Figure 1: Evolution of the Industrial Policies



(A) Overall



(B) Proportion of Industrial Policies, by Government Level

Figure 2: Geographic Distribution of the City-Level Industrial Policies

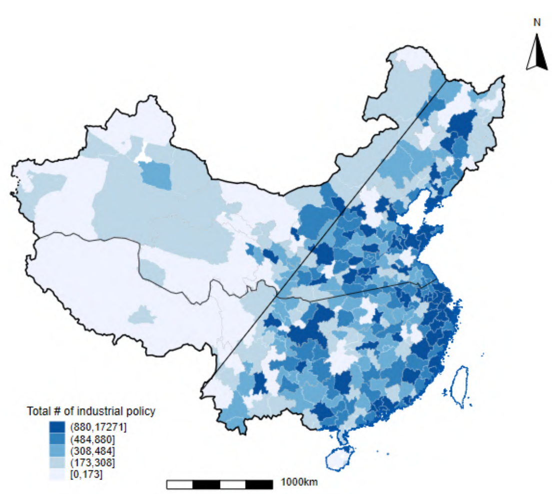


Figure 3: Time Trend of Policy Target Industries within the Manufacturing Sector Over Time

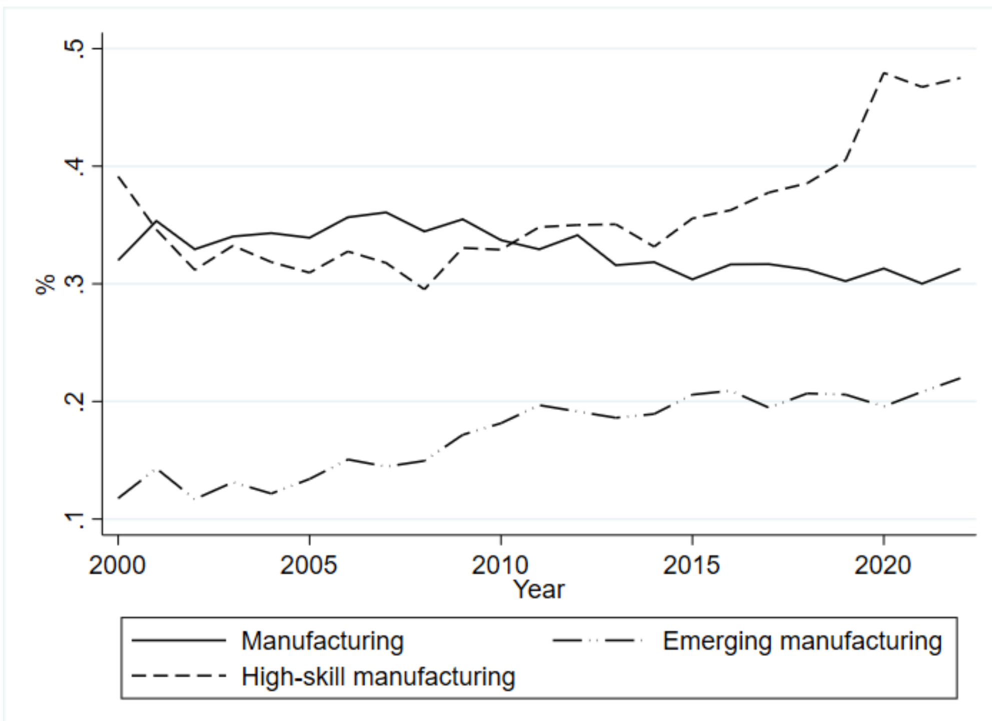
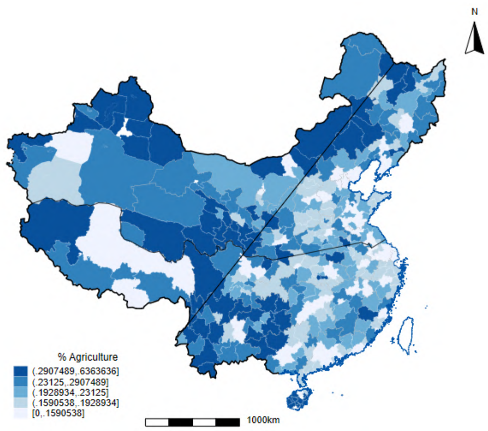
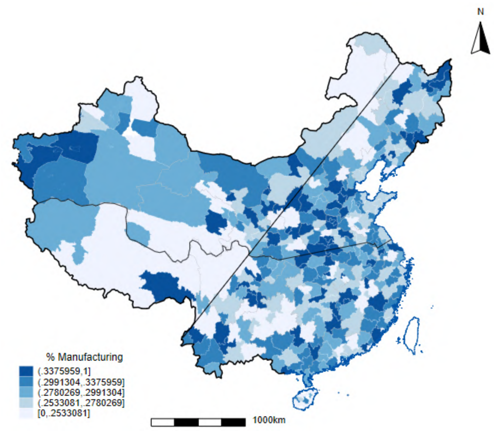


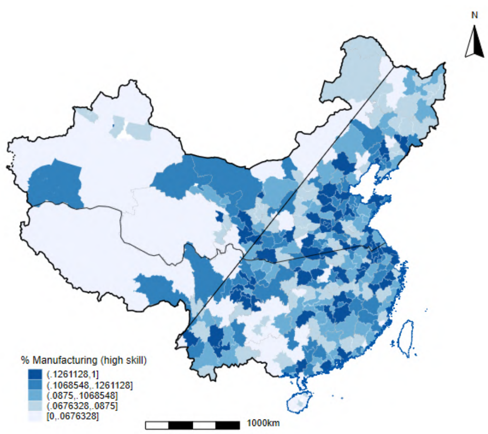
Figure 4: Geographical Distribution of Policy-Targeted Industries



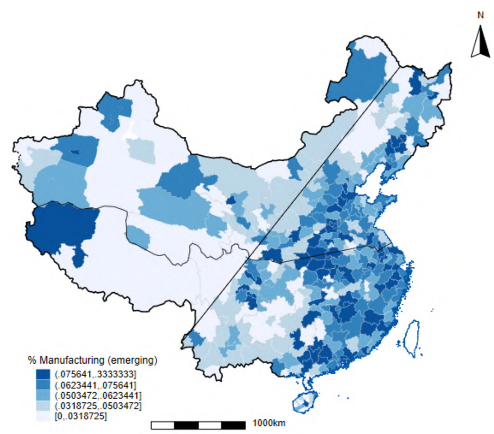
(A) % Agriculture



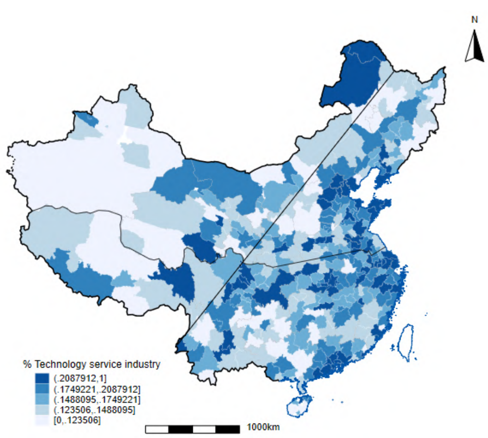
(B) % Manufacturing



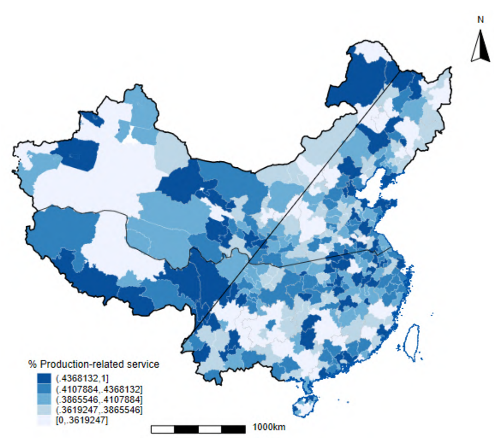
(C) % High-skill Manufacturing



(D) % Emerging Manufacturing

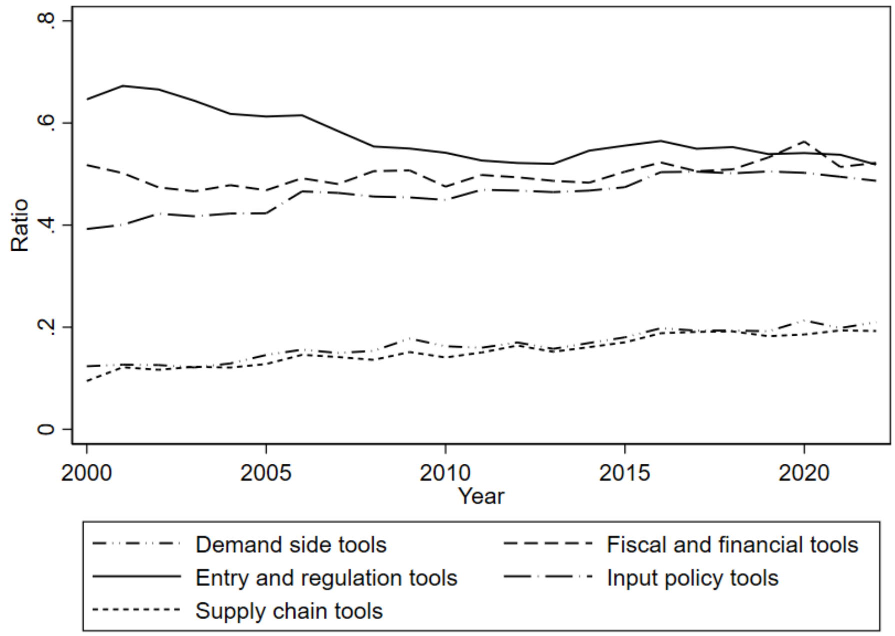


(E) % Technology-related Service

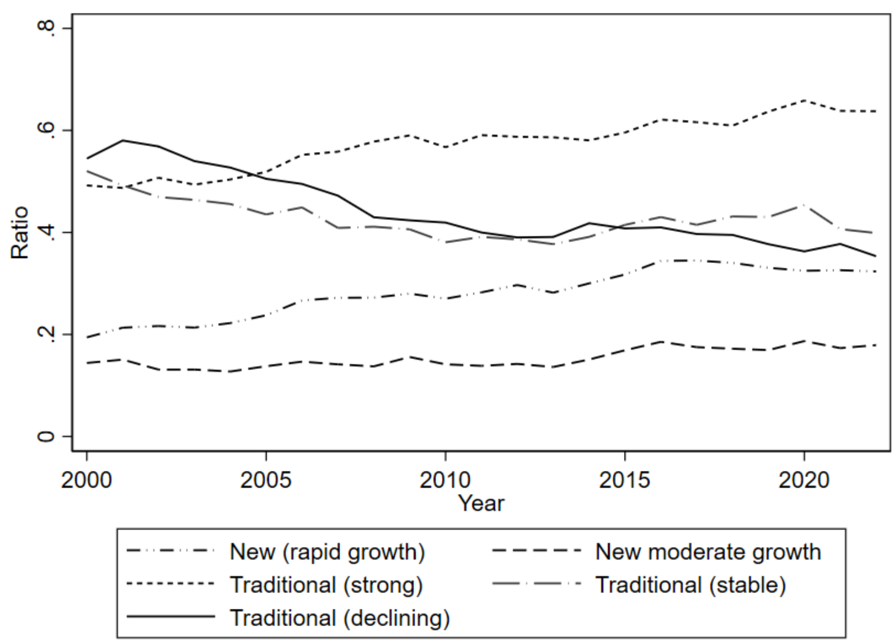


(F) % Production-related Service

Figure 5: Time Trend of Industrial Policy Implementation Tools

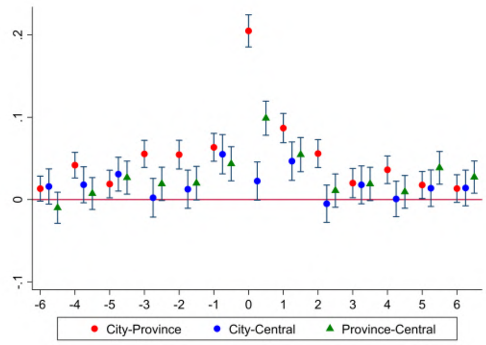


(A) By Tool Category



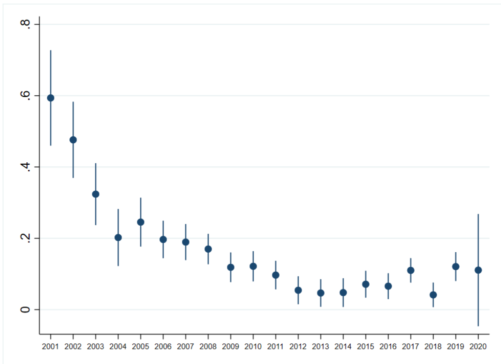
(B) By Usage Growth Pattern

Figure 6: Policy Top-down Pass-through

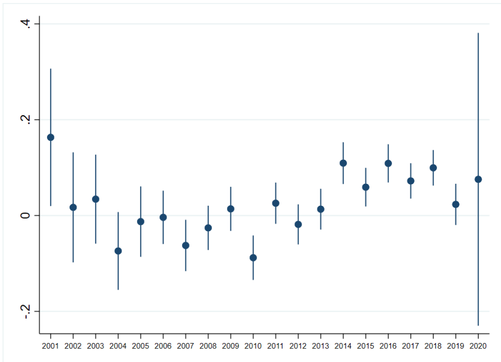


Notes: This figure plots the coefficients and the corresponding 95% confidence intervals of estimating Equations (5) and (6). The red dots represent the coefficients estimated for β_t^p in Equation (5), blue dots for β_t^n in Equation (5), and green triangles for β_t^n in Equation (6). The unit of observation is 4-digit industry-city-year level, and the sample coverage is 2001-2020. Standard errors are clustered at the city-by-industry level.

Figure 7: The Dynamics of Policy Pass-through



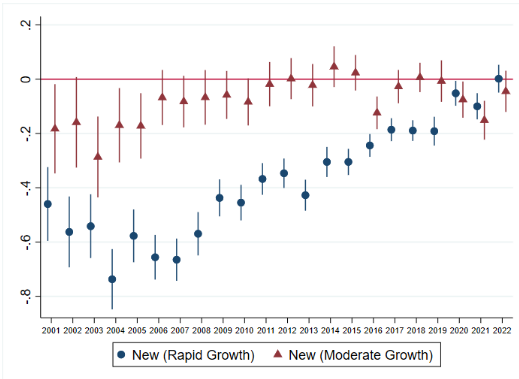
(A) Policy Pass-through (Province)



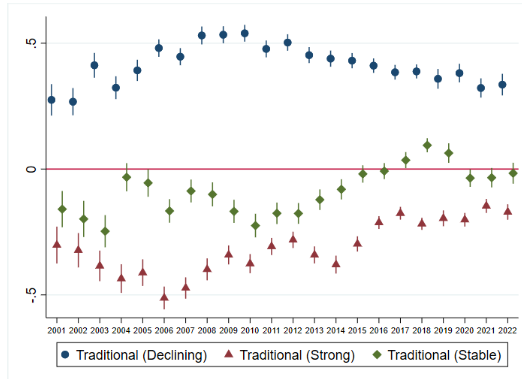
(B) Policy Pass-through (Nation)

Notes: This figure plots the coefficients and the corresponding 95% confidence intervals of estimating Equation (8). The unit of observation is 4-digit industry-city-year level, and the sample coverage is 2001-2020. Standard errors are clustered at the city-by-industry level.

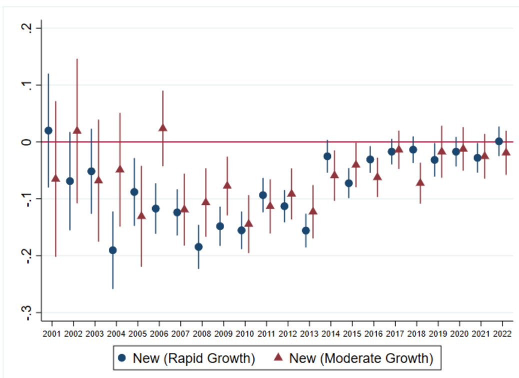
Figure 8: Time Trend of Tool Adoption by Government Level



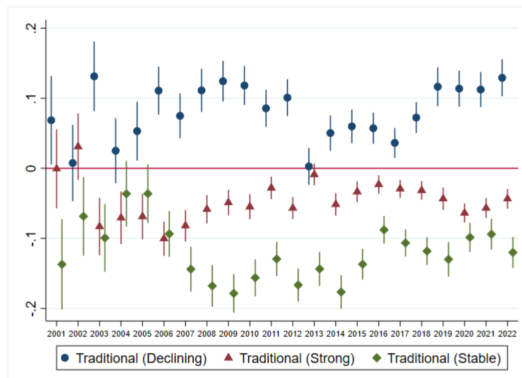
(A) New Tools: Central vs. City



(B) Traditional Tools: Central vs. City



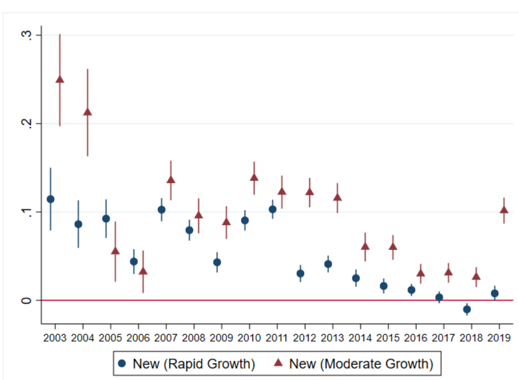
(C) New Tools: Provincial vs. City



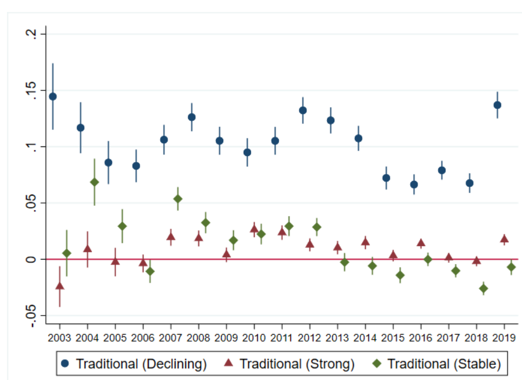
(D) Traditional Tools: Provincial vs. City

Notes: This figure plots the estimated coefficients for β^n_{kt} and β^p_{kt} by estimating Equation (10). Panels (a) and (b) compare the central government to the city-level governments. Panels (c) and (d) compare the provincial-level governments to the city-level governments.

Figure 9: Time Trend of Tool Adoption By City GDP



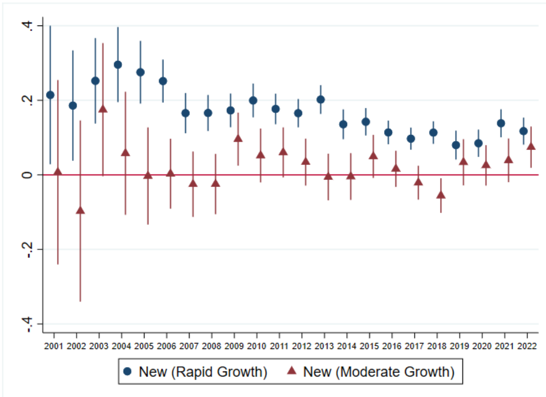
(A) New Tools



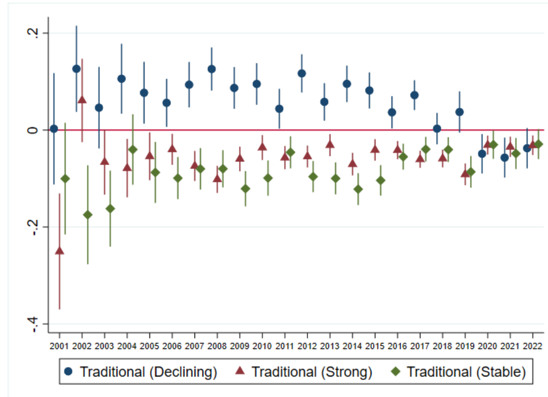
(B) Traditional Tools

Notes: This figure plots the estimated coefficients for β_{kt} by estimating Equation (11) to illustrate the time trend of tool adoption by city's development level.

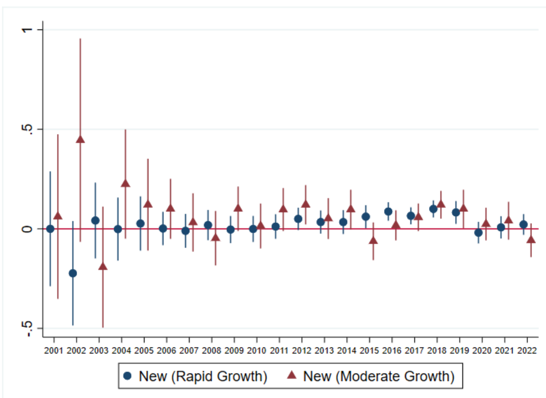
Figure 10: Time Trend of Tool Adoption (Manufacturing)



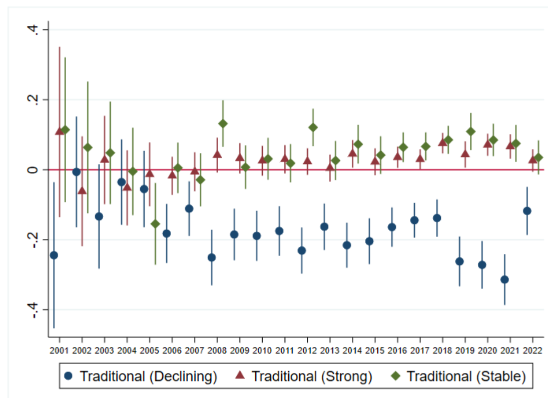
(A) Manu. vs. Others (New Tools)



(B) Manu. vs. Others (Traditional Tools)



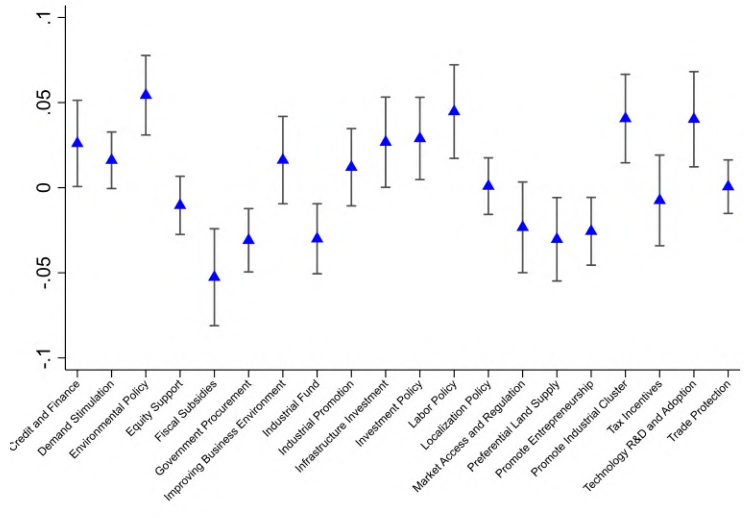
(C) Skill-intensive vs. Others Manu. (New Tools)



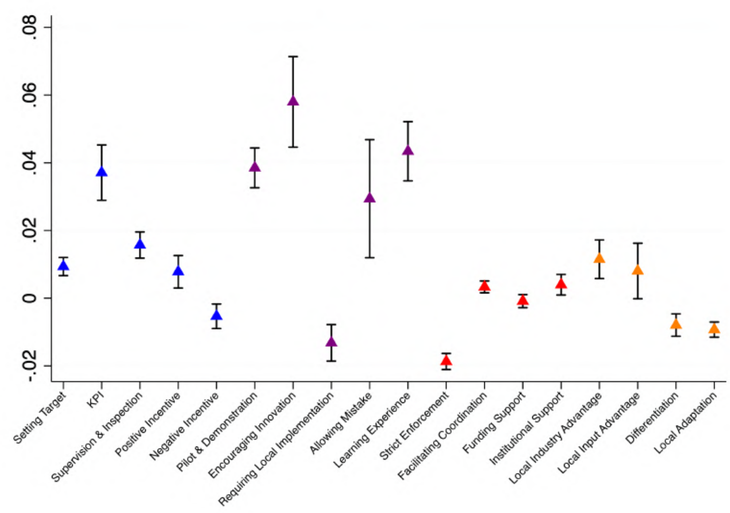
(D) Skill-intensive vs. Others Manu. (Traditional Tools)

Notes: This figure plots the estimated coefficients for β_t by estimating Equation (12) to illustrate the time trend of tool adoption in the manufacturing industry versus other industries, and, within the manufacturing sector, skill-intensive industries versus other traditional industries.

Figure 11: Within-industry Change in Policy Tool and Implementation Method



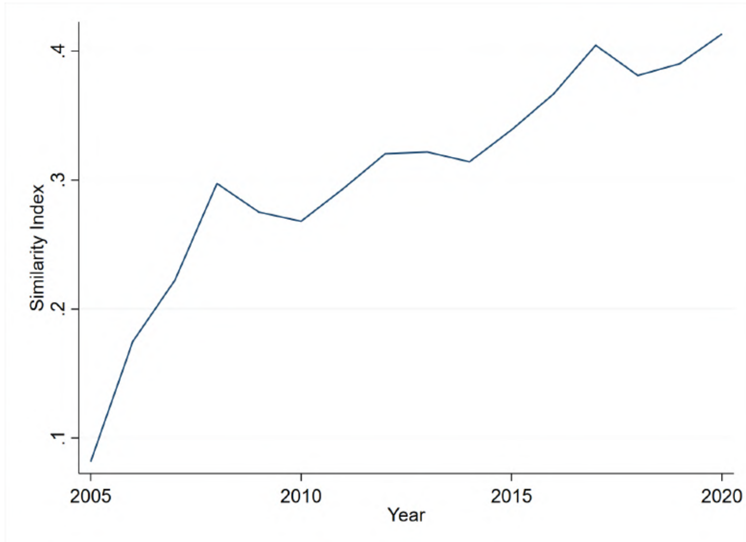
(A) Policy Tool



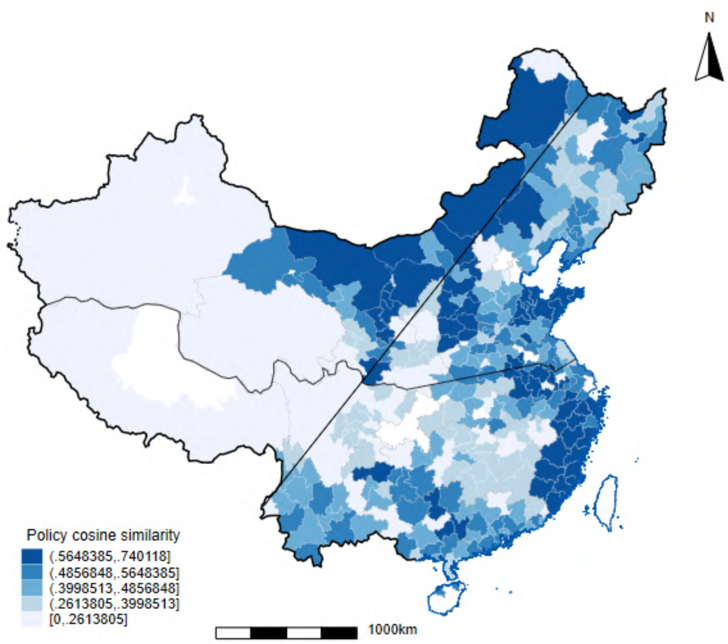
(B) Policy Implementation Method

Notes: This figure plots the estimated coefficients for β_k by estimating Equation (13) for various tools and policy implementation methods, where a positive coefficient indicates an increased likelihood of tool utilization as the industry matures (more years from the initial target year in the city).

Figure 12: Policy Sector Similarity



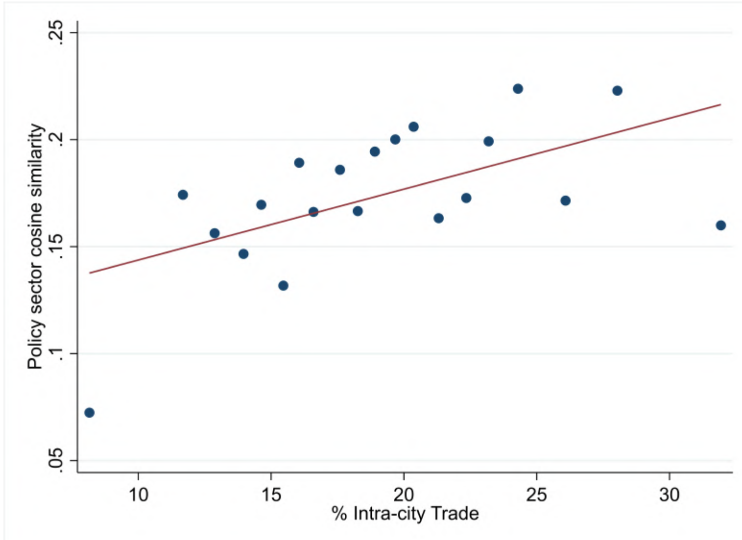
(A) Evolution of Policy Sector Similarity



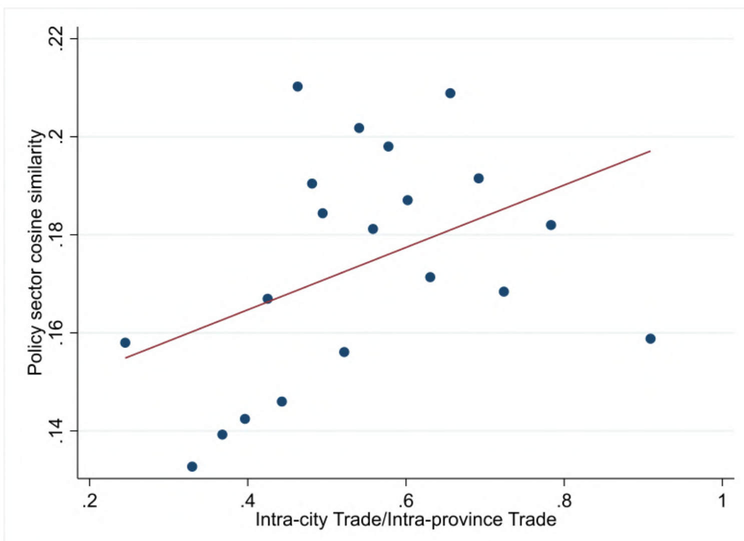
(B) Geographical Distribution of Policy Sector Similarity

Notes: This figure plots the overtime evolution and geographical distribution of policy similarity. Policy similarity is calculated as the cosine similarity of industry-level policy vector between city pairs, focusing on intra-province similarities. The city-year level policy similarity index is the average similarity for each city with all other cities in the same province.

Figure 13: Policy Sector Similarity and Local Protectionism



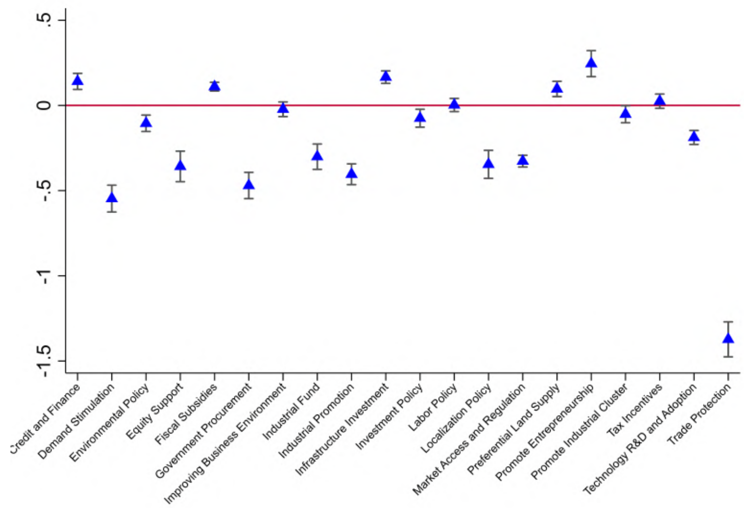
(A) %Intra-city Trade (Intra-city Trade/Total City Trade)



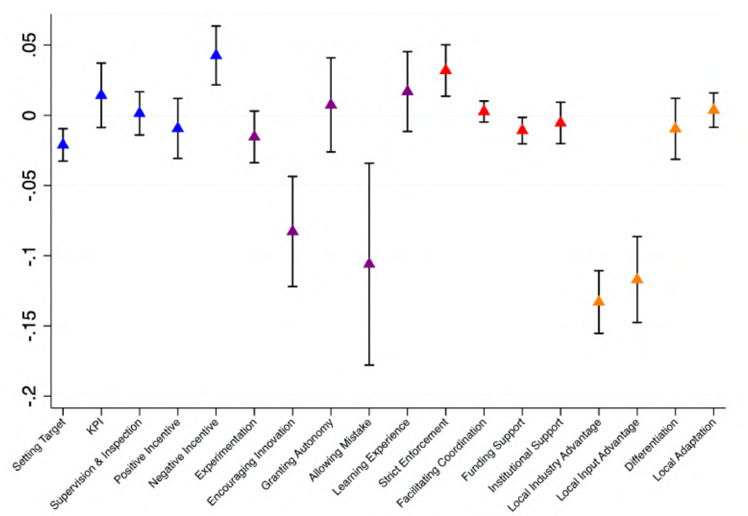
(B) %Intra-city Trade (Intra-city/Intra-province Trade)

Notes: This figure presents the binscatter plot for the citie's similarity index and their intra-city trade share. Panel (a) uses the share of intra-city trade in total trade volume on the x-axis, and Panel (b) uses the share of intra-city trade in total intra-province trade on the x-axis. Policy similarity is calculated as the cosine similarity of industry-level policy vector between city pairs, focusing on intra-province similarities. The city-year level policy similarity index is the average similarity for each city with all other cities in the same province.

Figure 14: Policy Diffusion and Policy Tool and Implementation



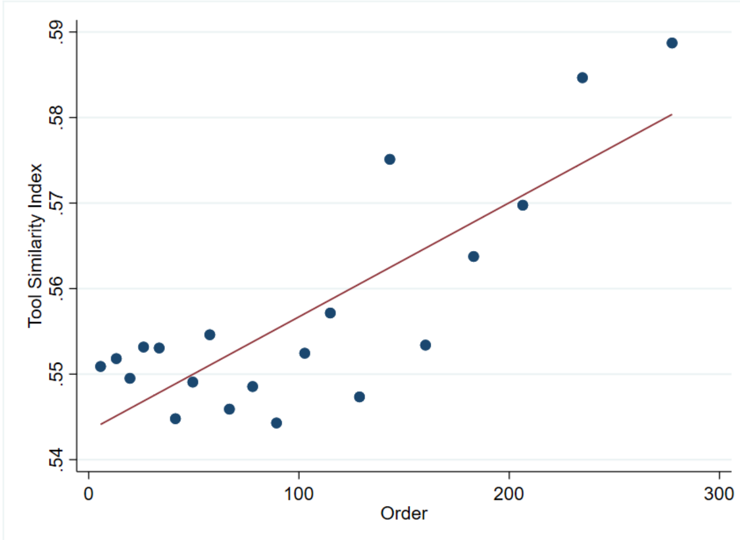
(A) Policy Tool



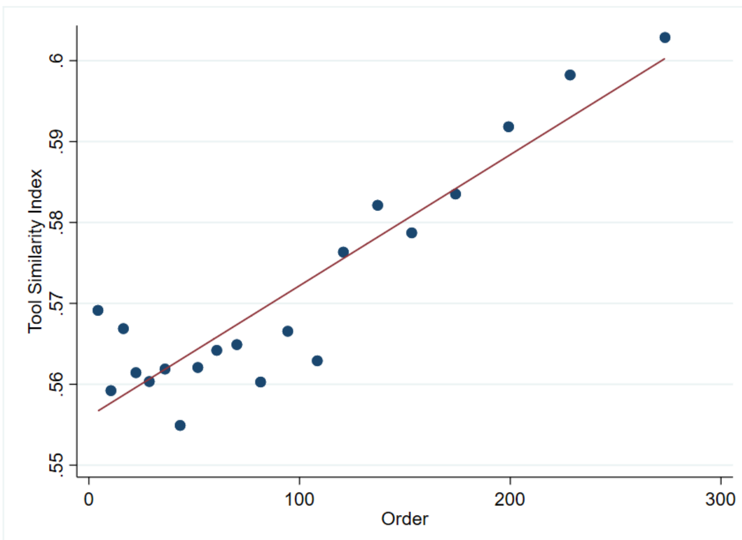
(B) Policy Implementation Method

Notes: This figure plots the coefficients and the corresponding 95% confidence intervals of estimating Equation 17 for each industrial policy tool and policy implementation method. The unit of observation is policy level, and the sample coverage is 2001-2020. Standard errors are clustered at the city-by-industry level.

Figure 15: Policy Diffusion and Policy Tool



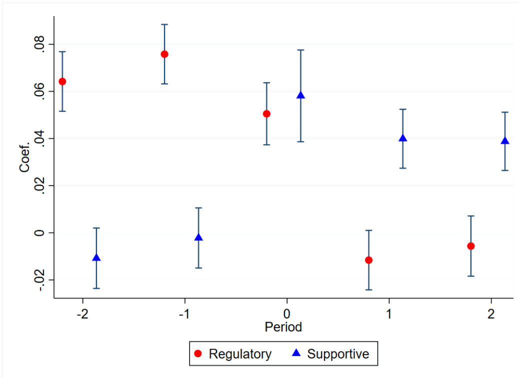
(A) Tool similarity with provincial gov.



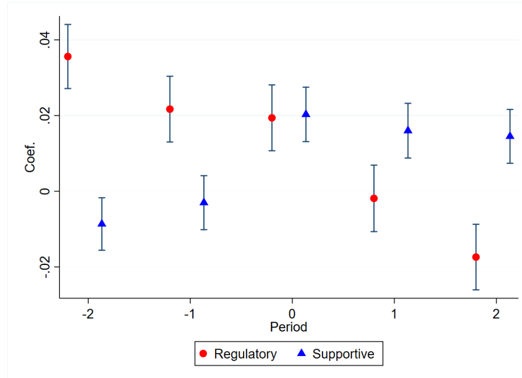
(B) Tool similarity with central gov.

Notes: This figure presents the binscatter plot for the city's order of entering each sector and tool similarity index. The unit of observation is city-industry-year. The horizontal axis is the order that each city enters each industry, and the vertical axis is the tool similarity index between city-level government and upper-level governments. Panel (a) uses a similarity index between city and province-level government on the y-axis, and Panel (b) uses a similarity index between city and central-level government on the y-axis. Tool similarity is calculated as the cosine similarity of the tool vector within each city-industry-year cell between city-level government and upper-level government.

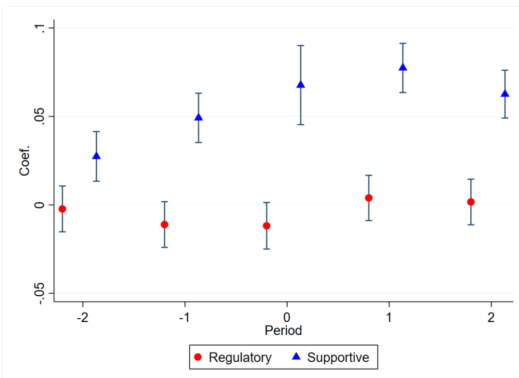
Figure 16: Effect of Industrial Policy: Subsidy, Tax Deduction, and Long Term Debt



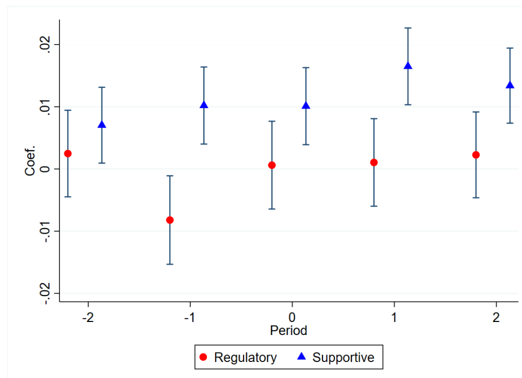
(A) Subsidy (City-by-industry FE)



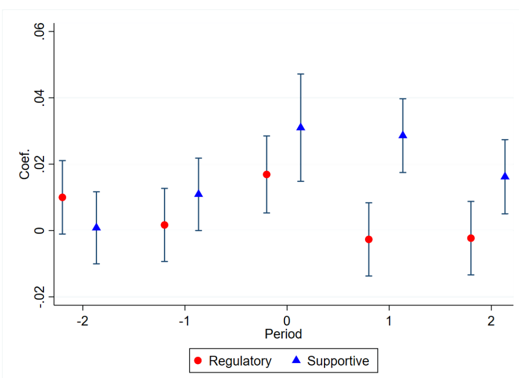
(B) Subsidy (Firm FE)



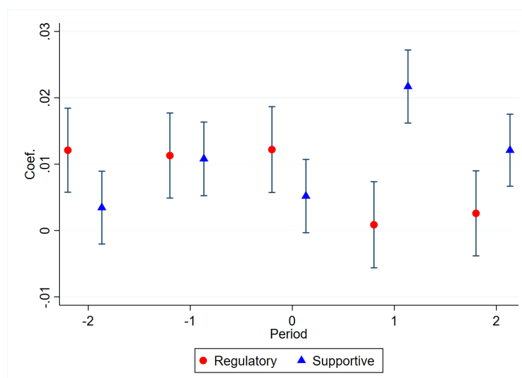
(C) Tax Deduction (City-by-industry FE)



(D) Tax Deduction (Firm FE)



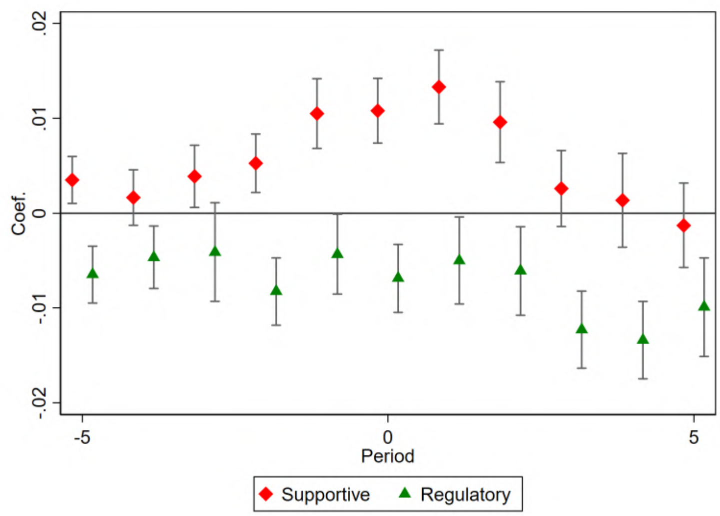
(E) Long Term Debt (City-by-industry FE)



(F) Long Term Debt (Firm FE)

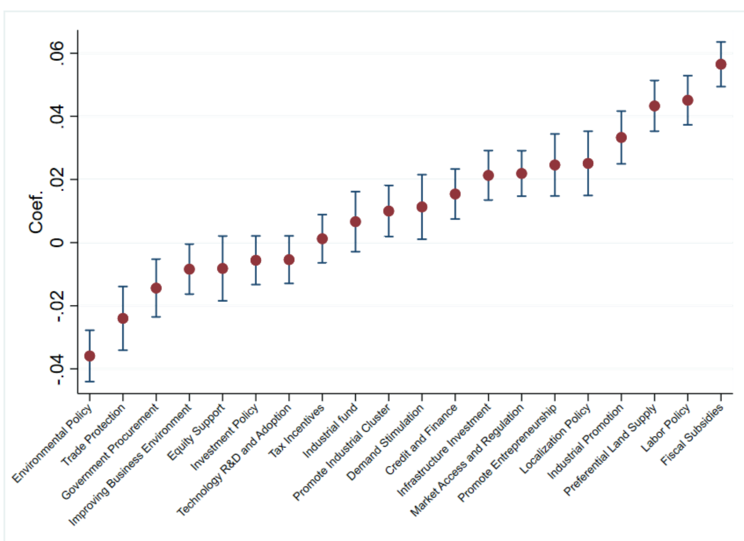
Notes: This figure plots the coefficients and the corresponding 95% confidence intervals of estimating Equation 19. The unit of observation is firm-year level, and the sample coverage is 2008-2020. Panel A, C, and E control for city-by-industry and year fixed effects. Panel B, D, and F control for firm and year fixed effects. Standard errors are clustered at the city-by-industry level.

Figure 17: Dynamic Effects of Supportive vs. Regulatory Industrial Policies on New Firm Entry



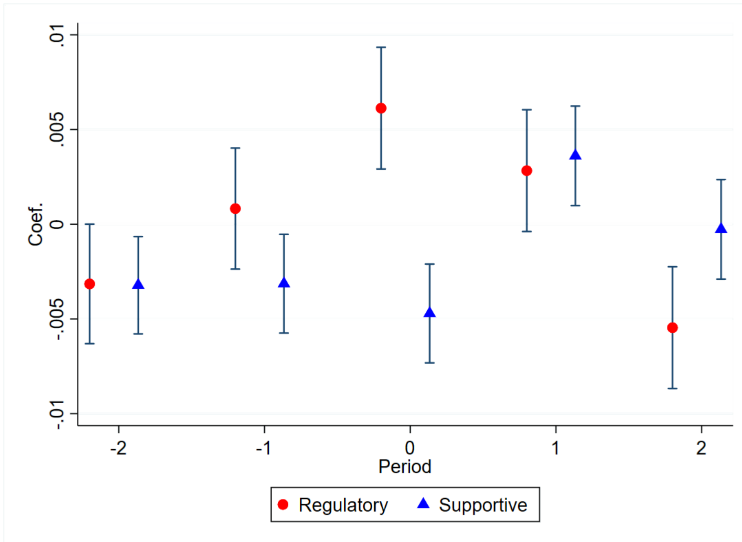
Notes: This figure plots the coefficients and the corresponding 95% confidence intervals of estimating Equation 20. The unit of observation is 4-digit industry-city-year level, and the sample coverage is 2001-2020. Standard errors are clustered at the city-by-industry level.

Figure 18: Effects of Industrial Policy Tools on New Firm Entry



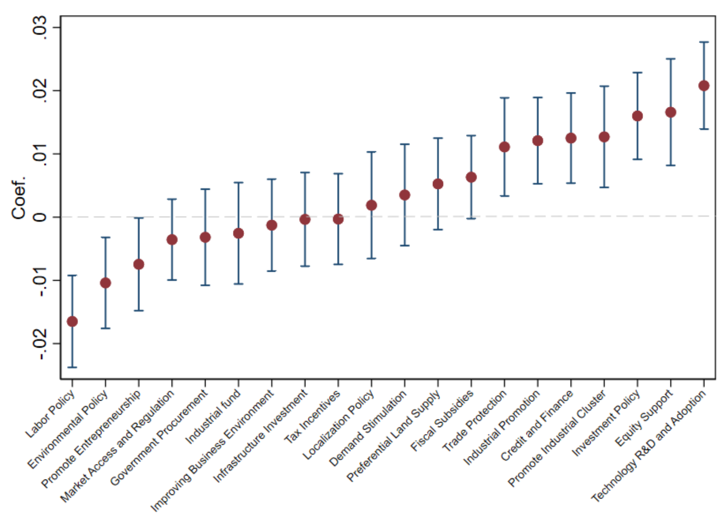
Notes: This figure plots the coefficients and the corresponding 95% confidence intervals of estimating Equation 21 for each industrial policy tool. The unit of observation is 4-digit industry-city-year level, and the sample coverage is 2001-2020. Standard errors are clustered at the city-by-industry level.

Figure 19: Dynamic Effects of Supportive vs. Regulatory Industrial Policies on Firm TFP



Notes: This figure plots the coefficients and the corresponding 95% confidence intervals of estimating Equation 19. The unit of observation is firm-year level, and the sample coverage is 2008-2020. TFP is calculated from firm revenues, and the regression controls for city-by-industry fixed effects as well as the year fixed effects. Standard errors are clustered at the city-by-industry level.

Figure 20: Effects of Industrial Policy Tools on Firm TFP



Notes: This figure plots the coefficients and the corresponding 95% confidence intervals of estimating Equation 22 for each industrial policy tool. The unit of observation is firm-year level, and the sample coverage is 2008-2020. Standard errors are clustered at the city-by-industry level.

Table 1: Comparing LLM versus Keyword Search

	Informativeness of Title Keywords			Informativeness of Full Text Keywords		
	>= 90%	>= 80%	>= 70%	>= 90%	>= 80%	>= 70%
# of keywords	50	239	518	38	641	3,602
# of policies	19,394	168,309	328,495	4,947	116,057	645,920

Note: This table presents the number of unique title (full text) keywords associated with each informativeness threshold and the number of policies that contain at least one title (full text) keyword above the threshold. The informativeness of a keyword is defined by the proportion of policy titles (full texts) that our LLM approach identifies as industrial policies among all the titles (full texts) that contain the keyword.

Table 2: Industrial Policy Shares, by Government Level

	Industrial Policy			Overall
	#	% in documents	% in all IP	
Central	101,250	30.86	13.18	328,142
Province	344,321	26.82	44.81	1,283,813
City	295,698	23.49	38.48	1,258,638
District/County	27,040	21.60	3.52	125,182
Township	78	12.83	0.00	608
Total	768,387	25.64	100.00	2,996,383

Note: This table presents the distribution of industrial policies by the level of the issuing government entity. Each level of government includes all affiliated government departments and entities at the same level.

Table 3: Industrial Policy Tones, by Government Level

	Supportive		Suppressive		Regulatory	
	#	Row %	#	Row %	#	Row %
Central	57,200	56.49	3,168	3.13	40,882	40.38
Province	238,621	69.30	3,923	1.14	101,777	29.56
City	219,986	74.40	4,148	1.40	71,564	24.20
Overall	515,807	69.58	11,239	1.52	214,223	28.90

Table 4: Industrial Policy Objectives, by Government Level

	All	Central	Province	City
Promote Key Industry				
Promote strategic industry	0.22	0.20	0.21	0.24
Promote pillar industry	0.05	0.03	0.04	0.06
Promote emerging industry	0.10	0.07	0.09	0.13
Support traditional advantageous industry	0.11	0.09	0.12	0.11
Upgrade traditional industry	0.12	0.09	0.12	0.14
Support green industry	0.13	0.09	0.13	0.14
Promote other key industry	0.09	0.08	0.09	0.10
Promote Innovation				
Promote innovation	0.17	0.14	0.16	0.18
Promote new technology adoption	0.08	0.06	0.07	0.10
Promote Social Welfare				
Urbanization	0.04	0.02	0.03	0.07
Stimulate employment	0.13	0.10	0.12	0.15
Promote social equity and welfare	0.26	0.19	0.25	0.29
Observations	741,269	101,250	344,321	295,698

Note: Each cell reports the proportion of the government documents within each government level that states the policy objective.

Table 5: Industrial Policy Target Sectors, by Government Level

	All	Central	Province	City
Agriculture	0.17	0.14	0.19	0.17
Manufacturing	0.29	0.35	0.28	0.28
Manufacturing (emerging)	0.05	0.05	0.05	0.06
Manufacturing (high skill)	0.11	0.12	0.11	0.11
Service	0.49	0.47	0.48	0.50
Service (high skill)	0.18	0.15	0.18	0.18
Production related service	0.40	0.41	0.40	0.41
Technology related service	0.20	0.21	0.20	0.20
Lifestyle service	0.29	0.28	0.27	0.32
Observations	741,269	101,250	344,321	29,5698

Note: Each cell reports the share of the government documents within the same government level that targets the sector.

Table 6: Industrial Policy Implementation Tools, by Government Levels

	All	Central	Province	City
Fiscal and Financial Tools				
Credit and Finance	0.14	0.11	0.12	0.18
Tax Incentives	0.20	0.20	0.16	0.23
Equity Support	0.05	0.04	0.04	0.06
Fiscal Subsidies	0.41	0.25	0.39	0.48
Entry and Regulation Tools				
Industrial Fund	0.07	0.04	0.06	0.09
Promote Entrepreneurship	0.06	0.04	0.05	0.08
Investment Policy	0.13	0.11	0.12	0.16
Improving Business Environment	0.18	0.13	0.15	0.22
Market Access and Regulation	0.35	0.42	0.34	0.34
Trade Protection	0.09	0.19	0.08	0.07
Input Policy Tools				
Labor Policy	0.22	0.16	0.21	0.27
Preferential Land Supply	0.13	0.06	0.10	0.17
Infrastructure Investment	0.18	0.11	0.16	0.23
Technology R&D and Adoption	0.24	0.21	0.23	0.27
Environmental Policy	0.13	0.09	0.12	0.16
Demand Side Tools				
Consumer Subsidy	0.05	0.04	0.05	0.07
Government Procurement	0.07	0.05	0.07	0.08
Industrial Promotion	0.10	0.07	0.10	0.12
Supply Chain Tools				
Promote Industrial Cluster	0.14	0.08	0.12	0.18
Localization Policy	0.05	0.03	0.04	0.06
Observations	741,269	101,250	344,321	295,698

Table 7: Industrial Policy Conditionality, by Government Level

	All	Central	Province	City
Firm Location	0.44	0.32	0.45	0.47
Specific Firms	0.16	0.19	0.17	0.15
R&D Investment or Specific Technology	0.11	0.08	0.10	0.12
Firm Age	0.09	0.06	0.08	0.10
Firm Ownership Type	0.13	0.17	0.11	0.12
Firm Scale	0.33	0.24	0.30	0.38
Observations	741,269	101,250	344,321	295,698

Table 8: Industrial Policy Organizational Arrangement, by Government Level

	All	Central	Province	City
Incentive Scheme				
Setting Target	0.48	0.36	0.49	0.52
KPI	0.13	0.05	0.11	0.18
Supervision & Inspection	0.45	0.37	0.47	0.46
Positive Incentive	0.13	0.06	0.12	0.18
Negative Incentive	0.30	0.25	0.28	0.33
Experimentation and Learning				
Pilot & Demonstration	0.21	0.18	0.21	0.23
Encouraging Innovation	0.06	0.05	0.06	0.07
Requiring Local Implementation	0.13	0.14	0.13	0.14
Allowing Mistake	0.02	0.01	0.01	0.02
Learning Experience	0.15	0.14	0.15	0.15
Local Condition				
Local Industry Advantage	0.12	0.05	0.11	0.15
Local Input Advantage	0.08	0.04	0.07	0.09
Differentiation	0.18	0.17	0.16	0.20
Local Adaptation	0.42	0.24	0.39	0.51
Organizational Support				
Strict Enforcement	0.45	0.48	0.44	0.44
Facilitating Coordination	0.65	0.50	0.64	0.71
Funding Support	0.43	0.28	0.42	0.50
Institutional Support	0.36	0.30	0.34	0.39
Observations	741,269	101,250	344,321	295,698

Table 9: Summary Statistics for Firm Registration

Variable	Mean	Std. dev.	Min	Max
New registration capital (billion RMB)	191.28	14,226.42	0	16,057.89
New registration # of firms	26.83	381.76	0	118,629.00
Cumulative registration capital (billion RMB)	1,425.19	40,109.63	0	16,238.90
Cumulative registration # of firms	229.16	2,330.35	0	535,472.00
RCA^p	1.29	9.70	0	455.78
RCA^n	1.55	14.50	0	3,975.96
AA	0.00	0.01	0	1.00

Note: The table reports the summary statistics for key measures based on the firm registration data. The unit of observation is 4-digit industry-city-year level, and the sample coverage is 2001-2020.

Table 10: Sector Choice and Regional Revealed Advantage

	(1)	(2)	(3)	(4)	(5)
L.RCA^n	0.000779***			0.000432***	-0.00713***
	(7.85e-05)			(7.17e-05)	(0.00103)
L.RCA^p		0.00896***		0.00839***	-0.00636*
		(0.000436)		(0.000458)	(0.00369)
L.AA			3.459***	3.138***	6.250***
			(0.127)	(0.120)	(0.373)
L.RCA^n**log(GDP)*					0.00326***
					(0.000651)
L.RCA^p**log(GDP)*					0.00144***
					(0.000179)
*L.AA*log(GDP)*					-0.545***
					(0.0554)
log(GDP)					-0.130***
					(0.0176)
City FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	2,803,600	2,803,600	2,803,600	2,803,600	2,335,760

Note: This table reports the PPML estimation results of Equation (4). The dependent variable is a dummy variable indicating whether each city implements an industrial policy targeting each industry in each year. The unit of observation is 4-digit industry-city-year level, and the sample coverage is 2001-2020. Standard errors are clustered at the city-by-industry level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 11: Policy Pass-through from Central to Local Governments

	(1)	(2)	(3)	(4)
Policy^p	0.354***	1.809***	1.746***	0.385***
	(0.00724)	(0.0382)	(0.0550)	(0.00843)
Policy^n	0.219***	1.609***	1.303***	0.250***
	(0.0210)	(0.127)	(0.180)	(0.0246)
Policy^p*log(GDP)		-0.200***	-0.202***	
		(0.00502)	(0.00516)	
Policy^n*log(GDP)		-0.189***	-0.196***	
		(0.0163)	(0.0168)	
Policy^p*log(# Cities)			0.0338	
			(0.0217)	
Policy^n*log(# Cities)			0.163**	
			(0.0708)	
Policy^p*Connection$_s$				-0.140***
				(0.0140)
Policy^n*Connection$_s$				-0.125***
				(0.0422)
Policy^p*Connection$_m$				0.0106
				(0.0163)
Policy^n*Connection$_m$				-0.0124
				(0.0501)
log(GDP)		0.209***	0.218***	
		(0.0236)	(0.0240)	
Connection$_s$				0.254***
				(0.0415)
Connection$_m$				-0.000102
				(0.0493)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	2,803,600	2,335,760	2,335,760	2,803,600

Note: This table reports the results of estimating Equation 7. Connection$_m$ is the indicator for political connection between city mayor and provincial governor and secretary, Connection$_s$ for city secretary and provincial governor and secretary. The unit of observation is 4-digit industry-city-year level, and the sample coverage is 2001-2020. Standard errors are clustered at the city-by-industry level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 12: Policy Persistence and the Change of Local Politicians

	Full Sample		Lateral Move	
	(1)	(2)	(3)	(4)
L.Policy	0.367***	0.368***	0.276***	0.252***
	(0.00888)	(0.00893)	(0.0240)	(0.0300)
Policy^p	0.136***	0.117***	0.105***	0.108***
	(0.00594)	(0.00762)	(0.0199)	(0.0238)
Policy^n	0.0275***	0.0195**	0.0158	0.00229
	(0.00615)	(0.00779)	(0.0213)	(0.0255)
L.Policy*Change	-0.0497***	-0.0511***		
	(0.0124)	(0.0126)		
Policy^p*Change		0.0268**		
		(0.0111)		
Policy^n*Change		0.0188*		
		(0.0112)		
Change	0.00240	-0.00655		
	(0.00677)	(0.0100)		
L.Policy (Same Politician)			0.0910***	0.135***
			(0.0271)	(0.0328)
L.Policy (Neighbor Cities)				0.0352
				(0.0320)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	2,663,420	2,663,420	153,162	153,162

Note: This table reports the results of estimating Equation (9). Change is an indicator which takes value 1 if the city secretary or mayor is different from last year. The unit of observation is 4-digit industry-city-year level, and the sample coverage is 2001-2020. Columns (1)-(2) use the full sample, and columns (3)-(4) use only the subsample of politicians' lateral move across cities— the city party secretary or mayor serving as the party secretary or mayor of another city in the previous year. Standard errors are clustered at the city-by-industry level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 13: Policy Diffusion and Overcapacity: Entry and Capital

	log(# New Entry+1)	log(Value New Cap.+1)	log(Value Avg. New Cap.+1)
Policy	0.0666***	0.143***	0.0828***
	(0.00466)	(0.0186)	(0.0160)
Policy*Order	-0.0139	-0.123**	-0.141***
	(0.0150)	(0.0598)	(0.0516)
Constant	1.039***	2.930***	2.080***
	(0.000556)	(0.00221)	(0.00191)
City-by-Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
City-by-Industry Trend	Yes	Yes	Yes
Observations	2,172,240	2,172,240	2,172,240
R-squared	0.892	0.754	0.635

Note: This table reports the results of estimating Equation (14). Order represents the percentile of the order in which a city adopts a policy for an industry, with lower values indicating earlier adoption. The unit of observation is 4-digit industry-city-year level, and the sample coverage is 2001-2020. Standard errors are clustered at the city-by-industry level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 14: Policy Diffusion and Overcapacity: Firm Performance

	log(Revenue)		log(Profit)	
	(1)	(2)	(3)	(4)
Policy	0.0434***	0.00959*	0.0593***	0.0155***
	(0.00478)	(0.00498)	(0.00515)	(0.00411)
Order	-0.103***		-0.138***	
	(0.0101)		(0.0112)	
Policy*Order	-0.331***	-0.117***	-0.337***	-0.0738***
	(0.0202)	(0.0218)	(0.0219)	(0.0183)
Constant	4.263***	4.474***	5.456***	5.803***
	(0.00260)	(0.00127)	(0.00282)	(0.00107)
Firm FE	No	Yes	No	Yes
City, Industry FE	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes
Observations	5,689,798	5,067,242	3,754,407	3,096,270
R-squared	0.635	0.839	0.297	0.831

Note: This table reports the results of estimating Equation (15). Order represents the percentile of the order in which a city adopts a policy for an industry, with lower values indicating earlier adoption. The unit of observation is 4-digit industry-city-year level, and the sample coverage is 2008-2020. Standard errors are clustered at the city-by-industry level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 15: Policy Diffusion and Sector Choice

	(1)	(2)	(3)	(4)
L.RCA^n	0.00319***	0.00258***		
	(0.000329)	(0.000705)		
L.RCA^p			0.0159***	0.00673***
			(0.000975)	(0.00129)
Order	-0.773***		-0.749***	
	(0.0104)		(0.0107)	
L.RCA^n*Order	-0.00509***	-0.00419**		
	(0.000826)	(0.00190)		
L.RCA^p*Order			-0.0139***	-0.00766*
			(0.00181)	(0.00393)
Constant	-0.916***	-0.885***	-0.935***	-0.889***
	(0.00266)	(0.00134)	(0.00303)	(0.00159)
City, Industry FE	Yes	No	Yes	No
City-by-Industry FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,133,450	1,366,005	2,133,450	1,366,005

Note: This table reports the results of estimating Equation (16). Order represents the percentile of the order in which a city adopts a policy for an industry, with lower values indicating earlier adoption. The unit of observation is 4-digit industry-city-year level, and the sample coverage is 2001-2020. Standard errors are clustered at the city-by-industry level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 16: Effect of Industrial Policy: Subsidy, Tax, and Debt

	log(Subsidy)		Tax deduction rate		1(Long-term debt)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Supportive vs. Regulatory/Suppressive						
$Policy^{+}$	0.0599***	0.0184***	0.0533***	-0.00269	0.0229***	0.0110***
	(0.00405)	(0.00349)	(0.00282)	(0.00199)	(0.00321)	(0.00254)
$Policy^{-}$	0.0327***	0.0159***	-0.00822	-0.00935	0.0183**	0.0107***
	(0.00491)	(0.00429)	(0.000349)	(0.00948)	(0.00992)	(0.00315)
log(Register capital)	0.289***		-0.0560***		0.0228***	
	(0.000725)		(0.000529)		(0.000605)	
Observations	3,075,274	3,174,825	5,144,683	5,624,432	5,970,610	6,633,852
R-squared	0.265	0.671	0.211	0.705	0.160	0.566
Panel B: Heterogeneity by Size						
$Policy^{+}$	-0.366***	-0.0280**	-0.00125	-0.0114	-0.0182***	-0.00790***
	(0.00997)	(0.0130)	(0.00704)	(0.00699)	(0.000806)	(0.000927)
$Policy^{+}$*log(Register capital)	0.0627***	0.00732***	0.00230**	0.00127	0.00429***	0.00106***
	(0.00144)	(0.00189)	(0.00105)	(0.00106)	(0.000118)	(0.000138)
log(Register capital)	0.270***		-0.0567***		0.0214***	
	(0.000851)		(0.000625)		(7.14e-05)	
Observations	3,075,274	2,663,526	5,144,683	4,835,261	5,970,610	5,580,712
R-squared	0.266	0.667	0.211	0.690	0.160	0.571
City-by-industry FE	Yes	No	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the results of estimating 18. The unit of observation is firm-year level, and the sample coverage is 2008-2020. Standard errors are clustered at the city-by-industry level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.