Decoding China's Industrial Policies*

Hanming Fang[†] Ming Li[‡] Guangli Lu[§]

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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, LLMs allow us to extract structured information on detailed policy dimensions, including context and scope, targeted industries, tools, implementation mechanisms, and intergovernmental relationships, etc. Combining these newly constructed industrial policy data with microlevel firm data, we document thirteen key facts about China's industrial policy that explore the following critical questions. Which industries are targeted and how does this align with local comparative advantage? What policy tools are deployed, and how does their use vary across different levels and regions of governments, as well as over the various phases of development of an industry? We also examine the impact of these policies on firm behavior, including entry, production, and productivity growth, and highlight the heterogeneous effects of different policy tools. In addition, we explore the political economy of industrial policy, focusing on top-down transmission mechanisms, policy diffusion, and persistence across regions. Finally, we document spatial inefficiencies and industry-wide overcapacity as potential downsides of industrial policies.

Keywords: Industrial Policy; Large Language Models; Policy Diffusion; Relative Comparative Advantage.

JEL Codes: L52, O25, C55.

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†Department of Economics, University of Pennsylvania, 133 S. 36th Street, Philadelphia, PA, United States, 19104; and the NBER. Email: hanming.fang@econ.upenn.edu.

‡School of Management and Economics, Chinese University of Hong Kong, Shenzhen, China. Email: liming2020@cuhk.edu.cn.

§School of Management and Economics, Chinese University of Hong Kong, Shenzhen, China. Email: luguangli@cuhk.edu.cn.

1 Introduction

Industrial policy is experiencing a powerful resurgence around the world. From the US CHIPS Act aimed at bolstering semiconductor production, to the European Green Deal prioritizing renewable energy and sustainable industry, and India's "Atmanirbhar Bharat" for self-reliance, governments across the globe are launching initiatives to secure competitive advantages in critical sectors. 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 underscore the rent-seeking inefficiencies 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. 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 initial 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. Beyond the question of whether there should be industrial policy, there are more important questions: Which sector(s) should be targeted? Which tool(s) should be 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 can government strike a delicate balance to boost entry and improve productivity while preventing excessive entries and potential overcapacity? What is the role of political incentive and administrative capacity 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*. This is precisely the literature gap that our study seeks to fill, using a detailed and large-scale analysis of industrial policy documents in China's diverse administrative landscape.

China presents a unique laboratory for investigating the above fundamental questions about the choice, implementation and effectiveness of industrial policy. First, China's extensive use of industry policies to shape the its sectoral development and technological capabilities (Naughton, 2021; Naughton et al., 2023) makes it especially valuable to investigate the role of industry policies in its substantial structural transformation and technological upgrading. Second, China's hierarchical government structure, where central authorities establish strategic guidelines while local governments exercise discretion over policy adoption and implementation, yields rich variation in local policies. Local governments, heterogeneous in their economic fundamentals, state capacity, and political incentives, vary significantly in both policy choices and tool selection, allowing researchers to examine the determinants and 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 coordination failures.

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, as well as a comprehensive understanding of internal policies 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 span the past 20 years, covering all levels of government from the central to city level. With the help of large language models (LLMs), we systematically analyze more than 3 million policy documents to build a structured data set that encompasses a wide array 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. Significantly, we integrate this 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. We employ large language models (LLMs) to systematically summarize, classify, and extract structured information from the texts of these policy documents about: whether the policy document constitutes an industrial policy; the issuing government; the list of targeted industries; policy tone; the list and classification of policy tools; measures of policy strength; the conditionality of the policy; references to other governments; citations of other policies; policy targets; policy dates; measures to monitor, evaluate, and incentivize lower-level governments; measures that grant discretion and promote policy innovation and learning; policy implementation measures such as funding support, coordination, mandatory enforcement, and development of institutional capacity; local adaptation of policies. In addition, we use LLM to map the targeted industries from text to standardized industry codes. The richness of these insights 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 a policy exists; rather, the key to understanding its impact lies in the nuanced details of its implementation. The timing of policy initiation, the choice of policy tools, the selection of target sectors, the role of local conditions, the organizational and administrative mechanisms in place, and the dynamic interactions between various levels of government all play critical roles in shaping the effectiveness of these policies. Although this information is embedded within the documents, only LLMs make it possible to extract and structure such detailed multidimensional data on China's industrial policy landscape. 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 that measures industrial policy at the national level by the targeted industries in the Five-Year Plan year plans or the industries that receive more subsidies (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 with excessively long documents and complex questions. The risk of LLM hallucination — the tendency of LLM 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, including: decomposing complex questions into sub-questions 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 classification 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 appear in policy texts post LLM queries.Importantly, building on the the literature that integrating responses from multiple LLMs can significantly reduce hallucination (Li et al., 2024a), we integrate responses from multiple LLMs for critical tasks such as the identification of industrial policies, mapping each policy to standardized industry codes it targets, and the classification of policy tools. Lastly, we verify the validity of our approach using word clouds and manual verification of random policies. We also show the validity with several smell tests and cross-validate using time series of industrial policies in the electronic vehicle (EV) industry, demonstrating that the distribution of policies aligned well with known policy milestones and dynamics.

Overall, our procedure first successfully identifies 0.77 million industrial policies from the data of the 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, with a rising proportion having a supportive tone. Geographically, we find more industrial policies in more developed regions, 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. Across sectors, manufacturing and production-related services receive the highest overall focus, accounting for 32% and 45% of all policies, reflecting the governments' focus on these sectors. In terms of policy tools, we guide the LLM to classify them into 21 detailed types following the literature. Although fiscal subsidy is the most common policy tool that appeared in 43% of the policies, still more than half of the policies do not employ fiscal subsidy, suggesting the significant 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 meaningful variations across regions and sectors, suggesting a potentially significant bias from studying any single policy dimension separately; interestingly, we find that the industrial policy tools deployed in these documents evolve over the phase of a sector's development, from entry subsidies to R &D to supply chain clustering, for example, which is a feature that will be totally missed using the existing measures of industrial policy in the literature. In terms of policy objectives, the promotion of strategic industries is the most common, mentioned in 56% of the policy documents. Regarding conditionality, regional focus, firm sizes, and R&D are the most common forms of policy eligibility. Regarding the central-local relationship, we confirm the hierarchical structure where lower-level governments rely on guidance from the higher-level from policy citation data. In terms of policy implementation, the setting of targets is common, appearing in 79% of the policies, and coordination between government entities is also common, particularly at the central government level. In addition, we find that local adaption is prominent at the city level (34%). Lastly, around 20% of the policies encourage experimentation.

At the core of our empirical analysis are five sets of facts we document on China's industrial policy. These facts provide a rich empirical account of how local governments choose which industries to support, the variation in the use of policy tools across different regions and industries and over time, and the ways in which these policies affect firm entry, productivity, and capital investment. Our findings reveal not only the successes of China's industrial policies but also the inefficiencies and unintended consequences, such as overcapacity and local protectionism.

The first two sets of empirical facts examine the economic rationality and political economy of the local governments' choice of targeted sectors. We find that economic rationale, political motives and the administrative and fiscal capacity of local governments play a crucial role in the choice of targeted sectors and policy tools, which is consistent with the model of Juhász et al. (2023). On the economic rationality front, we show that, consistent with what is suggested by the theory, regions tend to target industries with relative comparative advantage, and more developed regions are better at this targeting (Fact 1). To the extent that more developed regions have stronger administrative and fiscal capacity, the results also highlight the importance of such capacity in making an appropriate policy choice. On the political economy of policy formation and passthrough, we show that city-level government follows upper-level government in policy-targeted sector choice, and the passthrough is stronger for less developed regions and for regions with no connection with upper-level government, and is stronger when political competition is stronger (Fact 2(a)). Examining the time trend of policy pass-through, we find that 2013 is a turning point —- the pass-through reversed the previous declining trend and started to get stronger with the wave of political centralization (Fact 2(b)). In addition, we also examine the time-consistency in sector choice, an important issue in policy implementation (Juhász and Lane, 2024). We find that policy exhibits a certain persistence over time. Interestingly, persistence is shifted by the change of local politicians and tends to mimic previous policies of the new politician in the city he previously served (Fact 2(c)). The result confirms the rotation of politicians as an important policy-learning mechanism. To the extent that politician experience is part of the administrative capacity, the results further confirm its importance in sector choice.

The third set of empirical analysis focuses on the policy tools used, a unique and critical aspect in policy implementation contained in our granular policy data. We find that local governments and more developed regions are early users of new policy tools, which are later spread throughout the country and adopted by higher-level governments (Facts 3(a) and 3(b)). That is, even though local governments tend to follow upper governments in sector choices, they nevertheless have flexibilities in implementation, and it is the local governments, who have more information on the ground, that are the main agent 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 with industry, with skill-intensive manufacturing industries using new policy tools more frequently compared to other traditional industries (Fact 3(c)). Interestingly, consistent with the idea of industry policies as customized public services (Juhász et al., 2023), we find that within each individual industry, local governments are evolving their industrial policy tools over time to accommodate the development phase of the industry, from tools to boost entries (such as entry subsidies, encouragement of entrepreneurship) to tools for industry advancement (such as R&D, supply chain enhancement) , indicating the local governments' dynamism in the implementation of industrial policies (Fact 3(d)).

In the fourth and fifth sets of empirical analysis, we associate policy information with diverse firm data sources to evaluate the effectiveness of the policies and explore their potential efficiency and inefficiency implications. We find that industrial policies are effective in providing firms in the targeted industries extra monetary benefits (Fact 4(a)), and thus significantly boost entry (Fact 4(b)), but the association with firm productivity is mixed: While there is a positive but short-lasting association between supportive policies and firm productivity in general, importantly, the association between policy and firm productivity depends on the specific tools used and their implementation, as multiple mechanisms interact in potentially opposite directions (Fact 4(c)). The results highlight the importance of variations in policy implementation on policy outcomes, echoing the emphasis of Rodrik (2004, 2009) on the "how" of industry policies. Lastly, we demonstrate a trend of increasing interregional policy homogeneity and that the level of homogeneity is strongly correlated with local protectionism in trade (Fact 5(a)). However, empirical evidence suggests that simply imitating the strategies of pioneering regions or replicating successful policies from other contexts often proves to be ineffective or even counterproductive (Fact 5(b)). This underscores the critical point that industrial policy is far more complex than just a matter of copying successful models—it requires careful adaptation to local conditions, administrative strength, and fiscal reality. In addition, Facts 5(a) and 5(b) highlight the challenges in coordinating policies to incentivize local governments to boost entries to a sector on the one hand and to avoid protectionism and over capacity from homogeneous and excessive entries on the other hand.

Literature Our paper primarily contributes to the growing literature and debates on industrial policy. In addition, it also contributes to the literature on the use of LLM in social science studies.

First, we contribute to the growing literature on industrial policy (See Juhász et al. (2023) for a comprehensive review). There is a large theoretical literature on industrial policy (Baldwin, 1969; Krueger, 1990; Krugman, 1992; Harrison and Rodríguez-Clare, 2010; Itskhoki and Moll, 2019; Lin et al., 2013). The earlier empirical literature on industrial policy mostly focuses on describing what happens to the policy-targeted industries, and most of which find industrial policies had been generally ineffective or counter-productive (Baldwin and Krugman, 1986; Head, 1994; Luzio and Greenstein, 1995; Irwin, 2000; Hansen et al., 2003). More recent literature zoom in to specific settings with a careful identification design to evaluate whether industrial policy elicited the desired behavioral response (e.g. Lane, 2022, 2020; Juhász, 2018; Choi and Levchenko, 2021). These studies produce results that are much more favorable to industrial policy. Much of these studies focuses on whether an industrial policy should be implemented and which sectors should be targeted, Barwick et al. (2023) advance the analysis by examining the design of industrial policy. They structurally estimate an industry equilibrium model to measure different types of hidden subsidies in the shipbuilding industry and assess their welfare consequences.

Our research advances the study of industrial policies on three major fronts. First, existing literature often examines industrial policy within a specific context, which may contribute to the mixed findings on its effectiveness. By applying generative AI 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 time period, with the potential to reconcile and synthesis previous debates in the literature. This approach reveals not only the effectiveness but also the potential downsides of industrial policies. Second, we demonstrate the potential for using LLMs to decode complex policy environments in broader contexts. By structuring unorganized text into a detailed dataset, we provide a new way to analyze the complexities of industrial policy in a large, diverse economy. The unprecedented dataset created through our analysis serves as a foundation for future research on the optimal design of industrial policies, offering insights that can be applied beyond China to broader institutional settings. As global interest in industrial policy continues to grow, understanding the nuances of policy implementation and adaptation at both central and local levels will be crucial for assessing the long-term impact of these policies on economic growth and innovation. Third, by using LLMs to extract granular information, we show that industrial policy is multifaceted. Elements such as policy initiation, the choice of implementation tools, organizational structure, top-down pass-through, and cross-regional learning and diffusion are all critical to understanding the efficiency and effectiveness of industrial policies. Our approach captures these nuanced dimensions, enabling us to go beyond policy consequences (by assuming policies are exogenous), exploring how specific sectors are chosen, why certain tools are used, and how industrial policies evolve over time and across regions. As such, our big data-based research complements case study/structural approaches.

Industrial policy in China has been of large scale while evidence for its effectiveness has been mixed at best.[1] Naughton (2021) provides a detailed narrative of the evolution of China's industrial policy through the past 20 years.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 et al. (2021), with a dynamic structural model, evaluate different types of subsidy tools of industrial policies in the setting of China's shipbuilding industry and highlight the nuances in policy designs. Branstetter et al. (2023) document negative impact of government subsidies on

[1]See estimates of Chinese industrial policy for 2019 by DiPippo et al. (2022).

firms' ex-post productivity growth.[2]. Liu (2019) further takes into account the industrial linkages in determining the optimal sector to be targeted by industrial policy. Our research offers by far the most comprehensive view of the landscape of industrial policies in China, with a detailed analysis spanning over 20 years and reaching the city level— previous research has generally been limited to national or provincial analyses relying on specific policy documents like Five-Year Plans. By examining policy variation across sectors, regions, and tools, we capture the unique regional dynamics that shape policy implementation, which depend heavily on local administrative and fiscal capacity. 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 designing these policies. Additionally, we address the critical issues of local protectionism and inter-regional competition, which mirror trends in global de-globalization. By adding a spatial dimension, we offer a deeper understanding of how China's politically centralized and economically decentralized RDA system influences policy transmission and adaptation, and the inefficiencies that can arise when regions replicate each other's policies. Our findings thus provide a balanced perspective, highlighting both the benefits and the potential risks of industrial policies in China's dynamic economic landscape.

Methodologically, we contribute to the fast-growing literature in economics and finance that leverage text big data (Gentzkow et al., 2019; Goldstein et al., 2021), especially those employ LLM to analyze text data (e.g. Li et al., 2024b; Lopez-Lira and Tang, 2023; Li et al., 2023; Kim et al., 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 et al. (2023) measure the exposure of each occupation to generative AI based on LLM's analysis of the occupation's task statement. Jha et al. (2024) use LLM to create a firm-level investment score from conference calls. Chen et al. (2024) apply LLM to measure matching quality in the labor market, demonstrating the ability of LLM to recover overlooked information in categorical variables from texts. Li et al. (2024b) use LLM to measure corporate culture, as well as its determinants and consequences, from analyst reports, demonstrating LLM's ability to extract causal relationships from texts. Our study differs from current research in two important ways. First, we apply generative AI for complicated information extraction rather than text classification or prediction tasks, and demonstrate its effectiveness. Contemporaneous applications of LLMs are typically on short texts of a couple of sentences or paragraphs. In this paper, we demonstrate the capabilities of LLMs in performing multiple complex tasks over extended texts, where LLMs' hallucination issues become more pronounced. In order to achieve the goal, we designed a careful, multi-stage methodology to address the unique challenges posed by excessively long documents and extensive prompts, maximizing the LLM's interpretative accuracy. In response to the model's limitations, particularly in handling lengthy prompts without losing context, we divided our queries into targeted rounds that progressively built upon each other. This allowed us to process nuanced elements across documents, such as intergovernmental relationships and policy implementation details, that are typically inaccessible via traditional machine learning methods or standard AI applications. Second, our study

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

tackles the critical issue of hallucination— a pervasive problem with LLMs, where models can generate plausible yet inaccurate responses. We introduce several novel strategies to address such hallucination issues. Specifically, we highlight the effectiveness of integrating multiple LLMs to mitigate hallucinations (Li et al., 2024a). Additionally, we underscore the importance of extracting all response-relevant text to improve response quality, enhance transparency, and facilitate further improvement. To improve prompt clarity, we employ LLMs to systematically search for counterexamples and to decompose complex questions into detailed steps. This method effectively reduced hallucination by encouraging the model to reference specific phrases, ensuring responses aligned closely with the actual content of the documents. 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 multi-dimensional policy information. We also systematically compare the performance of LLM with an alternative keyword search approach. While certain tasks— such as mapping policies to standardized industry codes— are inherently infeasible for traditional keyword-based approaches, we demonstrate the advantages of LLMs over keyword methods even in tasks where keywords are applicable, owing to their ability to understand meaning in contexts.

The remainder of the paper is organized as follows. Section 2 reviews existing measures of industrial policies, discusses the advantages of LLM in analyzing industrial policies, and lays out the technical details of applying LLM in analyzing policy documents. Section 3 describes the data and the main variables. Section 4 presents a detailed description of the industrial policy data canonicalized using LLM, categorized by key thematic dimensions. Section 5 leverage the vast and rich dataset constructed through the LLM analysis to uncover and document thirteen important facts about China's industrial policy over the past two decades. Section 6 concludes.

2 Measuring Industrial Policy

2.1 Existing Measurement of Industrial Policy

In recent literature, several approaches have been developed to measure and analyze industrial policies. These approaches primarily rely on structured policy frameworks like five-year plans, specific policy shocks, and, de facto measures based on firm subsidy data. More recently, there has been an emerging effort to develop text-based methods based on official government documents. Below, we broadly categorize the existing measures into three groups and carefully compare them with our LLM-based method.

The first group of studies relies on structured policy frameworks or specific policy shocks. First, for studies focusing on China, five-year plans have long been used as a crucial source for measuring industrial policy. These plans are issued at various government levels, from national to provincial, and often define the key "pillar" or "encouraged" industries that are prioritized for development. Barwick et al. (2021) analyze the provincial five-year plans, identifying priority industries through keyword searches for terms such as "pillar industry" to measure policy impacts. Similarly, Cen et al.

(2024) focus on national-level five-year plans, identifying "encouraged industries" at the four-digit industry level using keyword searches and linking these industries with government subsidies post-plan issuance. Chen et al. (2017) also explore the role of national five-year plans, using keyword searches to identify specific industrial policy initiatives. These studies highlight the structured and long-term nature of policy planning in China, using five-year plans as a framework to direct industrial development. Other studies leverage specific policy shocks to provide another avenue for measuring industrial policy. For example, Wei et al. (2023) examine the impact of a specific national innovation policy, InnoCom, implemented in 2008, which aimed to stimulate technological innovation. Branstetter and Li (2022) analyze the"Made in China 2025" initiative, a comprehensive strategy to upgrade China's manufacturing capabilities, as a specific industrial policy shock. Both studies focus on identifying the effects of targeted, large-scale policy interventions on specific industries and regions. In a similar vein, scholars also rely on various historical contexts with exogenous shocks of industrial policies worldwide. For example, Juhász (2018) evaluates the famous infant industry argument using the disruption to trade resulting from a blockade against Britain in the 19th century during the Napoleonic Wars (1803-1815). Lane (2022) study the impact of industrial policy on industrial development by considering an important episode during the East Asian miracle: South Korea's heavy and chemical industry (HCI) drive in the 1970s.

The second group of studies employs data-driven approaches, which combine firm-level administrative data with policy interventions to measure the intensity and impact of industrial policy. For example, Aghion et al. (2015) use the ASIF dataset to develop policy support measures by aggregating firm-level information on subsidies, tax holidays, interest payments, and tariffs. This allows for the construction of policy support intensity measures at the city-industry level. Similarly, Branstetter and Li (2023) analyze total subsidies received by public firms using data from CSMAR to assess the impact of government subsidies on firm performance. DiPippo et al. (2022) further expand on this by comparing industrial policy spending across countries, using firm-level data to evaluate the effectiveness of policy interventions. Compared to the first approach, the second approach only focuses on the industries or firms that actually receive extra government monetary support. On the other hand, it may fail to capture the failed policies that were not implemented well, nor the ones that mainly utilize other implementation tools like consumer subsidy, government procurement, government equity fund, etc.

Finally, the use of government documents as a source for policy analysis has become increasingly prominent. Sinclair and Zhang (2023) leverage official documents from China's State Council, scrapping 444 policy documents issued after 2008 and filtering them to focus on those that are relevant to industry-specific policies. Their analysis focuses on policies with positive tones and attempts to identify policies using keywords like "promote" and "develop". Recent advancements in text-based methods have enabled the analysis of industrial policy using machine learning techniques. For example, Juhász et al. (2022) utilize the Global Trade Alert (GTA) database to analyze industrial policies across countries, industries, and time periods. They manually classify a subset of policies and then apply the BERT model to classify the full dataset, identifying a total of 28,000 policy observations. Their approach highlights the potential of text analysis to handle large volumes of policy documents and extract detailed insights about policy interventions. Goldberg et al. (2024) also utilize a subset of the GTA data, focusing specifically on the chip industry, while Evenett et al. (2024) develop the New Industrial Policy Observatory (NIPO) database to track new industrial policies globally. This text-based method relies on monitoring and reporting by the Global Trade Alert team, focusing on the content and motive behind policy interventions to better understand the scope and effectiveness of industrial policies. Compared with the previous literature, the text-based method is able to provide a more comprehensive coverage of industrial policies and contains more detailed information on the implementation of the policies. However, the method relies on significant manual work— the WTA 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— thus making the method infeasible for studies at a more granular level, which may involve a much larger volume of longer and unstructured documents.

In sum, these varied approaches demonstrate the evolving nature of industrial policy analysis, with methodologies ranging from policy shock analysis to data-driven and text-based approaches. Each method offers unique insights into the target and effectiveness of industrial policies, allowing researchers to evaluate their impact on firm behavior, market dynamics, and broader economic outcomes. Yet, these methods are subject to two major constraints. First, existing measures focus primarily on identifying the targeted industries, overlooking the much richer information contained in policy documents. Critical details, such as specific implementation tools, eligibility conditions, and the government's underlying objectives or rationale for targeting particular industries, often remain unmeasured. Traditional methods fall short of capturing this multi-dimensional complexity. Second, current measures predominantly operate at the national or, at best, provincial level. However, to fully comprehend the mechanisms of industrial policy within a country like China, it is essential to understand policy implementation at more granular levels, such as cities or districts. Understanding the dynamics of policy passthrough from the central government to local governments, along with the patterns of local policy learning and experimentation, requires detailed local-level analysis, which has been largely absent in the existing literature. This is where newer methods, such as LLM, come into play, enabling deeper analysis of complex, unstructured text data and offering the potential to overcome these limitations.

2.2 Policy Documents and LLM

The government documents provide a wealth of information. In this section, we outline how we leverage LLM to systematically extract and organize each of these key elements from the textual data.

2.2.1 Prompts: What Can We Learn from Policy Documents

In the first part of our analysis, we categorize the insights that can be systematically extracted from government documents into four broad categories: First, we identify industrial policies from the universe of government policy documents. This involves determining whether a particular document can be classified as an industrial policy, following a clear, consistent definition. Second, we determine the tone of each policy document, and then focus on identifying the specific tools used to implement the policy. These could include fiscal and financial incentives (e.g., subsidies, tax breaks), regulatory changes, entry support (e.g., land allocation, infrastructure development), and demand-side tools (e.g., government procurement, consumer subsidies). Third, we zoom in on more policy details. This category captures the full range of information provided in the documents about the policy's scope and operation, such as the date of issuance, the effective period, the objectives of the policy, the eligibility criteria for firms to receive policy support, and the specific mechanisms and organizational arrangements for implementation. These details are crucial for understanding how the policy is intended to work and who stands to benefit. Lastly, we learn about the intergovernmental relationships in policy setting from the documents. This aspect 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. This is important for understanding the hierarchical structure of policy diffusion and local experimentation.

Using these four categories, we guide the LLM to comprehend and process the highly unstructured text data and systematically structure it into a well-organized dataframe. By prompting the LLM to follow this line of thinking, we transform the raw, lengthy policy texts into a manageable dataset that enables detailed empirical analysis. Each policy document is thus broken down into these core components, allowing us to capture the complexity of industrial policy design, implementation, and intergovernmental coordination across China.

Defining industrial policy As the first step of the process, we must be clear about the definition of industrial policy to identify them from the universe of government policy documents. There has been wide discussions on the exact definition of what constitutes an industrial policy among scholars and practitioners. In trying to identify the industrial policies from the World Trade Alert database, Juhász et al. (2022) apply a relatively narrow definition as the policies with: 1) stated goal of changing the relative prices across sectors or direct 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 extranational, state. In a similar vein, Naughton (2021) defines industrial policy as "any type of selective, 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."

An alternative, broader definition would also have some benefits, because it might help us identify some common features across countries and also compare and contrast very different countries in a systemic way. For example, Knight (2014) calls China a "developmental state," using a broad definition that permits him to focus on the presence of an overarching national goal of economic development, as well as an incentive structure that rewards government officials for pursuing growth. This very effectively draws out the commonalities between China, Japan, and Korea in their high growth eras, while leaving the differences to one side. In another sense, a broad definition allows authors to bring in regulation, fiscal and monetary policy, and innovation and human resource policy. For example, Brandt and Rawski (2019) 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.

In this project, we follow Juhász et al. (2022) and Naughton (2021) to use a relatively narrow definition of industrial policy. Industrial policy refers to government policy measures taken to guide industrial development and directed at changing the 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 social resources, or influences the long-term composition of the economic structure through the 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. It is important to note that, while every policy may turn out biasing towards certain sectors— for example, Hukou reforms that relax labor mobility restrictions may benefit labor-intensive industries more, and joining the WTO may benefit export-oriented industries more— we do not consider these general policies as industrial policies in our study. 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, distinguishing it from broader economic reforms or general public policies that indirectly affect certain industries. Moreover, this also minimizes the risk of conjecture with LLMs which is a common source of hallucination.

More precisely, to determine if some document qualifies as industrial policy, we apply the following criteria: First, the subject of industrial policy must be the government (including various levels of government and subordinate departments). If the text involves company development or collaboration between non-governmental entities, it is not industrial policy. Second, industrial policy must involve government policy measures. If the text merely reports economic progress or describes activities like government relocation or recruitment, it is not industrial policy. Third, industrial policy must be directly biased towards a specific industry or specific economic activity. General policies not targeting specific industries or activities are not industrial policies. For example, policies that aim to boost long-run economic growth without a biased target on a specific industry, are not counted as industrial policies. Fourth, industrial policy aims to affect the economy's long-term structure. Policies addressing short-term economic shocks, like responses to the COVID-19 pandemic, do not qualify as industrial policy.

As industrial policy is defined as policies that target specific industries, we can thus identify the industries being targeted in each industrial policy document. We identify the industry at the most granular 4-digit industry level. In particular, 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 be spillovered by 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 specifies the policies for the battery industry.

Lastly, we also examine the "tone" or intent behind the policy— whether it aims to promote, regulate, or suppress a certain industry. Promotional policies focus on advancing sectors through initiatives like 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 control, such as setting industry standards, enforcing environmental regulations, market regulation, corporate oversight, and ensuring safety in production. These aim to regulate industry behavior and establish norms. Suppressive policies, on the other hand, seek to limit or phase out certain sectors, including actions like restricting overproduction, supporting market clearing, eliminating outdated production capacity, controlling real estate speculation, or curbing energy-intensive industries[3].

Policy implementation tools What policy levers are used to conduct industrial policy? One of the most critical aspects of the rich information extracted from government documents is the categorization and identification of the implementation tools used in industrial policies. However, there is no universally agreed-upon framework for categorizing these tools, and the approaches vary significantly across different studies and institutions. For example, the United Nations Conference on Trade and Development (UNCTAD)'s Multi-Agency Support Team (MAST) has developed a coding system for trade-related policy measures that includes 12 categories, ranging from capital control to subsidies, tariffs, migration measures, and others. Similarly, Juhász et al. (2022) employed the more detailed taxonomy used by the Global Trade Alert (GTA) project to track various policy interventions globally. These approaches, while comprehensive in terms of import and export measures, tend to focus predominantly on national-level policies with a specific emphasis on trade-related interventions.

Our approach builds on the foundation established by these frameworks but extends it to account for the unique characteristics of domestic industrial policy, especially at the local government level. We retain several categories related to trade and international competitiveness, such as entry subsidies, import/export controls, financing tools, and fiscal subsidies, as these 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 frequently deployed by local governments. These include labor subsidies, preferential land allocation, industrial funds, and policies promoting industrial clusters—tools that are more tailored to regional economic development and reflect China's decentralized industrial governance structure.

In this extended framework, we classify policy tools into a few broad categories. The first category is a group of traditional financial measures that align with international frameworks, such

[3]Environmental policies can fall into either promotional or suppressive categories depending on their emphasis: if focused on pollution control, they are suppressive, while promoting green development makes them promotional.

as credit and finance provisions, tax incentives, equity support, and fiscal subsidies. These tools are critical for reducing the financial burden on firms, stimulating investment, and encouraging sectoral growth. The second is a set of tools directly aimed at promoting market entry, enhancing entrepreneurship, and regulating competition. Tools include industrial funds that offer venture capital support, policies that encourage entrepreneurship, and regulatory mechanisms to improve the business environment. Additionally, measures such as market access regulations and trade protection instruments (e.g., import/export controls and non-tariff barriers) are key components in shaping the competitive landscape and controlling market access for both domestic and foreign firms. The third category includes tools that subsidize input at different production stages. The input category covers policies designed to ensure the availability of critical resources required for industrial development. This includes labor policy (such as training programs and wage subsidies), preferential land supply (such as reduced land costs for industrial use), and infrastructure investments (including transportation and energy infrastructure). Additionally, this category addresses government efforts to promote R&D and technology adoption, as well as policies aimed at encouraging environmental protection through green credit and subsidies for sustainable practices. The fourth category covers tools that aim to stimulate consumer demand and ensure that firms can access large and stable markets. Measures include demand stimulation through consumer subsidies, government procurement that prioritizes domestic industries, and industrial promotion policies such as public exhibitions and trade fairs to increase product visibility and market access. The final category focuses on supply chain-related policies that promote the integration of industrial clusters and support local supply chains. These tools are designed to encourage the localization of supply chains and stimulate agglomeration economies. Industrial cluster policies, for instance, aim to create economic zones where firms can benefit from proximity to suppliers, customers, and competitors. Localization policies further ensure that industries utilize local labor, suppliers, and resources, strengthening regional economies and promoting self-sufficiency. By expanding the categorization to include these region-specific tools, we capture a fuller picture of how Chinese industrial policy is implemented across different levels of government and sectors, providing a deeper understanding of the mechanisms driving industrial development at both the local and national levels.

By organizing the industrial policy tools into these five distinct categories, we provide a comprehensive framework that reflects the comprehensive tools of China's industrial policy, and that is more appropriate for analysis of industrial policy at sub-national level. This categorization allows us to systematically assess the range of tools used by the government to achieve its industrial 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 broader economic goals.

Policy details In addition to identifying the specific tools used for policy implementation, a comprehensive analysis of government documents often reveals even more critical details. These documents typically include information on the issuing government body, the policy's effective duration, objectives, eligibility criteria for support, and the specific mechanisms for implementation. With the power of LLMs, we can extract detailed information on these dimensions, thus providing a richer understanding of industrial policies beyond just the surface-level tools.

First, we examine the conditionality of policy support, which refers to the requirements or conditions that enterprises must meet in order to qualify for policy support. These criteria serve as the filters through which governments target specific types of firms, ensuring that the policy benefits are allocated according to the intended objectives. Based on the extracted information, the common conditions found in Chinese industrial policies can be usually categorized by the following dimensions: the firm's scale or strength, firm age, R&D investment or specific technological qualifications (e.g., patents, R&D platforms, or high-tech capabilities), firm location, ownership structure (SOE, POE, foreign-invested enterprises, etc.), designated specific firm, or others.

Second, policy documents usually state the goals of industrial policies which reflect the strategic and social priorities of the government. The objectives outlined in the documents often provide insight into the rationale behind each policy and the broader goals the government hopes to achieve. 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, social goals such as employment, equity, or urbanization, etc.

By extracting and categorizing both the conditionality and stated goals of industrial policies, we can develop a deeper understanding of how government strategies are structured. These dimensions add crucial layers of complexity to the analysis, providing insights into not just what policies are being implemented, but how and why. Furthermore, we guide LLM to read about the rich implementation details found in government policy documents, which allow us to evaluate the government's strength and effort in executing industrial policies, particularly in terms of the organizational arrangements within different levels of government. These details give us a clearer picture of how effectively the policies are carried out and the administrative measures used to ensure their success.

To assess the strengths of the policy, we evaluate the content along two dimensions. First, we consider how substantive the policy measures are: Does the policy contain vague, broad statements, or does it include highly specific, actionable measures with clear goals, supervision, punishment, and incentive mechanisms? Second, we assess the intensity of these measures: Are the policy objectives and mechanisms weakly defined, or are they backed by strong, detailed directives with clear enforcement strategies, where the government invests significant manpower and material resources to ensure implementation?

In particular, from the documents, we can extract information about four broad categories of local governments' organizational arrangements related to policy implementation. We guide LLM to read through the documents and evaluate the strengths of the policies from these four dimensions. First, performance evaluation, punishment, or incentives— The policy documents often specify how government divisions, lower-level governments, and their officials will be evaluated. This includes identifying any performance metrics, potential punishments for underperformance, 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. Second, encouragement of local governments' policy innovation— Many policy documents highlight how lower-level departments, governments, and officials are encouraged to engage in policy innovation. This reflects the government's willingness to allow local experimentation and adaptability in achieving the policy goals. We can track how and to what extent lower-level actors are given the freedom or incentives to innovate within the policy's framework. Third, methods of policy enforcement— Documents may also contain specific measures or arrangements designed to advance the implementation of the policy. This can include task forces, cross-departmental collaborations, 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. Lastly, adaptation to local conditions— Policy documents often reflect how a policy has been adapted to the specific local conditions of the region where it is being implemented. 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 needs of different areas.

By systematically extracting these details using LLMs, we are able to construct a comprehensive view of the organizational and administrative underpinnings of industrial policy implementation, offering a more nuanced understanding of how these policies are executed and enforced across different regions and levels of government. This adds an important layer to our analysis, allowing us to assess not just the intent behind the policy, but also the organizational structure and mechanism of its implementation.

Intergovernmental relationship In addition to analyzing the content of industrial policy documents, we extract valuable insights regarding 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 coordinated, aligned, or adapted across government levels.

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 refers to distributing the policy to other government levels or departments for implementation. Implementation involves citing policies as the basis for specific actions, highlighting their continued influence. Basis for policy occurs when a policy is formulated based on higher-level laws or frameworks. Policy continuation or abolition captures whether a policy continues or replaces a previous one, leading to its abolition. Lastly, policy coordination

[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.

reflects how the current policy aligns with existing ones to ensure consistency and avoid conflicts.

By analyzing policy documents, references to higher or lower government bodies can be categorized based on their purpose. Mentions of upper government often relate to implementing higher-level policies, citing 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. Additionally, there are miscellaneous mentions of lower government relevant to policy enforcement and governance.

By analyzing both the explicit mentions of government levels and the policy citation network, we can better understand the hierarchical coordination of policies across China's multi-level governance system. The top-down transmission of policy goals, alongside local adaptation and experimentation, plays a crucial role in shaping the implementation of industrial policies at different levels. 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 the central directives and local innovations contribute to the broader industrial landscape.

2.2.2 Implementation

Model

LLMs are advanced deep learning algorithms with billions of parameters, making them ideal tools for analyzing texts to conduct various complex summarization, extraction, and classification tasks. Trained on vast text corpora from diverse textual sources, these models learn the inherent meanings of language and vast knowledge through various text prediction tasks. They are further refined to follow human instructions and incorporate human feedback. Consequently, they excel at various complex text tasks, with the volume of training data and the number of parameters governing the model's knowledge base, its reasoning ability, and its ability to grasp complex and nuanced meanings in texts. While LLMs exhibit remarkable capabilities, they are not without limitations. In particular, LLMs may generate responses even when they are uncertain or they potentially misunderstand the instructions, especially in the context of complex queries and extensive textual inputs. These unwarranted responses often contain inaccuracies—a phenomenon commonly referred to as "hallucination."

Overall, it is helpful to think of LLM as a well-read research assistant who read millions of books, papers, articles, documents, online content, or other textual sources, it possesses certain level of expertise in various domains, and it has a sophisticated understanding of words, jargon, sentences, and paragraphs within contexts. Yet, this research assistant is overconfident and may return false responses even when it is uncertain or it misunderstands the instruction. When employing this research assistant for a specific task, we need to give clear instructions to avoid misunderstanding, as well as take other strategies to reduce hallucinations to obtain more accurate results.

Given the complexity of our tasks—which demand comprehensive knowledge, particularly proficiency and knowledge in Chinese—we employ the Gemini-1.5-flash-001 model developed by Google DeepMind. This language model has been trained on an extensive corpus of multilingual texts from diverse sources comprising 6.5 trillion of tokens (or 4.9 trillion of words), equivalent to the word count of millions of books. It thus encompasses a vast repository of knowledge requisite for our analysis. According to user evaluations on authoritative platforms such as Chatbot Arena (formerly LMSYS), the Gemini-1.5-flash-001 model ranks favorably compared to certain versions of GPT-4, specifically GPT-4-0314 and GPT-4-0613, and most Chinese LLM models in tasks conducted in both English and Chinese, underscoring the model's superior performance in handling complex tasks.

Gemini-1.5-flash-001 exhibits a strong capability to process long texts of up to one million tokens, or approximately 750,000 words, without significant deterioration in performance. According to user evaluations on Chatbot Arena, it ranks much higher than GPT-4-0314 and GPT-4-0613 in handling longer query. This capacity is particularly attractive, as it allows us to provide both the complete policy texts and the necessary definitions and guidance to the language model. Such comprehensive input is crucial because many of our inquiries require an extensive contextual understanding of entire documents, and numerous cases involve complex issues that demand clear definitions and precise guidance. For example, determining whether a policy constitutes industrial policy depends on multiple factors: whether it is issued by the government, whether it targets and favors specific industries or specific economic activities, whether it includes concrete policy tools, and whether it aims to shift economy's long-term composition. Since the relevant information is interrelated and scattered across different sections of the policy document, querying the LLM with the full text is essential.

Moreover, assessing whether a policy specifically targets and favors certain industries or activities—as opposed to being a general policy without direction—and whether it aims to shift the long-term composition of the economy—as opposed to responding to short-term economic shocks—involves complex and nuanced judgments, as many texts contain elements of either directions. It could take hours to explain to human research assistants. Providing clear definitions and guidance, along with counterexamples, is therefore crucial for the output quality. However, both the full texts and the definitions and guidance are necessarily lengthy. Notably, the median length of our policy documents is 1,160 words, with the 90th percentile reaching 5,461 words. Additionally, a clear definition of industrial policy and common policy tools alone comprises 2,406 words. The Gemini-1.5-flash-001 model thus aligns well with our demands.

Overview of processes

We conduct two major rounds of LLM queries using titles and full texts of policies. The first round encompasses all policy documents in our sample. The second round focuses on a subset identified as industrial policies, determined by combining the industry policy scores from the first round LLM query with the orthogonal assessment from a different LLM model on policy titles. We separate the queries into two rounds because the performance of the LLM model deteriorates with excessively long prompts, despite the model's strong performance in processing long texts. Additionally, building on recent findings (Li et al., 2024a), we integrate orthogonal judgments from additional LLMs or have one LLM critically review the outputs of another for several critical questions, besides the two major rounds of LLM queries. Such integration and critical reviews have been shown to substantially improve performance across applications.

In the first major round, our queries address several key aspects: whether the policy document constitutes an industrial policy; the issuing government; the list of targeted industries; policy tone; the list and classification of policy tools; measures of policy strength; the conditionality of the policy; references to other governments; citations of other policies; and policy targets. The second major round of queries delves into additional dimensions and repeats some first-round questions to enhance the output quality: policy issuance dates and effective periods; the list of targeted industries; policy tone; measures related to setting targets, monitoring, evaluating, incentivizing, and punishing lower-level governments; measures that grant discretion and promote policy experimentation, learning, and tolerance of failure; policy implementation measures such as funding support, coordination, mandatory enforcement, and developing institutional capacity; local adaptation of policies; and continued references to other governments and citations of other policies. Appendix B provides a detailed list of variables.

Major prompts

To mitigate the hallucination in LLM responses, we employ various prompt design techniques to enhance output accuracy throughout the prompts of different rounds. First, we provided comprehensive and clear definitions to reduce ambiguity. For instance, we included a detailed 2,406-word definition of industry policy and policy tool categories based on existing literature, equipping the model with nuanced understanding necessary for accurate analysis. When necessary, we provide common counterexamples to each definition to reduce the ambiguity in understanding through multiple iterations of experimentation with prompts, often based on different random subsamples to increase sampling coverage.

In addition, we provide structured and clear guidelines in prompt for the LLM to analyze the text, and when necessary, we decomposed complex problems to guide the model's analytical process step by step. For example, before determining whether a policy constitutes industrial policy, we require the LLM to answer eleven specific questions pertaining to multiple aspects of industrial policy.

Additionally, we took several general prompt strategies widely found to be useful in different applications: we set the temperature parameter to zero to obtain more consistent outputs, we assign the LLM a role as a China industrial policy expert to remind it the proper knowledge base to refer to in its analysis, we repeatedly emphasize the importance of basing answers on the text itself, we permit the model to respond with "I don't know" rather than forcing the model to return likely incorrect outputs, we repeatedly stress conservative judgment in classification questions to mitigate false classifications, we remind the LLM to ensure response consistency across multiple interrelated questions, we use consistent formatting and clear section delimiters to ease the understanding of LLM, we repeatedly remind the LLM to pay attention to critical texts or critical response instructions, and we encourage thorough and step-by-step analysis.

Importantly, we require it to provide, for each major question, not only the answer but also associated confidence levels, concise reasoning, and all relevant text extracted directly from the original text. Including confidence levels and reasoning ensures that the LLM's responses are careful and logically consistent. The provision of relevant text and reasoning further improves transparency. Crucially, by verifying whether the policy texts contain these keywords, we can directly mitigate hallucinations. Using this strategy, we eliminate a significant amount of erroneous policy citations. Additionally, the inclusion of relevant text and reasoning allows for continual improvement by employing another LLM to critically review the responses.

Refinement with additional LLM analysis

For key questions regarding the determination of industry policy, the list of relevant industries, and the classification of policy tools. We employ additional LLM models and integrate responses from these models to improve the accuracy of the final results, aiming to minimize hallucination and improve output quality.

Determination of industrial policy To conduct an additional-round LLM evaluation of industrial policies, we select policies that meet a minimal threshold based on the first-round LLM results. Specifically, we include policies where either (1) the LLM industry score is available and exceeds 30, or (2) the LLM industry score is missing, but the reasoning provided by the LLM lacks explicit indications that the text is not about industrial policy. We choose this threshold conservatively to ensure that virtually all potential industrial policies are included.

In the additional-round LLM analysis, we employ a more advanced but costlier LLM model, Gemini-1.5-pro-exp-0827, a model that is also developed by Google DeepMind that is even more knowledgeable and has stronger capability to conduct complex tasks than Gemini-1.5-flash-001. Due to cost concern, we only query it with the policy titles—the most informative components of the policy texts regarding their nature. In the prompt, besides the definition of industrial policies, we instruct the LLM that policies not targeting industry and clearly concerning eight types of issues (e.g., internal government management) are likely not industrial policies, however, since this relationship is not deterministic, it must comprehensively consider all relevant information to reach the final judgment.

In particular, we obtained these eight types of common non-industrial-policy titles by instructing an LLM to summarize titles of 10,000 random selected policies according to the definition of industrial policies. We then manually read to further summarize the output of the LLM summary. These two-step strategies thus ensure that all common non-industrial-policy types are summarized and that there is no misclassification. We aim to be conservative in providing counterexamples so that only obvious counterexamples are provided to reduce the likelihood of misclassification.

To identify the prevalent categories of counter-examples, we first instruct an LLM to summarize the titles according to the definition of industrial policies on a 10,000 random sample of the selected policies after the first-round LLM. We then manually review and further condense the LLM's summaries. This two-step strategy ensures that all common non-industrial policy types are comprehensively captured and that misclassifications are minimized. We adopt a conservative approach and only maintain obvious counter-examples so as to reduce the likelihood of misclassification in the additional-round LLM analysis.

We obtain several highly correlated scores from the additional-round LLM analysis, and the most useful one concerns the extent to which the policy is definitely not an industry policy. We combine this score with the first-round LLM scores and determine a policy to be an industrial policy if the first-round LLM score is above 60 and the difference between the first-round score and this score is greater than 15. In other words, we select policies that exhibit relatively strong signals of being industrial policies, ensuring that the strength of the positive signal surpasses that of the negative signal by more than a certain threshold. Through these procedures, we identify 770,819 industrial policies out of a total of 3 million policy documents.

Extracting Industries and Matching to Standardized Industry Codes Recognizing the critical importance of accurately identifying industries from policy texts, we implement several additional measures to enhance the quality of LLM outputs. Specifically, we extract lists of target industry-related text in both the two major rounds of LLM queries using the full policy texts. While the responses from both rounds largely overlap, most policy texts encompass multiple industry names—a common characteristic in our sample—some relevant text represent the main targets of the policies, whereas others are merely briefly mentioned. To address this distinction, we employ an additional LLM to critically review the relevant text lists from both rounds in conjunction with the full policy texts. It is tasked with adding any missed relevant text, eliminating erroneous ones due to hallucinations, and, most importantly, differentiating major policy targets from briefly mentioned industries. Our results indicate that this step primarily serve to select the major policy targets from the texts, with only minor additions and deletions.

In the final step, we supply the list of relevant text corresponding to the major policy targets, along with a comprehensive list of standardized three-digit industry codes and names, to a more advanced LLM model, the Gemini-1.5-pro-exp-0827 mentioned earlier. We instruct this model, acting as an expert on Chinese industries, to map the extracted industry names to standardized industry names and industry codes.

In summary, we employ a multi-step methodology: the initial three LLM queries are utilized to accurately extract all relevant text lists related to the principal policy targets, while the final query, leveraging a more advanced model, maps these relevant text lists to standardized industry classifications. We do not directly map the full policy texts to the complete industry list due to both cost considerations and the potential degradation of LLM performance associated with excessively long text. Including the exhaustive list of industry names in addition to the policy text would substantially increase the length of the input text, potentially impairing the LLM's effectiveness.

Moreover, the extracted relevant text allow for continual refinement afterwards.

Policy tools Another critical part is the extraction and classification of policy tools. As detailed above, we categorize policy tools into 21 distinct groups, following established literature, with an additional "other" category encompassing any instruments not captured by the predefined classes. To enhance accuracy, we provide detailed definitions to the prompt. Importantly, we design two set of questions within the first round of LLM prompt: one set of questions specifically ask the LLM to return a list of policy tool keywords from the policy text, and the other set asks the LLM to classify each piece of relevant text into the relevant policy tool categories. We do not restrict each keyword to a single category to reduce the false negative classification. By separating the extraction and classification tasks, we ensure that each policy tool identified by the LLM is directly linked to at least one piece of relevant text present in the raw text. In contrast, directly prompting the language model to determine whether a policy contains specific policy tools may lead the model to hallucinate and produce false positive responses. This issue may arise even when we require the model to return relevant text from the policy text along with the classification.

We manually check the output of the first-round LLM's responses, all policy tool relevant text from the policy text are almost always extracted to the relevant text list, and there are few false positives in the list. Yet, because we do not restrict each piece of relevant text to a single policy tool category, there are false positives in the classification of the piece of relevant text. We thus conduct an additional-round LLM query by supplying the definition of policy tool category along with corresponding outputs from the first-round analysis, including the subset of relevant text classified to the category, and the confidence level and the reasoning of such classifications. Importantly, for each policy category, we provide counter examples of misclassifications. We obtain the counter examples by asking another LLM model to summarize misclassifications from a random sample of 10,000 responses related to each policy tool category from the first-round analysis. We then manually review and further condense the LLM's summaries. This two-step strategy ensures that all common misclassifications are comprehensively and accurately captured. We adopt a conservative approach and only maintain obvious counter examples, so as to reduce the likelihood of misclassification in the additional-round LLM analysis. Section A showcases an example list of counter examples we provide to the additional-round LLM.

Finally, we combine scores from the first-round LLM response with the scores from the second-round critical review to arrive at the final classification.

2.2.3 Verification

Word cloud and manual check We present two important verifications of the key variables in our LLM-analyzed data set. First, we present evidence for manual checks as well as a set of word cloud results for the determination of industrial policies, the policy targeted sector(s), and the industrial policy tools deployed. The results provide the most straightforward check of the validity of the LLM analysis.

Determination of industrial policies Table A1 presents a random selection of 10 titles from the texts identified as industrial policies and 10 titles from those not identified as such. Several observations emerge from this comparison. First, nearly all texts identified as industrial policies are arguably so, while those not identified generally pertain to social affairs, letters of opinion, specific regulatory approvals for individual firms, or personnel promotions.

[Table A1 about here]

Second, industrial policies are diverse and concern different industries or economic activities at various stages of policy implementation. Some policies directly target specific industries like tourism, while others focus on economic activities such as entrepreneurship or science and technology. Additionally, some involve the pilot stages of programs, whereas others pertain to the implementation or audit of fund usage.

Third, there are usually no specific keywords that readily identify a policy as an industrial policy. Conversely, even when titles contain keywords seemingly related to industrial policies—such as "company," "assets," "supporting funds," or "credit union"—the texts may not actually pertain to industrial policy upon closer examination.

Taken together, these observations highlight the advantages of using Large Language Models (LLMs), which understand jargon and contextual meanings within texts. LLMs evaluate sentences, paragraphs, and entire documents holistically to reach conclusions, rather than focusing solely on individual words.

To gain an overview, we present the word cloud based on keywords in titles of industrial policies vs non-industrial policies below. Although, as previously discussed, not all industrial policies contain informative keywords and some non-industrial policies may include relevant ones, we still observe distinct patterns in keyword usage between the two categories. Terms such as "service sector", "advanced technology", "environment," "science and technology," "firm," "industry," "planning," "project," "digitalization," "execution plans," "fund," "special fund," and "subsidy" appear more frequently in industrial policies. In contrast, terms associated with individuals, administration, public affairs, or announcement—such as"Chinese People's Political Consultative Conference," "reply," "meeting," "comrade," "appointment," "dismissal," "proposal," "social insurance," "announcement," and "education bureau"—are more likely to appear in the titles of non-industrial policies. A set of terms such as "committee," "office," "notice," "opinion," and "projects," that can be linked to both industrial and non-industrial policies equally appear in both sets of word clouds. Overall, the distinct pattern in these keywords help confirm that the LLM models systematically identify industrial policies from other policies.

[Figure A1 about here]

Notably, by incorporating an additional-round LLM analysis, we significantly enhance the quality of our policy classification. Specifically, when determining industrial policies based solely on first-round scores, a threshold of 90 serves as a reasonable cutoff that balances the trade-off between false positives and false negatives. Under our final criteria—which integrate scores from both rounds—317,714 policies with first-round LLM scores equal to or greater than 90 are filtered out, while 179,703 policies with first-round scores below 90 are retained. Considering that our final sample comprises 770,819 industrial policies, these adjustments have a substantial impact. Most of the filtered-out policies pertain to public affairs, administrative matters, replies to public inquiries, proposals by the Chinese People's Political Consultative Conference, law enforcement, public services, and information disclosure. In contrast, the majority of the filtered-in policies are arguably industrial policies, though they may focus on specific targets or represent relatively weak forms of industrial policy, such as promotional activities or labor policies aimed at the R&D sector. Table A2 presents random samples of the policies that were filtered out and filtered in according to the final criteria compared with setting the threshold at 90 based on first-round LLM industry score.

[Table A2 about here]

Target industries To assess the validity of the LLM's mapping of policies to target industry codes, we generate word clouds based on extracted industry names and the full policy texts for two standardized industry codes identified by the LLM: electric vehicles and electricity production. The electric vehicle sector is a well-known target of industrial policy, and the electricity production sector includes solar energy, another prominent target of industrial policy.

Examining the word cloud based on extracted industry names for electric vehicles as depicted in Figure A2, the most frequent keywords—"vehicle," "electric vehicle," "new energy," "clean technology," "electric-powered," "energy saving," "battery charging," "green," "power battery," "manufacturing," "equipment," "materials," "enterprises," "industry," and "product"—are all closely related to the electric vehicle industry. Interestingly, since policies often target multiple industries with shared characteristics, high-tech sectors such as shipping and pharmaceuticals also appear in the word cloud. Turning to the word cloud based on full policy texts, in addition to the aforementioned keywords, terms such as"limited liability company," "project," "technology," "critical," "science and technology," "innovation," "supporting," "encourage," "promote," and "execution" frequently occur. This indicates that the policies may target specific firms, establish projects to support the sector, and that the electric vehicle industry is perceived as a high-tech sector with an emphasis on innovation and technology.

[Figure A2 about here]

A similar pattern emerges from the word cloud on electricity production as shown in Figure A3. In the word cloud based on extracted industry names, frequent keywords include"electricity," "energy," "energy saving," "industry," "manufacturing," "new energy," "firm," "critical," "project," "clean," "green," and"coal." This reflects that the industry code of electricity production encompasses traditional production method using coal. Similar to the case of the electric vehicle, industries that utilize electricity, such as agriculture, are also mentioned. In the word cloud based on full policy texts, again, similar to the case of electric vehicle, we see additional keywords related to policy implementation and firms.

[Figure A3 about here]

Overall, these results confirm the validity of the LLM approach in extracting industry names from policy texts and mapping these industry names to standardized industry codes.

Policy tools Figure A4 presents the word clouds based on list of policy tool keywords extracted regarding four types of policy tools: tax incentives, fiscal subsidies, credit policies, industrial funds, respectively. They are commonly used, and importantly, they all involve some form of monetary or funding support, so it is possible that the LLM may confuse one with another. An examination at the word clouds reveals that each category of policy is associated with terminology that aptly reflects the characteristics of its specific policy type. For tax incentive policies, terms such as"tax," "exemption," "deduction," "income tax," "fee," "preferential policies," "business tax," and"value-added tax" appear with high frequency. Similarly, fiscal subsidy policies prominently feature words like"fund," "subsidy," "provide," "fiscal," "project," "support," "government," "agriculture," "industry," "encouragement," "arrangement," and"science and technology." In the realm of credit policies, the most frequent terms include"loan," "credit," "financial institution," "interest subsidy," "guarantee," "pledge," "guidance," "funds," "bank," and"financial." Policies pertaining to industrial funds are characterized by recurrent terms such as"fund," "industrial," "venture investment," "set up," "startup investment," "shareholding," "capital," "innovation," "specific fund," and"projects." Collectively, these lexical patterns observed across the different policy categories corroborate the validity of the LLM's classification results regarding industry tools.

[Figure A4 about here]

By incorporating the additional-round LLM analysis, we significantly enhance the quality of our policy classification. In particular, the number of unique policy tool categories decrease from 6.37 before the additional-round LLM analysis to 4.42 afterwards. Section A presents the common types of misclassifications on four major policy tool categories that the second-round LLM analysis excludes from the first-round results. Each of the four categories involve certain form of funding support so that it is easy for the LLM to confuse one with the other, for example, fiscal subsidies may be confused with tax incentives, industrial funds, or credit policies. Some first-round misclassifications arise because some policy tools may be commonly used in the corresponding activities of the policy text, but they are not explicitly mentioned. For example, it is likely that "Encourage the promotion and application of new technologies" is through tax incentives, but as tax incentive is not explicitly mentioned, it is excluded by the additional-round LLM.

[Section A about here]

Verification from the time series

An alternative approach to validate our findings is to examine the temporal distribution of industrial policies. To this end, we focus on the policies affecting the electric vehicle (EV) industry. Wei Miao, the former Minister of Industry and Information Technology who led China's EV industrial policy, details the policymaking process from the national government's perspective in his recently published book.

There were two major national policies. The first was the "Interim Measures for the Administration of Fiscal Subsidy Funds for the Demonstration and Promotion of Energy-Saving and New Energy Vehicles", commonly known as "Ten Cities, Thousand Vehicles," introduced in 2009 to promote the adoption of electric vehicles across cities. This policy, along with specific measures designed by local governments, served as a pilot program to test the feasibility of developing the EV industry. Drawing on the experience from these initial pilots, the central government concluded that the policies were successful overall, the development of the EV industry was promising, and that industrial policies should continue with stronger support. Consequently, the central government issued the second major policy, the "Notice on Continuing the Promotion and Application of New Energy Vehicles", in 2013. Beyond providing stronger support, this policy stipulated that fiscal subsidies would gradually phase out by 2020, compelling companies to develop their capabilities without the expectation of perpetual policy support.

As shown below in Section 4.8, Figure 10a presents the fraction of industrial policies related to electric vehicles out of all identified industrial policies over time. We observe a sharp rise in the number of policies in 2010, shortly after the 2009 national policy, as numerous localities began rolling out pilot subsidies for electric vehicles. An even sharper increase follows after 2013, corresponding with the second major national policy. Anticipating seven years of sustained policy support from the central government, cities expanded their industrial policy initiatives significantly. Moreover, consistent with the phase-out of subsidies by 2020, we see a marked increase in national government policies just before 2020 and a sharp decline thereafter. Interestingly, provincial and city-level policies stepped up slightly after 2020.

Overall, the trends in policies identified from the data closely mirror the policymaking process described by the leading policymaker, supporting the validity of our empirical results.

2.3 Discussion: LLM method and existing measures

To assess the efficacy of our LLM approach, we compare it with a hypothetical scenario wherein a researcher relies on manual keyword searches. Notably, certain textual analyses performed by the LLM are inherently infeasible using keyword-based methods. For example, identifying major target industry names from the plethora of names mentioned in each policy 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, identified as a 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 name presents significant challenges to traditional approach. 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 instance, keywords like "new energy", "clean technology", "intelligent", "digital", "power battery", "energy saving", which reflect features or directions of China's electric vehicle sector, cannot be directly matched to the industry classification of "electric vehicle manufacturing."

In light of these challenges, we focus on the identification of industrial policies—a critical component of our textual analysis—where a keyword approach might be potentially feasible. We begin by selecting informative keywords from both policy titles and full texts. Assuming that a researcher conducting a manual search can consider only keywords appearing with sufficient frequency, we restrict our attention to those occurring at least 100 times in policy titles or full texts. However, an immediate obstacle arises: the vast number of such keywords—12,002 unique keywords from policy titles and 141,199 from full texts—makes it challenging to thoroughly verify their informativeness manually within a reasonable timeframe.

We define and rank the informativeness of each keyword 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. 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.

[Table A4 about here]

In Table 1, we present 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 results involve many keywords to identify a decent amount of industrial policies. First, we define the informativeness of a keyword 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. For example, the informativeness of 239 (651) unique title (full text) keywords are greater than 80%. Yet, only 168,309 (116,057) policies at least contain one such keyword in its title (full text), much smaller than the 770,819 industrial policies that we identify from the LLM approach. Extending the threshold, the informativeness of 518 (3,602) unique title (full text) keywords is greater than 70%. 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. Yet, even with an extended threshold at 70%, only 328 495 unique policies are identified as industrial policy based on 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. 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 keyword meeting the same informativeness threshold.

[Table A5 about here]

These findings underscore the importance of contextual understanding and confirm the advantages of the LLM approach. 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.

[Table A6 about here]

In contrast, the policies identified by the LLM do not contain extremely high-frequency informative keywords by design. Thus, if the LLM approach contains classification errors, there may be instances where the LLM model is most likely to exhibit such errors. Nevertheless, these policies are arguably related to industrial policy in one way or the other. Some are not captured by keyword approaches due to unique phrasing—for example, the unique keyword"Xiufeng Residents Tour Xiufeng" refers to a local tourism program. Moreover, many of these policies concern sectors such as the housing market, mining, and tourism, which are not often associated with industrial policy; some focus on individual firms, and others address standard setting or fee setting rather than traditional measures such as subsidy or tax incentives aimed at promoting industrial development. The LLM approach successfully identifies such policies as industrial policies as well.

3 Data

3.1 Policy Documents

Our primary data set comprises a comprehensive collection of government documents issued by central and local governments in China since 2000. This core data set was sourced from PKU-Law.com, an authoritative online platform hosted by the Peking University Law School. It includes a broad 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 supplemented this data set with continuous web scraping. This process involved systematically collecting data from official websites across 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. This large-scale data collection effort expanded the scope of the dataset by incorporating the latest policies from multiple administrative levels, enhancing the completeness and richness of the data.

We identify and remove duplicate documents based the title of the document, the issuing entity, and publication date. After deduplication, the final data set contains 3.1 million unique policy documents for the years 2000 to 2022. Each document provides detailed information on the issuing government body, the policy's effective period, and its objectives, from which we identified 0.78 million documents specifically related to industrial policies. This data set serves as an invaluable resource for analyzing the full spectrum of China's industrial policies, covering a wide range of government efforts aimed at promoting, guiding, or regulating specific industries or economic activities. The policies leverage tools such as subsidies, tax incentives, trade protection measures, resource allocation, etc.— all aimed at shaping the long-term structure of China's economy.

The industrial policy documents offer rich information on targeted industries, policy objectives, the instruments used to promote or regulate these sectors, eligibility requirements for policy support, and detailed implementation mechanisms, such as political incentives, local experimentation, and government coordination. In addition, documents often highlight the relationships between specific policies and higher-level government directives, providing a layered understanding of policy enforcement and adaptation across different administrative levels. LLM allows us to convert this extensive textual data into structured information for detailed analysis.

3.2 Other Data Sets

3.2.1 Firm

We combine the policy data set with rich firm-level data to investigate the (in)effectiveness of the industrial policies in promoting entry, competition, innovation, and long-term growth of the targeted industries.

Registration 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 registered firms—over 200 million in total—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, exit, and stock.

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.[5] 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 annual report data. As

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

such, we also use this data set to cross-validate our findings from the annual report 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 a longer time horizon and in more dimensions.

VAT The last firm-level data set is a unique dataset from the State Taxation Administration (STA) 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, industry classification and ownership type of buyer and seller firms, the tax levied, product descriptions, and transaction values, thereby facilitating an in-depth examination of all business transactions subject to VAT invoicing requirements. VAT filing is required for all transactions in order to claim input tax credits, and failures to comply are strictly punishable by law[6]. We use this data set to construct city-to-city trade flows in order to measure the extent of local protectionism and analyze its relationship with industrial policies.

3.2.2 Politicians

To facilitate understanding of the political economy behind industrial policies in China, we further enriched our data set with a manually collected data set on politicians at the provincial and prefectural levels. This supplementary data set includes 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. These data points provide valuable context for understanding how individual political characteristics and networks might influence the formulation, implementation, and outcomes of industrial policies at the local level. 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.

In Section 5.2, we elaborate on how these political variables are integrated with our policy data, offering insights into the intersection of political leadership and economic policy outcomes.

[6]It's important to note that there are certain exceptions to transactions that fall outside the purview of the VAT invoice policy. For instance, 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.

4 Description of Industrial Policy

In this section, we present an initial exploration of the industrial policy data analyzed using LLM, offering key insights into the evolution of China's industrial policy over the past two decades. We first take an overview of the temporal and regional distribution, and then provide a detailed description of the industrial policy data, categorized by key thematic dimensions. By organizing the data into themes such as targeted industries, policy instruments, implementation details, and intergovernmental relationships, we aim to offer a comprehensive view of China's industrial policy landscape over the past two decades.

4.1 Overview

Table 2 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. It shows that the upper-level governments issue a larger proportion of industrial policies— at the central level, 31% of government documents are industrial policies, accounting for 13% of all industrial policies identified by LLMs; at the provincial level, 27% of government documents are industrial policies; and at the city-level, only 23% of the government documents are identified as industrial policies. Due to the significantly smaller volume of government policies at the county or township level, our analysis below only focuses on the central, provincial, and city level industrial policies

[Table 2 about here]

One notable trend observed from the LLM-analyzed data is the increasing prevalence of industrial policy in government documents across all administrative levels—central, provincial, and municipal. Over the past 20 years, there has been a marked rise in both the volume and complexity of industrial policies, reflecting the growing importance of government intervention in shaping economic development.

Figure 1 provides a first look at the temporal distribution of policy documents, highlighting the prominence and growing importance of industrial policy across different levels of government. Panel (a) shows the number of total government documents issued (blue line), the subset of documents specifically related to industrial policies (red line), and the proportion of industrial policies as a percentage of all documents (green line). 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. While the total volume of documents surged, the proportion of industrial policy documents fluctuated, with a significant increase in recent years, suggesting heightened governmental focus on industrial policy as a key tool for shaping economic development. Panel (b) breaks down the ratio of industrial policies by government level, comparing central (blue line), provincial (red line), and city (green line) governments. The central government consistently shows a higher proportion of industrial policy documents compared to city governments, although all exhibit upward trends over the years.

[Figure 1 about here]

Figure 3 provides a geographic overview of the distribution of industrial policies across China. The map highlights significant regional variation in the number of industrial policies issued, with a clear concentration in wealthier and more industrialized regions. Coastal provinces such as Guangdong, Jiangsu, and Zhejiang exhibit a much denser concentration of industrial policies, reflecting their economic prominence and stronger government involvement in promoting industrial growth. In contrast, the central and western regions, particularly those with less developed economies, show a lower frequency of industrial policies. This uneven distribution suggests a policy focus that skews towards wealthier and more industrially advanced areas, where the potential for economic growth and technological advancement is greater.

[Figure 3 about here]

This geographic disparity in policy issuance underscores the role of regional economic disparities in shaping China's industrial policy priorities, with wealthier regions benefiting from more targeted interventions aimed at fostering innovation, upgrading industries, and driving economic growth. This finding is interestingly 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.

4.2 Policy Direction

Table 3 presents the distribution of policy direction by the level of the issuing government entity. It shows that the upper-level governments issue a larger proportion of industrial policies with regulatory tone, while local governments focus more on supportive measures— at the central level, 40% of government documents are directing at regulating the industry; at the provincial level, the ratio is 29%; and at the city-level, only 24% of the government documents are identified as industrial policies with regulatory.

[Table 3 about here]

Figure 2 then plots the time trend of policy direction by the level of the issuing government entity, highlighting the growing prominence of supportive industrial policies at all levels of government— a trend consistent with the growing number of industrial policy documents.

[Figure 2 about here]

4.3 Industry Distribution

The LLM-analyzed data enables us to systematically identify the specific industries targeted by various industrial policies. These include sectors critical to China's long-term development goals, such as manufacturing, technology, and renewable energy. We analyze how policies have evolved to target different sectors over time and across regions, highlighting gradual shifts in government priorities and an uneven geographical focus.

[Table 4 about here]

Table 5 provides a breakdown of the target sectors (by 2-digit industry code or key industry characteristics[7].) of industrial policies, categorized by government level—central, provincial, and city. The proportion of policies targeting each sector is listed for all levels of government combined, as well as separately for each government tier.

[Table 5 about here]

The agriculture industry, while primarily rooted in traditional sectors, draws substantial focus from all tiers of government, with local governments representing a greater share of this attention. Manufacturing and production-related services receive the highest overall focus, accounting for 32% and 45% of all policies, suggesting a close link between traditional manufacturing and the services supporting production processes. Notably, the central government emphasizes manufacturing even more, with 38% of its policies targeting this sector. This central government focus on manufacturing highlights the national strategy to strengthen industrial production and competitiveness. On the other hand, the city-level government emphasizes slightly more on production-related service industries to support industrial development.

Zooming into the service sector, technology-related services and high-skill services also receive significant attention across all levels, with the focus slightly higher at the city level (24% and 21%, respectively). This indicates that local governments are increasingly targeting these sectors, aligning with the national drive towards technological innovation and service-oriented economic development. Zooming into the manufacturing sector, emerging manufacturing and high-skill manufacturing sectors account for a smaller proportion of policies overall (6% and 12%, respectively), but they receive steady attention from both central and city governments, reflecting a targeted push towards innovation and modernization within the manufacturing sector.

This distribution of policy focus indicates a coherent strategy across government levels, where the central government prioritizes large-scale industrial and manufacturing goals, while local governments emphasize emerging sectors, services, technological upgrades, and agriculture, reflecting regional economic specialization.

Figure 4 provides a visual overview of the distribution of industrial policies across key sectors. While in the data construction process and the following empirical analysis, we map the targeted industry of industrial policies to 4-digit industry code, we start by describing the trends and patterns at 2-digit level. In Panel (a), we observe the changing importance of different sectors—manufacturing, production services, and agriculture—over time. While the proportion of industrial policies targeting agriculture has declined, there is a notable increase in the policies aimed at production services, reflecting the broader shift in China's economy towards service-oriented industries. Meanwhile, manufacturing continues to receive consistent attention, suggesting its central role in China's economic strategy, particularly in advanced sectors such as electronics, machinery, and automotive industries. Panel (b) delves into the manufacturing sector, comparing traditional

[7] See https://www.stats.gov.cn/sj/tjbz/gjtjbz/

manufacturing with high-skill and emerging manufacturing industries. The proportion of industrial policies targeting high-skill manufacturing (green line) has seen a steady rise, particularly in recent years. This shift reflects China's growing emphasis on technological upgrading and innovation within its industrial policy framework. In contrast, policies related to traditional manufacturing have remained stable, while emerging manufacturing sectors (red line) have seen gradual but consistent growth in policy focus. It is worth noting that, while the focus of industrial policies has gradually shifted toward the emerging and high-skill sectors, traditional manufacturing and agriculture still take a large share of industrial policies.

[Figure 4 about here]

Figure A5 further presents a breakdown of the targeted industry at 3-digit level for the most frequently targeted within the manufacturing and the service sector. In panel (a), we observe the time trends for six key manufacturing subcategories, including general machinery manufacturing, motor vehicle manufacturing, electronic product manufacturing, specific machinery manufacturing, basic chemical manufacturing, and pharmaceutical manufacturing. Notably, motor vehicle manufacturing (red line) has shown a significant rise in policy focus, particularly post-2020, which aligns with China's ambitions to become a global leader in electric vehicles. Meanwhile, electronic product manufacturing (blue line) and general machinery manufacturing (green line) have maintained steady policy attention, reflecting their enduring role in China's industrial base. Pharmaceutical manufacturing (purple line) has experienced more recent growth in focus, which may be linked to the increasing importance of health-related sectors, especially in the wave of population aging. Panel (b) highlights trends in six key service industry subcategories: internet services, software publishing, real estate, research and development (R&D), commercial services, and financial services. Internet services (green line) and software publishing (orange line) have seen a substantial rise in policy attention, particularly in recent years, underscoring China's push toward digitalization and the development of its tech industry. Meanwhile, R&D services (yellow line) have also experienced a significant uptick, reflecting the government's prioritization of innovation and technological advancement. Commercial services and financial services, while remaining important, have shown relatively steady trends over the period.

[Figure A5 about here]

Lastly, we examine the regional distribution of different industries. Figure 6 exhibits significant regional disparities, with a noticeable skew towards wealthier, more developed areas. Panel (A) and (B) compare the geographical distribution of policies targeting agriculture with those focusing on manufacturing. Agriculture policies are more concentrated in less developed inland regions, especially in central and western provinces, reflecting the continued importance of agriculture in these areas. In contrast, manufacturing policies are heavily concentrated in the coastal regions, particularly in provinces like Guangdong, Zhejiang, and Jiangsu, underscoring their roles as key industrial hubs. Panel (C) shows that high-skill manufacturing policies are predominantly concentrated in the economically strong eastern and middle regions, aligning with China's strategic focus on technological advancement and industrial upgrading in these areas, and panel (D) suggests that the emerging manufacturing industries, which often involve new technologies and innovation-driven sectors, are skewed towards wealthier coastal regions, especially the south-eastern regions. Lastly, panels (E) and (F) plot the regional distribution of the service sector. Interestingly, the geographical distribution of technology-related services, such as software and internet industries, aligns closely with the regional distribution of high-skill manufacturing. This suggests that advanced manufacturing and technology services receive coordinated policy support. Production-related services are tied more closely to manufacturing industries, further reinforcing the alignment between 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, where high-skill manufacturing aligns with technology-related services, and traditional manufacturing aligns with production-related services. This suggests a targeted approach where regions specialize in interconnected sectors, particularly in wealthier coastal areas.

[Figure 6 about here]

4.4 Implementation Tools

Industrial policy documents contain detailed information on the instruments used to promote or regulate industries. Through LLM analysis, we identify and classify the specific tools employed in each policy and examine their prevalence across different sectors and regions. This analysis also highlights the variation in policy instruments based on regional economic development and the stage of industry growth.

We broadly categorize the industrial policy tools into four categories: those offering broad fiscal subsidies or financial assistance, those designed to encourage the establishment of new firms and enhance industry competition, those supporting firms during the production phase, and those intended to stimulate market demand. Table 6 reports the share of usage (defined as the percentage of policy documents that report using the tool) for each industrial policy tool with a breakdown into different government levels. This breakdown provides insights into the types of tools used to implement industrial policies and how their usage varies by government level.

There are several commonly seen industrial policy tools across all levels of government. The most frequently used one is fiscal subsidy— with 43% of the policy documents mentioning the use of the tool— consistent with the common belief that industrial policies are usually carried out with some kind of government subsidies. It is also worth noting that there are still more than half of the industrial policies not carried out in the form of fiscal subsidy— likely suggesting the significant bias of the data-driven method in quantifying industrial policies via government subsidy. Following fiscal subsidies, market access and regulation (37%), technology R&D and adoption (25%), labor policy (23%), and tax incentive (20%) are all frequently used tools in general.

[Table 6 about here]

While there are shared characteristics across various government levels, there are also significant distinctions among them. The central government predominantly employs market access and regulation as industrial policy tools (44%), followed by fiscal subsidies (26%), technology R&D and adoption (21%), tax incentives (20%), and trade protection (20%). The emphasis on market access and regulation highlights the central government's pivotal role in managing entry into crucial sectors and establishing regulatory standards. Trade protection likely addresses concerns at the national level regarding defending domestic industries against international competition. At the city level, fiscal subsidies (49%), market access and regulation (36%), labor policy (28%), and technology R&D and adoption (28%) are the most frequently utilized tools. The provincial government's choices lie between those of central and city-level governments, resembling the latter more closely. The stark difference between central and local governments reflects the central role in setting industry standards and guidelines while local entities focus on offering financial and non-financial incentives to support local businesses, especially amid intense regional competition for attracting investment and encouraging entrepreneurship in key industries. Moreover, the proactive engagement of local governments in supporting specific industries with specific tools is evident in their more pronounced use of labor policies (28% at the city level versus 16% at the central level), infrastructure investment (23% at the city level compared to 12% at the central level), and encouragement of industrial clusters (18% at the city level compared to 8% at the central level).

We then examine the time trend of industrial policy tool choice. Figure 7a shows the time trends for the usage of different industrial policy tool categories over the past two decades. First, fiscal and financial tools, such as subsidies and tax incentives, have remained relatively stable over the observed period. This consistent use suggests the continued importance of financial interventions, like subsidies, as a key element in industrial policies across different government levels. Second, tools aimed at regulating market entry have been in gradual decline, mainly due to the reduced reliance on market protection measures, either domestic local protection method or international trade protection method. This decline indicates a shift in policy focus away from restrictive entry and competition regulation towards 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 investment in skilled labor and technological development. Fourth, supply chain-focused tools, including policies promoting industrial clusters and localization, and demand-based tools, such as government procurement and demand stimulation, have nearly doubled in use, growing from around 10% to 20% over the observed period. This reflects the increasing importance of supply chain management to support industrial development on the supply side, as well as stimulating market demand as an important component in China's industrial policy mix to complement supply-side interventions. Overall, these trends reveal a gradual shift toward more targeted and selective policy tools instead of the tradition market protection methods.

[Figure 7 about here]

To sharpen the time trend and better capture the evolution of industrial policy tools over time, we categorize them into five distinct groups based on their initial usage and growth patterns. The first group consists of tools that started with low usage but grew rapidly over time. These include industrial funds, promoting industrial clusters, environmental policy, and promoting entrepreneurship. All these tools show a strong upward trend, indicating increasing policy focus on fostering innovation, encouraging entrepreneurial activity, nurturing local supply chain, and addressing environmental concerns. The second group also started with low usage but experienced more moderate growth. This includes 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. The third group includes tools that have been traditionally popular and have seen steady growth over time. These are infrastructure investment, labor policy, technology R&D and adoption, and fiscal subsidies. The fourth group includes tools that have remained stable, with consistent usage over time. These are credit and finance, preferential land supply, investment policy, and improving business environment. The third and fourth groups represent stable pillars of industrial policy. They continue to play a fundamental role in shaping the industrial landscape. The fifth group includes tools that have experienced a significant decline in usage. These include market access and regulation, tax incentives, and trade protection. This steep decline suggests a move away from protective measures toward a domestically and internationally more integrated market.

4.5 More Policy Details

Objective Each industrial policy document contains explicit goals that guide its design and implementation. These objectives range from promoting key industries and fostering innovation to enhancing social welfare. Table 7 examines these objectives in detail, broken down by government level— central, provincial, and city. The first panel outlines objectives related to promoting and supporting key industries. Promoting strategic industries is by far the most common objective, mentioned in 56% of all policy documents. The focus on strategic industries is consistent across government levels, with the central government slightly more engaged (58%) compared to provincial and city levels. City governments show a higher emphasis on promoting emerging industries (20%) compared to other levels, reflecting local governments' focus on fostering new economic sectors, possibly to enhance regional competitiveness. Policies aimed at upgrading traditional industries are also prevalent, particularly at the city level (15%), indicating local efforts to modernize established sectors.

[Table 7 about here]

The second and third panels look at objectives related to innovation and social welfare. Consistent with the significant proportion of industrial policy tools to encourage innovation, R&D and technology adoption remain a key focus across all government levels, with roughly 23% policies dedicated to this goal). Objectives related to social equity and welfare are present in 33% of all documents, with relatively even distribution across government levels. Meanwhile, city governments place more emphasis on stimulating employment (21%) and urbanization (10%), reflecting local concerns about job creation and regional development.

These patterns demonstrate the varying focus across government levels, with the central government concentrating on strategic industries and innovation, while local governments have a slightly more balanced objective in promoting emerging industries, employment, and urbanization.

Requirement In addition to outlining the policy objectives, each industrial policy document specifies the requirements that firms must meet to be eligible for support. Table 8 categorizes these eligibility conditions and provides a breakdown by government level—central, provincial, and city. Nearly half of all policies (48%) have a regional focus by specifying firm location as an eligibility criterion, with a slightly higher emphasis at the city level (50%) compared to the central government (40%). This reflects the importance of geographically targeted policies, particularly at the local level, where regional development is a priority. Firm size is also frequently mentioned (52%), with city-level policies placing the most emphasis on this criterion (57%)[8]. About 29% of policies include R&D and technological investment as eligibility conditions, with a slightly higher focus at the city level (32%). Policies targeting specific firms (25%) or ownership types (20%) are evenly distributed across government levels. However, central government policies focus slightly more on firm ownership type (25%), likely reflecting national-level priorities for supporting certain types of enterprises (e.g., state-owned enterprises). In addition, around 35% of policies mention other conditions, such as firm performance or market share.

[Table 8 about here]

4.6 Central-Local Relationship

An essential feature of China's industrial policies is the intergovernmental coordination between central and local governments. Our data captures the hierarchical relationships and interactions between different levels of government, such as how central directives are adapted and implemented at provincial and city levels. The LLM analysis allows us to explore these vertical relationships, examining how policies are cascaded down from the central government and how local governments tailor these policies to regional contexts. Additionally, the data provides insights into how local governments experiment with policies, both in sector choice and in the choice of implementation methods, reflecting the dynamic nature of industrial policy formulation and implementation in China.

First, we explore the dynamics through the lens of policy citation networks. Frequently, policies reference other policies, either to signal adherence to a hierarchical governmental strategy or for other reasons. For instance, a governmental policy might cite a higher-tier government's policy to illustrate a top-down policy transmission, enabling the adoption and execution of the superior

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

government's directives with more specific implementation tactics or to leverage them to enhance the policy's authority. Policies that reference others of the same governmental level often aim for coordination, focusing on department-specific implementation details. As an example, a city-level fiscal department might refer to a municipal industrial policy to elaborate on fiscal subsidy arrangements.

Figure 8a illustrates the dependency ratios over time for industrial policies at different levels of government. Specifically, it shows the percentage of city-level policies citing provincial government policies (green line), the percentage of provincial policies citing central government policies (red line), and the percentage of city-level policies citing central government policies (blue line). Three key trends emerge: First, before 2013, both city (blue line) and provincial (red line) 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 (green line). This growing interdependence between city and provincial governments reflects an increasing reliance on provincial-level frameworks to guide local policy decisions. It also suggests stronger vertical integration within subnational levels of governance. Third, post-2013, there is a noticeable reversal in the previous trends. Both city and provincial governments began to cite central government policies more frequently, indicating a return to top-down coordination in the wake of national reforms or changing policy priorities. Additionally, the increase in city governments citing provincial policies accelerates during this period. However, after 2018, a slight reversal of these trends is observed, with some decline in dependency ratios, possibly reflecting a return to more localized policy experimentation or flexibility. These patterns demonstrate the evolving dynamics of intergovernmental coordination in China's industrial policy— periods of decentralization are followed by stronger central control.

[Figure 8 about here]

Figure 8b illustrates the within-government citation rate over time, representing the share of policies that cite government entities at the same level. This is a useful indicator of intra-government coordination across different departments within the same government tier. Two key trends emerge: First, both provincial (red line) and city-level (green line) governments show a steady increase in self-citation rates over time. This growth likely indicates improved coordination across departments within 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 (blue line) consistently exhibits the highest self-citation rate, followed by provincial and city governments. This hierarchy suggests that cross-departmental coordination is more prevalent at higher levels of government, where centralized decision-making and broader policy frameworks likely encourage more frequent inter-agency cooperation. The central government's higher self-citation rate also likely reflects its role in setting comprehensive national strategies, which are likely coordinated across multiple departments.

4.7 Policy Implementation

Lastly, we delve into the details of policy implementation. Table 9 highlights the role of political incentives and local adaptation in industrial policy implementation across different government levels—central, provincial, and city—providing insights into how these incentives vary by government tier.

Political KPIs are mentioned in a small portion of policies (4%), with a higher emphasis at the city level (6%). While positive incentives (e.g., rewards) are used in 9% of policies overall, negative incentives (e.g., penalties for non-compliance) are more common (22%). The central government employs negative incentives (25%) more frequently than provincial (21%) and city governments (19%), likely to enforce adherence to national policies. The use of both positive and negative incentives, especially at the central level, plays a crucial role in ensuring compliance and achieving desired policy outcomes.

Target-setting is prevalent across all government levels, appearing in 79% of policies and being most emphasized at the city level (81%). This reflects the widespread reliance on explicit targets as a core implementation strategy to establish clear goals for various sectors. Coordination between government entities is another important aspect, particularly at the central government level (45%), underscoring the need for inter-agency collaboration. This aligns with earlier findings from the policy citation network, where upper-level governments emphasize cross-department coordination more than local governments.

The table also highlights differences in encouraging policy experimentation and local adaptation. While 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 regional growth. Local adaptation is particularly prominent at the city level (34%) compared to the central government (19%), indicating the greater flexibility granted to cities in tailoring policies to their specific contexts. Provincial and city governments also often pilot new approaches to industrial policy, which, if successful, may be scaled up or adopted nationwide. This dynamic policy formulation process fosters an interactive feedback loop between central and local governments, where local experimentation informs national policy refinement. Around 20% of policies across all levels encourage such experimentation, with city-level governments slightly more engaged (21%), suggesting that local governments are key actors in testing and implementing innovative industrial strategies.

[Table 9 about here]

Utilizing the comprehensive data on policy execution, we guide LLM to assess the document content across two key dimensions: policy concreteness and policy strength. Figure 9 illustrates the mean scores for these dimensions at various government levels over time. Panel (a) depicts the scores for policy concreteness, while Panel (b) shows the scores for policy strength. The trends in both policy metrics reveal convergence—policies at the city level consistently maintain their substance and strength, provincial policies experienced a dip in strength leading up to 2013, and central policies exhibited a significant rise in strength after 2013, with both converging by 2020.

[Figure 9 about here]

4.8 Illustration with Key Industries

With the rich information extracted from industrial policy documents, as discussed above, we can gain a more comprehensive understanding of industrial policies in key sectors. To illustrate this, we present a comparative analysis of three of China's most hotly discussed industries in recent years: semiconductors (chips), electric vehicles (EVs), and solar energy. These industries have been at the forefront of China's industrial policy agenda, and their development provides a clear example of how targeted policies, coordination between government levels, and local adaptation can shape industry growth and innovation. By analyzing the differences in policy objectives, implementation tools, and government-level coordination across these industries, we gain insights into how China's industrial policy framework is adapted to foster the growth of strategic, emerging, and technologically advanced sectors.

Time trend Figure 10 shows the time trends of industrial policy activity for these three key industries. These trends highlight the differences in how policy support has evolved across government levels—central, provincial, and city—over time. In the semiconductor industry, local governments (especially at the city level) have been more active in recent years, with a noticeable boom in policy attention starting from 2018. This suggests a growing local-level enthusiasm to follow the national directives to boost domestic chip production amid global supply chain concerns. The electric vehicle industry saw policy attention emerge later compared to the other two industries, with local governments leading the charge. The city and provincial governments became especially active in recent years, reflecting the strong regional push to foster the EV industry as part of local economic development strategies, supported by both environmental goals and technological innovation. The solar energy industry initially gained strong policy support from the central government, particularly around 2005 to 2010. However, there has been a decline in local government enthusiasm over time. Amid the global financial crisis around 2008, the solar industry saw a boost in policy support on a global scale, resulting in a considerable decline in solar energy product prices. This led to a substantial reshuffling of the previous profitable companies in the domestic market[9]. Interestingly, during this period, while policy interest in the solar energy sector began to wane at the city level, it remained robust at the provincial level and even experienced some growth at the national level. The central government continues to emphasize solar energy as a key national priority, whereas local governments have become more responsive to market conditions and shifted their focus toward other sectors.

[9] https://36kr.com/p/2230777297628807

[Figure 10 about here]

Geographical distribution Figure 11 depicts the geographical distribution of policy support for the chip, electric vehicle (EV), and solar energy industries in China, and it shows clear regional patterns, reflecting the influence of local economic conditions and regional development strategies. The chip industry is concentrated in more developed regions, particularly in coastal provinces with stronger infrastructure, higher levels of human capital, and better access to technology and financing. This skew toward wealthier regions aligns with the high-tech and capital-intensive nature of semiconductor manufacturing, which requires significant resources and expertise. EV policy support is more evenly spread across inland regions, indicating a push to foster new industrial bases in this area. The regional distribution suggests that inland provinces, being the traditional manufacturing base, are focusing on EV production as part of their industrial upgrading strategies, potentially driven by both local initiatives and national efforts to diversify industrial development. The solar energy industry is most prominent in northwestern regions, which are well-suited for solar energy production due to favorable geographic conditions, including high levels of solar radiation and vast plain land with low occupancy rate and low development cost. The regional skew reflects China's broader strategy to utilize the country's diverse geography for renewable energy development, with northwestern provinces emerging as key players in solar energy production.

[Figure 11 about here]

Implementation tools We then examine the industrial policy tools utilized in each one of the three sectors. Table 10 compares the use of each policy tool and reveals different patterns of support for these industries.

As with the general feature, fiscal and financial support plays a significant role in all three industries, with the highest emphasis on fiscal subsidies, especially for chips (52%) and EVs (55%). Tax incentives are also widely used, with chips receiving the most support (34%), followed by EVs (31%). This is likely consistent with the wide tax deduction policies in R&D-related activities. Credit and finance support is more evenly distributed across the three industries.

[Table 10 about here]

Tools to promote entry and competition is also heavily utilized across the industries, with industrial funds being particularly prominent in the chip industry (20%)— consistent with several big waves of national industrial fund in the chip industry[10]. Market access and regulation is more emphasized in the EV and solar energy industries (35% and 36%, respectively), suggesting active local engagement in attracting new investment in these sectors. Improving the business environment is similarly prioritized across the three, with the highest focus on chips (26%).

Input tools like technology R&D and adoption are critical, especially in the chip industry (43%), reflecting the research-intensive nature of semiconductor development. Labor policy is most

[10] https://36kr.com/p/2796503120703107

emphasized in the chip sector (32%), indicating the importance of attracting and retaining talent in this high-tech industry. Infrastructure investment is prioritized for EVs (31%), suggesting that the physical infrastructure needed for EV adoption, such as charging stations, is a key focus.

Demand-based tools, especially consumer subsidies and industrial promotion, are more prominent in the EV industry, with consumer subsidies (18%) and government procurement (17%) playing a significant role in boosting EV adoption. This reflects the growing consumer market for EVs and the need for demand-side support to encourage widespread use.

Supply chain support, particularly through promoting industrial clusters, is most evident in the chip industry (31%), highlighting the importance of clustering and the complication of supply chain management in fostering innovation and efficiency in the semiconductor sector. The emphasis on localization policy is also more pronounced in chips (29%), indicating efforts to reduce reliance on foreign technologies and promote domestic supply chains.

These comparisons highlight how each industry relies on a distinct mix of policy tools. The chip industry benefits from strong fiscal support and R&D promotion, while the EV sector leans on infrastructure investment and demand-side measures like consumer subsidies. Solar energy shows a balanced approach but is more reliant on market access regulations and environmental policy.

More on implementation Lastly, Table 11 compares key aspects of policy implementation for the three industries, providing insights into how industrial policies are implemented at various levels, with specific attention to the roles of incentives, coordination, and adaptation. Negative incentives (such as penalties for non-compliance) are more prevalent in solar energy (23%) compared to chips (18%) and EVs (19%), while positive incentives (e.g., rewards or support) are used most in the chip industry (12%), which are consistent with the heavier central directive in the solar industry and active local enthusiasm in the chip and EV industry.

[Table 11 about here]

All three industries rely heavily on setting explicit targets, significantly higher than the all-industry average level. Encouraging experimentation is slightly more common in the EV (29%) and chip (27%) industries compared to solar energy (22%). This suggests that local governments may have more flexibility in experimenting with policy and technology in the newer sectors like EVs and semiconductors, which are still in a relatively nascent stage of growth compared to the more mature solar energy industry. Coordination between government agencies is a crucial feature across all industries, with the highest emphasis in the chip sector (46%). This highlights the complex nature of the semiconductor industry, where strong inter-agency coordination is necessary for successful policy execution.

Overall, the table illustrates that chip and EV industries are more localized, with significant local adaptation and experimentation, while the solar energy industry appears to be more centrally driven, with stronger negative incentives and target-setting mechanisms.

5 Five Sets of Facts of China's Industrial Policy

In this section, we leverage the vast and rich dataset constructed through the LLM analysis to uncover and document five sets of important facts about China's industrial policy over the past two decades. These insights offer a comprehensive view of how industrial policies have evolved, how they are implemented, and their effectiveness across different regions and sectors.

Our findings are organized into five major themes, covering the economic rationality and political economy of local governments' choices of policy targeted sectors, the evolution of policy tools, the effectiveness of these policies, and the spatial inefficiencies that emerge from regional competitions. The first three sets of empirical tests mainly employ the LLM-analyzed policy data, and the last two combine policy data with multiple micro-level firm data. By examining these themes, we shed light on the key mechanisms that shape China's industrial policy and its broader economic impact, providing valuable insights into the complex interactions between central directives and local adaptations.

5.1 Relative Comparative Advantage and Choice of Targeted Industry

Fact 1: Industrial policy is correlated with comparative advantage and absolute advantage.

As shown in Section 4.3, 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. We first examine the economic rationality behind China's local governments' industrial policy decisions.

It has been forcibly argued in the literature that the optimal trade policy should be correlated with a country's comparative advantage. Scholars of industrial policy debate on the "comparative advantage-following" strategy versus the "comparative advantage-defying" strategy when choosing the targeted sectors of industrial policies (Wade, 2015; Rodriguez-Clare, 2007). Lin and Chang (2009) and Lin (2015) assert that government efforts should remain within the economy's existing comparative advantage, because firms operating within existing comparative advantage are more likely to attain and sustain private profitability. In sharp contrast is the view of "infant industry argument," which believes that industrial policy should protect sectors in which they currently lack a comparative advantage, but may acquire such an advantage in the future as a result of the potential for productivity growth (e.g. Redding, 1999; Melitz, 2005; Greenwald and Stiglitz, 2006). Despite the hot and unsettled debates, recent empirical evidence on international comparisons consistently finds that, in the recent wave of rising industrial policies, countries tend to target industries with revealed comparative advantage (Juhász et al., 2022; Evenett et al., 2024).

To examine whether, at local level, China's internal industrial policies align with economic theory and the current international evidence— specifically the idea that current policies often target sectors where regions hold a comparative advantage— we zoom in to the 0.3 million city-level industrial policies and focus on the period between 2000 and 2020. We examine the city government's choice of policy-targeted sectors and its relationship with the cities' revealed comparative advantage and absolute advantage.

We begin by collapsing the policy data into city-(4-digit) industry-year cells. For each city-industry-year combination, we create a policy dummy variable, which is coded as "1" if at least one industrial policy targets the specific industry in the given city and year, and"0" otherwise[11]. This binary variable serves as the dependent variable in our empirical analysis, allowing us to test which sectors are selected by the city governments. On average, local governments' choice of the targeted sector is selective— on average 7% of industries in each city-year cell are targeted by industrial policies.

To test whether governments are targeting industries with revealed comparative advantage, we construct two key measures from firm registration data: revealed comparative advantage (RCA) and absolute advantage (AA). RCA measures the relative importance of an industry within a city compared to its overall importance in the province or country. It captures whether a city is more specialized in a particular industry than the broader region or nation. RCA is calculated at both the within-province level and the national level, allowing us to assess the industry's significance in both local and national contexts. Absolute advantage, on the other hand, reflects the absolute importance of an industry in a city, regardless of its relative significance. We measure this by calculating the stock number of firms (or their capital) in each city-industry-year cell. Absolute advantage indicates whether the industry has a large presence in the city, providing a direct measure of the industry's economic footprint in that region. To be more specific, for city c (in province p), industry s, and year t, the three measures are calculated as:

$$
\begin{aligned}
RCA^p_{cst} &= \frac{Capital_{cst}}{\sum_s Capital_{cst}} \Bigg/ \frac{\sum_{c\in p} Capital_{cst}}{\sum_s \sum_{c\in p} Capital_{cst}} \\
RCA^n_{cst} &= \frac{Capital_{cst}}{\sum_s Capital_{cst}} \Bigg/ \frac{\sum_{c} Capital_{cst}}{\sum_s \sum_{c} Capital_{cst}} \\
AA_{cst} &= \frac{Capital_{cst}}{\sum_s Capital_{cst}}
\end{aligned}
$$

Table 12 reports the summary statistics for key measures based on the firm registration data for the period of 2000-2020.

[Table 12 about here]

In summary, we estimate the following regression model. All specifications are estimated empirically using the Poisson pseudo-maximum likelihood (PPML) estimator which accounts for the large share of zeros in the dependent variable

$$\mathbb{1}(Policy_{cst}) = exp[\lambda_1 l.RCA^n_{cst} + \lambda_2 l.RCA^p_{cst} + \lambda_3 l.AA_{cst} + \delta_{st} + \gamma_{ct}] \times \epsilon_{cst} \tag{1}$$

[11] 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 specific policy document (a policy document mentioning no more than 5 4-digit industries); or the number of documents targeting the industry. Our results remain very robust with different measures of policies.

where the key variables are defined as above. δ_{st} represents industry-by-year fixed effects to control for industry-specific shocks, γ_{ct} denotes city-by-year fixed effects to capture unobserved city characteristics, and ϵ_{cst} is the error term. We first focus on within-industry across-city comparisons by controlling industry-by-year and city fixed effects, and then add city-by-year fixed effect for robustness check. We use the lagged terms on the right-hand side to avoid a mechanical correlation with the policy dummy due to that policy induces more new firm entries in the targeted industries.

[Table 13 about here]

Table 13 reports the regression results. As shown in column (1), we find a positive and statistically significant relationship between the national RCA measure and the likelihood of policy targeting. Specifically, a 1 standard deviation rise in RCA^n is associated with a 2.3% (=0.0015*14.5) increase in the likelihood of the industry being targeted. Similarly, column (2) suggests that the RCA within the province is also positively associated with policy targeting, and with a larger magnitude— when RCA^p increases by 1 standard deviation, the chance that the industry being targeted increases by 11.7%(=0.0176*9.7). Column (3) examines the correlation between the industry's absolute advantage in the city and the probability of policy targeting. Absolute advantage, based on the stock of firms or capital in a given industry, is also a strong predictor of policy targeting— when AA increases by 1 standard deviation, the probability that the industry being targeted increases by 3.9%(=2.98*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. In column (4), we run a horserace of the three variables. The findings indicate that while the coefficients for the within-province comparative advantage and the absolute advantage remain relatively stable, the coefficient for the national comparative advantage notably decreases. This outcome implies that cities are more responsive to competitions within the same province than to those spanning different provinces.

Additionally, we interact RCA and AA with the log of city GDP to test whether the impact of comparative and absolute advantage on policy choice varies with the city's economic development level. Table 14 presents the results of the regression analysis, highlighting a noteworthy heterogeneity: Regions with higher development levels tend to focus on industries possessing a revealed comparative advantage, whereas those with lower development levels are inclined to focus on industries with an absolute advantage. Targeting an industry with absolute advantage instead of comparative advantage likely suggests that the city is targeting an industry with national strength rather than local strength, which may be exposed to elevated risks of overcapacity. 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 less developed regions' growth potential and further enlarge regional disparities. We take a more serious examination of the overcapacity problem in Section 5.5.

[Table 14 about here]

5.2 The Political Economy of Policy Pass-through and Diffusion

Having examined the economic fundamentals of local governments' choices of targeted sectors, this section delves into the political economy features of China's industrial policy: the combination of top-down policy transmission and rich local adaptations. Both of these mechanisms are deeply ingrained in China's political framework. As Xu (2011) convincingly argues, China's economic success is founded on what he refers to as Regionally Decentralized Authoritarianism (RDA). This system is marked by a strong centralization of political authority combined with the decentralization of administrative and economic powers. The centralized political structure ensures the smooth transmission of policies from the central government to local governments, while the decentralized economic system—coupled with competition among local officials—fosters dynamism and experimentation at the local level. Additionally, the balance between these two mechanisms has not remained static. It has shifted over time depending on the central government's focus, which has oscillated between political stability and economic growth. Understanding this interplay between central directives and local adaptation is key to analyzing the political economy of China's industrial policies.

In this subsection, we combine industrial policy data with rich politician data to explore the political economy underpinning these policies. We begin by investigating the top-down policy transmission mechanism (Fact 2(a)), followed by an analysis of how this transmission has evolved over time (Fact 2(b)). Finally, we explore the regional diffusion of policies and the role of politician mobility in the diffusion (Fact 2(c)).

Fact 2(a): City-level government follows upper-level government in policy-targeted sector choice, and the pass-through is heterogeneous on city characteristics.

In this fact, we delve into how city-level governments align their industrial policy choices with those of upper-level governments (provincial and central). The analysis focuses on the "pass-through" effect—how closely city governments follow the sectoral choices of provincial and central governments in implementing industrial policies. This dynamic is essential to understanding how centrally coordinated policy directives are executed at the local level.

The regression equation estimates the relationship between city-level policy choices and those of provincial and central authorities. We include the forward and lag terms of 6 years window to allow for inter-temporal correlations in the pass-through.

$$Policy_{cst} = \sum_{t=-6}^{6} \beta_t^p Policy_{c(p)st}^p + \sum_{t=-6}^{6} \beta_t^n Policy_{st}^n + \delta_{sc} + \rho_t + \epsilon_{cst} \tag{2}$$

where the dependent variable $Policy_{cst}$ represents the industrial policy choice in city c, sector s, and year t, and the key independent variables $Policy_{c(p)st}^p$ and $Policy_{st}^n$ capture the policy choices at the provincial and central levels. The regression controls for city-by-sector fixed effects δ_{sc} and time fixed effects ρ_t.

Similarly, at province-industry-year level, the regression equation is specified as

$$Policy_{pst} = \sum_{t=-6}^{6} \gamma_t^n Policy_{st}^n + \delta_{sp} + \rho_t + \epsilon_{pst} \tag{3}$$

Figure 12 visualizes the estimated coefficients from the regression equation, showing the local response to upper-level government policies over time. The x-axis represents time, with event time ranging from six years before to six years after the issuance of upper-level policies. The y-axis shows the magnitude of the response. The three series plotted represent the following: The red dots indicate how city governments respond to provincial-level policies (β_t^p). It shows that the policy sector choice between city and provincial government is most strongly linked within the same year, along with some weak serial correlations present. The green triangle series represents how provincial governments follow central-level directives (γ_t^n), and the alignment shows similar patterns with the strongest correlation in the same year and weak serial correlation. The blue dot series captures how closely city policies align with central government directives (β_t^n). The results suggest that while there is some alignment, the response is generally weaker compared to the response to provincial policies, and is also weaker compared to the response of provincial policies to central policies. This is consistent with China's one-level-up political system, and provincial governments are more directly accountable to central authorities. In addition, the figure shows that policy alignment strengthens in the years immediately following the issuance of provincial and central policies but diminishes over time, suggesting that the impact of these policies may wane as local governments adapt or shift focus.

[Figure 12 about here]

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

$$Policy_{cst} = \beta_1 Policy_{c(p)st}^p + \beta_2 Policy_{c(p)st}^p \times X_{ct} + \beta_3 Policy_{st}^n + \beta_4 Policy_{st}^n \times X_{ct} + \delta_{sc} + \gamma_{ct} + \epsilon_{cst} \tag{4}$$

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

Table 15 presents the regression results. Columns (1)-(3) display the baseline findings using various sets of fixed effects. The results demonstrate that city governments follow policy sector choices made by provincial and central governments, with a stronger correlation observed between city and provincial policies compared to city and central government policies. Column (4) reports the results interacting upper-level policy indicators with log of GDP, and it shows that more developed regions exhibit weaker pass-through from provincial and central policies. This could be because these regions have greater capacity and resources to make independent industrial policy decisions, reflecting their specific local economic contexts and needs. In contrast, less developed regions may rely more on upper-level guidance, reflecting their dependence on centralized policy directives. Columns (5) and (6) further include interactions with the number of cities in the province— in provinces with a higher number of cities, there is more intense political competition among local governments. This competition intensifies the pass-through effect, as local officials may be more inclined to align their policies with upper-level governments to demonstrate political loyalty or to secure more resources and support. The regression results indicate that cities in more competitive political environments show stronger policy alignment with provincial and central directives.

[Table 15 about here]

Table 16 reports the results 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, may give local officials more latitude to diverge from centrally set policies. Essentially, personal relationships provide local leaders with informal political capital, enabling them to implement policies more suited to their local circumstances without strictly adhering to upper-level directives. It is worth noting that only connections with provincial party secretaries have this mitigation effect while connections with the provincial governor have no effect. Both the city mayor's and the city party secretary's connection matters.

[Table 16 about here]

In summary, this fact demonstrates that the pass-through of industrial policy from upper levels of government is a nuanced process shaped by local political dynamics, regional development levels, and the relationships between local and provincial officials. The figure offers a clear depiction of how city-level policies align with upper-level directives, varying over time and by government level.

Fact 2(b): Policy pass-through is correlated with political centralization over time.

Policy pass-through measures the extent to which local governments are following the upper-level government directives as opposed to local initiatives. The political literature documents a reversal towards centralization since 2013 (Fang et al., 2022b; Zhou et al., 2021; Bo, 2020; Lee, 2017). We examine the time trend in the policy pass-through from upper-level governments to local governments, with a special focus on whether the trend is consistent with China's political centralization cycle. The regression equation used to estimate the time-varying policy pass-through is:

$$Policy_{cst} = \sum_{t=2005}^{2} 020\beta_{1t} Policy^{p}_{c(p)st} + \sum_{t} \beta_{2t} Policy^{n}_{st} + \delta_{sc} + \gamma_t + \epsilon_{cst} \quad (5)$$

where we estimate how the policy choices at the city level ($Policy_{cst}$) align with those at the provincial ($Policy^{p}_{c(p)st}$) and national ($Policy^{n}_{st}$) levels over time, capturing both the temporal dynamics and the evolving relationship between different government levels.

The two panels in Figure 13 plot the estimated coefficients of β_{1t} and β_{2t} over time, representing the pass-through from provincial and national governments to city level, respectively. Panel (a) shows the time-varying response of city-level policies to provincial policies. The downward trend from year 2005 illustrates a decline in alignment before 2013, followed by a resurgence after 2013. This reflects a centralization trend, with provincial policies increasingly influencing local decisions. Panel (b) depicts the policy pass-through from the central government to city-level policies. The correlation between city and central policy choices 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.

[Figure 13 about here]

The pass-through of policy sector choice from provincial and central governments to city-level governments exhibited notable changes over time. Our data underscores 2013 as a pivotal year when policy sector choice and implementation became more centralized, reversing the earlier trend of decentralization. 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 government.

Fact 2(c): Regional policy persistence evolves with local politician's mobility.

In this fact, we explore the concept of policy persistence in China's industrial policy landscape, focusing on both its advantages and potential drawbacks. 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 local politician changes 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 either be continued or altered. This rotation provides an opportunity to study how political dynamics influence policy trajectories.

We begin by examining the serial correlation of policy choices over time. Specifically, we estimate the degree to which local policies are consistent across time periods and whether this persistence is interrupted by changes in local politicians. The regression equation is:

$$Policy_{cst} = \beta_1 Policy^p_{c(p)st} + \beta_2 Policy^n_{st} + \beta_3 Policy_{cs(t-1)} + \delta + \eta + \gamma_t + \epsilon_{cst} \tag{6}$$

This model assesses how policy choices from upper-level governments (provincial and national) and previous local policies ($Policy_{cs(t-1)}$) influence current local policy choices. Furthermore, we define a *Change* indicator which takes value 1 if the city secretary or mayor is different from last year. We also include an interaction term between policy and change indicators to examine how political transitions affect policy persistence

Table 17 reports the regression results, with column (1) reporting the baseline results and columns (2) and (3) including the interaction terms with the indicator of politician change. The results show that policy choices are highly serially correlated with a coefficient of 0.36, meaning that local policies exhibit a significant degree of persistence over time. However, this persistence is partially disrupted when a local politician is replaced. The regression results show that changes in local politicians have a significant negative interaction with policy persistence ($Policy \times Change$), indicating that these transitions disrupt the continuity of previous local policies. On the other hand, in the year of a shift in local leadership, local policies tend to align more closely with upper-level government directives— indicating the new local leaders' incentive to show political loyalty.

[Table 17 about here]

Seeing that policy persistence is shifted by the change of local politicians, we further examine the effect of local politicians per se on the local policy choice. To do so, we identify a 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. We examine the policy choice of the city and decompose the correlation to the correlation with city's previous year's policy choice and the local politician's previous city's previous year's policy choice, i.e., the persistence by location and the persistence of a politician.

Table 18 reports the regression results. Column (1) presents the baseline result examining policy persistence in the full sample. Column (2) uses the subsample with lateral moves and it shows that, when there is a shift in local politicians, the correlation with previous year's policy drops to 0.27. On the other hand, the correlation between the city's policy with the politician's previous city's policy is 0.09— the two almost add up to the overall policy persistence of 0.35. In column (3), we further control the cities' neighbor's policy as a placebo. The result suggests that the correlation is much weaker (0.04) and is not statistically significant.

[Table 18 about here]

This analysis sheds light on the role of political dynamics in shaping the continuity of industrial policies and highlights the delicate balance between policy persistence and political flexibility in China's industrial policy framework. The result confirms the rotation of politicians as an important policy-learning mechanism. To the extent that politician experience is part of the administrative capacity, the results also confirm its importance in sector choice.

To summarize, the first two sets of empirical analysis correspond to the two important aspects of policy choice, suggesting that the local government's choice of the policy targeted sector is jointly shape by economic rationales and political considerations. While the top-down pass-through reflects the political motive of local goverments' compliance of central directives, the economic rationale reflects the local governments' effort in local adaptation.

5.3 Policy Tool Experimentation and Diffusion

We then turn the focus to the choice of policy tools. In Section 4.4, we observe a notable rise in the variety of policy tools over time, and a more balanced use of the traditional tools and the new tools. The new tools tend to be more selective on firms as compared to the traditional general tax deduction and trade protection policies. However, the ultimate success of the policy implementation depends on the local government's fiscal and administrative capacity (Juhász and Lane, 2024). In this subsection, we explore the choice of implementation tools used in industrial policies across different dimensions. Specifically, we focus on three key aspects: how these tools vary across different levels of government (Fact 3(a)), across regions (Fact 3(b)), and across industries (Fact 3(c)). By analyzing the selection and adoption of both traditional and new tools, we aim to understand the factors driving these choices and how they have evolved over time. Observing the rich dynamics, we then zoom into within-industry variations by examining the dynamics of tool choice across different stages of industrial development (Fact 3(d)). Each of these facts provides critical insights into the mechanisms through which industrial policies are implemented in China.

Fact 3(a): Local governments are earlier adopters of new policy tools, central government is heavier user of traditional tools, provincial government is in between, and trends converge over time.

An important feature of China's industrial policy is the variation in the choice of implementation tools across different levels of government. We first explore how local, provincial, and central governments differ in their usage of new and traditional policy tools over time.

To track how the use of various tools, particularly new and traditional tools, evolves over time and how this evolution differs by government level, we estimate the following regression:

$$\mathbb{1}(Tool_{ikgst}) = \sum_{t=2005}^{2} 020\beta_t^n Year_t \times Level_n + \sum_{t=2005}^{2} 020\beta_t^p Year_t \times Level_p + \delta_s + \gamma_t + \epsilon_{ikgst} \quad (7)$$

where: $\mathbb{1}(Tool_{ikgst})$ is a binary variable indicating the use of a specific tool type k by policy i for industry s in government level g during year t, $Level_n$ is an indicator for central-level policy,and $Level_p$ is an indicator for provincial-level policy, city-level policy is used as the default group, $Year_t$ are year indicators, and δ_s and γ_t are industry and year fixed effects. For clarity in presentation, tools are classified according to their growth trends, as explained in Section 4.4. Specifically, k can represent one of these categories: rapidly emerging new tool, moderately growing new tool, stable traditional tool, increasing traditional tool, or a diminishing old tool.

Figure 14 illustrates the time trend in tool usage across government levels. Panels (a) and (b) plot β^ns— the coefficient estimated for the central government— to compare the central government versus the city-level government in tool usage. Panels (c) and (d) compare the provincial-level government and the city-level government by plotting the coefficients for the provincial-level government β^ps.

Panels (a) and (c) show that local governments (primarily city-level) tend to be earlier adopters of new tools, followed by provincial governments, with central governments adopting new tools more conservatively. Panels (b) and (d) demonstrate that central governments maintain a stronger preference for traditional tools such as market regulation and trade protection, while local governments are gradually reducing their reliance on these tools. Overall, the city-level governments are more proactive in experimenting with new instruments, reflecting their flexibility in adjusting policies to local needs and innovation, while the central government remains more consistent in its use of traditional tools, although its adoption of new tools has begun to increase in recent years. Moreover, these trends suggest a convergence over time, with all levels of government increasingly adopting new tools, although local governments are the main drivers of this shift.Overall, even though local governments tend to follow upper governments in sector choices, they nevertheless have flexibilities in implementation, and it is the local governments, who have more information on the ground, that are the main agent 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.

[Figure 14 about here]

Fact 3(b): The usage of policy tools in industrial policies varies significantly across regions, largely depending on the level of economic development.

Local governments' fiscal resources and administrative capabilities play crucial roles in determining these tools. It can be expected that cities with strong finances can typically employ extensive fiscal subsidies for their industrial policies, whereas less developed areas might depend on natural assets like inexpensive land. We then zoom in to the city-level documents to analyze how industrial policy tool selection varies by region.

To do so, we collapse the document-level data with detailed industry and tool information to the region-industry-year level to measure that in each region, each year, and each industry, which tools are used. In the empirical analysis, we focus on the sample of policy-targeted industries to focus on the choice of industrial policy tools conditional on the industry is targeted by the government. To be specific, we estimate the following regression:

$$\mathbb{1}(Tool_{kcst}) = \sum_{t=2005}^{2} 020\beta_t Year_t \times \log(GDP_{ct}) + \gamma_{st} + \epsilon_{kcst}, \tag{8}$$

where $Tool_{kcst}$ is a binary variable indicating the use of a specific tool type by policy k in city c for industry s during year t, $\log(GDP_{ct})$ 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 to control for sector-specific heterogeneities, and ϵ_{kcst} is the error term.

Figure 15 plots the estimated coefficients for β_t to illustrate the time trend of tool adoption by city development level. As seen in the left panel, more developed cities (with higher GDP) 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. This may reflect that the new tools need higher administrative capability and require more experimentation in the initial stage. Panel (b) shows that the more developed regions rely much more heavily on traditional tools like tax deduction and trade protection— the former aligns with the better fiscal condition and thus lower effective tax rate to attract investment in wealthier regions, and the latter may be due to the fact that they have more interactions with the international market. Less developed regions rely more on traditional tools such as preferential land supply where fiscal constraints limit the adoption of more expensive policy instruments.

[Figure 15 about here]

Fact 3(c): The choice of industrial policy tools depends on the targeted industry.

The third stylized fact examines the choice of industrial policy tools across different industries. Following our previous practice, we focus on the sample of policy-targeted industries but now focus on the within-city across-industry variations.

$$\mathbb{1}(Tool_{kcst}) = \sum_{t=2005}^{2} 020\beta_t Year_t \times Industry_s + \gamma_{ct} + \epsilon_{kcst}, \tag{9}$$

where $Industry_s$ are indicators for industry type— we first focus on the comparison between manufacturing industry versus other industries (i.e. $Industry_s$=1 for manufacturing industry and 0 for others), and then consider the subsample of manufacturing sector and focus on the comparison 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 to control for city-specific heterogeneities, and ϵ_{kcst} is the error term.

Figure 16 compares manufacturing industry with other industries and plots the estimated coefficients for each year. Panel (a) suggests that the fast growing new tools such as industrial fund, promoting industrial cluster, and encouraging entrepreneurship are more prevalent used in the manufacturing sector. Panel (b) indicates that manufacturing sectors more frequently use traditional market protection tools while less rely on other traditional tools such as fiscal subsidy or financial support.

[Figure 16 about here]

Figure 17 compares, within the manufacturing sector, skill-intensive industries and other traditional industries. Panel (a) suggests that skill-intensive manufacturing industries more frequently use the new tools such as demand stimulation, promoting industrial cluster, and encouraging entrepreneurship, etc. Panel (b) suggests that monetary incentives (fiscal and finance) are used more prevalently in the skill-intensive industries, while they rely less on the traditional market protection methods.

[Figure 17 about here]

Fact 3(d): Within each industry, the choice of tools evolves over time from entry promotion to industry upgrading.

While the third fact underscores notable heterogeneities in tool choice across various industries, which appear to be persistent over time, a more intriguing question is whether, within each individual industry, local governments are evolving their industrial policy tools over time to accommodate each industry's developmental phase. Specifically, for a given industry, do the tools employed during its early development differ from those utilized when the industry reaches a more advanced stage? For a given city, does the local government optimally choose different tools for different industries depending on each industry's development stage?

We first identify the first year when each industry is targeted in each city, and then calculate for each industry, each year, the number of years since first being targeted. We then estimate the following model at policy level:

$$\mathbb{1}(Tool_{ikcst}) = \beta^k Duration_{cst} + \delta_s + \gamma_{ct} + \epsilon_{ikcst} \tag{10}$$

$\mathbb{1}(Tool_{ikcst})$ is a binary variable indicating the use of a specific tool type 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_s and γ_{ct} are industry and city-by-year fixed effects. It is worthwhile to note that by controlling the city-by-year fixed effect, we are able to distinguish that within the same city, the local government uses different tools for different industries depending on the industry's development stage.

Figure 18 plots the estimated coefficients β^ks for various tools, 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). This underscores how local governments dynamically adjust industrial policy tools according to the industry's development stage. Initially, the focus is on entry subsidies, favorable land allocation, industrial funds, and entrepreneurship encouragement to boost competition, with government procurement serving as a demand source. Over time, the focus transitions to R&D, labor and talent development, and supply chain enhancement for industry advancement, increasingly relying on industrial promotion and consumer demand stimulation as demand sources. Overall, the results are consistent with the idea of industry policies as customized public services (Juhász et al., 2023)

[Figure 18 about here]

5.4 Effectiveness of Policy and Tool

The first three sets of empirical analysis mainly focus on the LLM-analyzed policy data, and in the following two sets of analysis, we combine our rich industrial policy data with detailed micro-level firm data. The success of industrial policies hinges not only on the choice of the targeted industry but, more importantly, on how these policies are implemented using various industrial policy tools. In this subsection, we attempt to shed some light on the effectiveness of different tools in achieving key policy objectives. Specifically, we explore three critical dimensions: 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 or characteristics (Fact 4(a)). 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 4(b)). Third, we assess whether industrial policies enhance firm productivity and analyze the differential effects of various tools (Fact 4(c)).

Fact 4(a): Industrial policies are effective in tax reduction, providing subsidy, and increasing firm leverage, and the effect depends on firm characteristics and the tools used.

First, to verify policy effectiveness, we use the firms' administrative tax record data to assess whether firms in industries targeted by industrial policies actually benefit from government support, such as tax reductions, subsidies, or improved access to finance. This analysis assures that the allocation of industrial policies aligns with their intended goals, particularly regarding providing meaningful support to firms in key industries.

We first regress various measures of policy support on the policy dummy. Specifically, in order to capture the heterogeneous effect of policies with different tones, we separately control for supportive policies versus regulatory policies. The regression equation is as follows:

$$Y_{isct} = \beta^{+} \times Policy^{+}_{sct} + \beta^{-} \times Policy^{-}_{sct} + \delta_i + \gamma_t + \epsilon_{isct} \tag{11}$$

where i is for firm, s for industry, c for city, and t for year. The dependent variables measure various dimensions of firm-level policy support: 1) effective tax rate defined as the ratio of taxes paid to before-tax revenue; 2) log of the total amount of subsidies received by a firm; 3) leverage ratio, calculated as the ratio of debt to total assets, serving as a proxy for a firm's ability to take on debt; 4) long-term Debt indicator: A binary variable indicating whether a firm has long-term debt, which can reflect the firm's ability to secure bank loans or other long-term financing. Policy indicator turns on when the city government c issues a policy targeting industry s in year t. As we focus on policy effectiveness, it is important to differentiate policies of different tones. Thus, we make full use of the LLM output and distinguish the supportive policies versus the regulatory and suppressing policies. $Policy^{+}$ representing supportive policy and $Policy^{-}$ representing regulatory and suppressing policy.

Table 19 presents the regression results. We begin by controlling for city-by-industry and year fixed effects to examine the average correlation between policies and firms in the targeted industries. We then add firm fixed effects, which enable us to track the same firms over time, allowing us to evaluate whether firms in policy-targeted industries receive more benefits under policy support. By doing this, we can identify whether the targeted industry overall and individual firms in the industry receive more subsidies, experience lower effective tax rates, or have better financing conditions compared to when they are not in a policy-targeted industry. Columns (1) and (2) find a 6% industry-wide average increase in firm subsidy, and the effect drops to 1.8% on the intensive margin after controlling firm fixed effect. Columns (3) and (4) suggest that firms in the targeted industry, on average, enjoy a 5 percentage point lower effective tax rate, and the effect turns null after controlling for firm fixed effect. Columns (5) - (8) present the results of firms' long term debt and leverage ratio, and they show a significant effect of policy support on firms' financing condition the extensive margin: the probability of acquiring long-term debt increases by 2.8% under policy support and the leverage ratio (debt/asset) increases by 0.7 percentage point. The effect turns null on the firms' intensive margin— suggesting that the positive effect at industry level may be mainly driven by the newly-entered firms having better access to bank financing.

[Table 19 about here]

Comparing the coefficients for supportive policies and regulatory policies reveals an interesting pattern worth further investigation— the analysis reveals that both supportive and regulatory policies exhibit positive correlations with firm benefits, including subsidies and improved financing conditions. Two potential explanations may account for the observed patterns. First, the positive coefficients for regulatory policies may arise from an endogenous targeting effect: regulatory policies are often directed at previously booming industries that were heavily supported by prior industrial policies. Consequently, the regulatory policy dummy becomes positively correlated with firm benefits that were accrued before regulation. Second, the policies themselves may directly result in increased firm benefits.

To disentangle these two channels—the endogenous targeting effect and the causal impact of policies on firm behavior— we conduct an analysis of the dynamic responses to supportive and regulatory policies. Specifically, we examine both forward and lagged terms of policy implementation to capture the temporal relationships between policies and firm outcomes.

$$Y_{isct} = \beta_0 + \sum_{l=-2}^{2} \beta_l^+ \times Policy^+_{sc(t+l)} + \sum_{l=-2}^{2} \beta_l^- \times Policy^-_{sc(t+l)} + \delta_i + \gamma_t + \epsilon_{isct} \tag{12}$$

The results unveil the different mechanisms that drive the positive contemporaneous correlation between policy indicators and firm outcomes for supportive policies and regulatory policies. Forward terms, indicating future policy targeting, are positively correlated with regulatory policies, while lagged terms are either negatively correlated or statistically insignificant. This temporal pattern supports the endogenous targeting channel, where regulatory policies aim to regulate previously booming and 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. These findings emphasize the importance of accounting for endogenous targeting when evaluating the causal impact of policy interventions.

[Figure 19 about here]

We further decompose the policy effect into different policy tools to examine their heterogeneous effect on firm benefits. We focus on the supportive policies and group the tools by their implementation methods as detailed in Section 4.4, and run the following regression:

$$Y_{isct} = \sum_{k} \beta_k \times Policy_{ksct} + \delta_i + \gamma_t + \epsilon_{isct} \tag{13}$$

The results are reported in Table 20. It is worth noting that the tools are often used in bundles, and the results aim to provide suggestive horse-race evidence on the role of each tool after controlling for other tools. We find that, first of all, fiscal and financial tools and tools to foster industrial clusters (mostly with special economic zones) are most effective in providing firms with subsidies and tax deductions. The effect of policy tools on firms' long-term debt and leverage ratio is mixed—tools to foster industrial clusters and tools targeting input and R&D are positively correlated with the firms' probability of acquiring long-term debt, while demand stimulation tools are positively correlated with firms' leverage ratio. On the contrary, tools aiming to boost firm entry have a negative or null effect on firm benefits, suggesting that the greater number of new firms dilutes the benefits for the average firm. The results suggest the importance of quantifying industrial policy from multiple dimensions. The heterogeneous results show that not all tools are positively correlated with firms' monetary benefits, and not all tools are complements to each other— for example, while fiscal-based tools are positively correlated with firms' subsidies, demand-based tools are negatively correlated.

[Table 20 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. Table 21 reports the regression results. It suggests that, on average, larger firms benefit more from industrial policies.

[Table 21 about here]

Fact 4(b): Industrial policies are effective in boosting new firm entry

Reassured that the industrial policies genuinely provide advantages 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.

On the extensive margin, 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 bins to determine the count of new firms and the value of new capital across each city, 4-digit industry, and year. We then run the following regression:

$$Y_{sct} = \beta^c \times Policy_{sct} + \beta^p \times Policy^p_{sc(p)t} + \beta^n \times Policy^n_{st} + \delta_{sc} + \gamma_t + \epsilon_{isct} \tag{14}$$

where s is for industry, c for city, and t for year. Y_{sct} is the log of the number of new firm registrations or the log of the value of new capital registration. $Policy_{sct}$ takes on value 1 if city c issue an industrial policy targeting industry s in year t, $Policy^p_{sc(p)t}$ takes on value 1 if the province of city c issue an industrial policy targeting industry s in year t, and $Policy^n_{st}$ takes on value 1 if the central government issues an industrial policy targeting industry s in year t. All other variables are defined as above.

Table 22 reports the regression results. We first control city-by-industry and year fixed effects, and then also include city-by-year time trend. The results show a significant response in firm entry to industrial policies— being targeted by the city-level government leads to a 13% increase in the number of new firms and a 32% increase in the volume of new capital formation. After controlling the city-industry specific trends, the effects are still significant— the growth rate of the number of new firms increases by 2% and of new capital increases by 7%. Comparing the city-level policy impact with provincial and central level government policies suggests that firm entry responds to local policies much more than to upper-level policies.

[Table 22 about here]

Next, we extend the regression with lag and forward terms to examine the dynamic response of firm entry to policies at different government levels. The regression equations are as follows:

$$Y_{sct} = \sum_{t=-6}^{6} \beta^+_t \times Policy^+_{sct} + \sum_{t=-6}^{6} \beta^-_t \times Policy^-_{sct} + \sum_{t=-6}^{6} \beta^{n+}_t \times Policy^{n+}_{st} + \sum_{t=-6}^{6} \beta^{n-}_t \times Policy^{n-}_{st} + \delta_{sc} + \gamma_t + \rho_{sc} + \epsilon_{sct} \tag{15}$$

All regressions control for city-by-industry and year fixed effects, and city-industry specific time trends.

Figure 23 and Figure 24 plot the estimated coefficients for β_ts and β^n_ts, separately for supportive policies and regulatory policies. As for supportive policies, both local and central policies trigger a significant increase in firm entry at time 0 (policy issue year). However, there is a notable difference in pre-trends: city-level policies are procyclical, with a positive pre-trend, while central-level policies are countercyclical, likely issued when industries show signs of slowing growth. The effects are contrary for regulatory policies— city-level regulatory policies lead to significantly lower entry rates and central-level policies are weakly correlated with increasing entry rates. This difference suggests nuance differences in government policy rationalities: local governments respond to better market conditions and issue more policies to boost further growth, while the central government's goal is more strategic and tends to issue policies when the key industries lack the momentum of growth.

[Figure 23, Figure 24 about here]

Zooming in to the city-level policies, we can further decompose the average positive effect into strongly supportive policies, supportive policies, and regulatory policies with the following regression equation.

$$Y_{sct} = \sum_{t=-6}^{6} \beta_t^{++} \times Policy_{sct}^{++} + \sum_{t=-6}^{6} \beta_t^{+} \times Policy_{sct}^{+} + \sum_{t=-6}^{6} \beta_t^{-} \times Policy_{sct}^{-} + \delta_{sc} + \gamma_t + \rho_{sc} + \epsilon_{sct} \quad (16)$$

[Figure 21 about here]

Figure 21 plots the estimated coefficients for β_t^{++}s,β_t^{+}s and β_t^{-}s, with Panel (a) plots the coefficients estimated controlling for city-by-industry and year fixed effects, and Panel (b) further controlling for city-year specific time trend. Both strong supportive policies and other supportive policies are associated with positive firm entry (panel (a)), and both trigger a significant increase in firm entry growth rate at the policy issue year (panel (b)). The effect of strong supportive policies is about twice as large as that of other general supportive policies. It is worth noting that there is a significant pre-trend for the effect of strongly supportive policies even after controlling for the trend. This suggests that the governments may increase policy strength procyclically in response to the booming market. The effect on the new firm entry growth rate started to decline after 3 years of the policy issue year. In sharp contrast, regulatory policies lead to a significant decrease in firm entry rates.

Lastly, we focus on the supportive policies only and investigate how different policy tools vary in their effectiveness in promoting firm entry. In theory, policies designed to lower entry barriers—such as subsidies, preferential access to land, and tax incentives—should encourage new firms to enter targeted industries. The regression equation is specified as follows:

$$Y_{sct} = \sum_{k} \beta_k \times Policy_{ksct} + \delta_{sc} + \gamma_t + \epsilon_{isct} \quad (17)$$

Figure 22 plots the estimated coefficients for each tool β_ks. It shows a big variation in the effect of policy tools on new firm entry. Fiscal subsidy, labor policies, preferential land supply, industrial promotion, promoting entrepreneurship, promoting industrial cluster, and methods for market access and regulation are most effective in boosting new firm entry, financing, tax deduction, and demand stimulation have relatively mild effects on attracting new 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, while on the one hand, may protect domestic or local firms, maybe at the cost of deterring foreign firms. Government procurements are usually biased toward larger or state-owned enterprises and thus may lead to more concentrated market share and deter the entry of smaller new firms.

[Figure 22 about here]

Fact 4(c): Industrial policies have mixed effect on firm productivity

On the intensive margin, we examine whether industrial policies drive investment and improve productivity in existing firms. Unlike the largely positive effects on preferential treatment and new firm entry, the impact on firm productivity is more complex and varied. The effectiveness of industrial policy on productivity depends heavily on the specific tools used and their implementation, as multiple mechanisms interact, leading to mixed outcomes.

Several mechanisms can operate simultaneously under different policies. Entry subsidies and low-cost land allocations promote new firm entry, fostering market competition. Labor subsidies, particularly for high-skilled labor, reduce labor costs and may enhance productivity by enabling firms to attract better talent. Industrial policies can also generate economies of scale, leading to productivity gains for firms in industry clusters by benefiting from shared resources, improved infrastructure, and a more skilled labor pool. 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. However, there are downsides. Policies encouraging new firm entry can lower the threshold for market participation, allowing less productive firms to enter, which may dilute overall productivity. Additionally, excessive entry could lead to overcapacity and resource crowding, even for high-performing firms. In sum, the impact of industrial policies on productivity results from a balance of multiple mechanisms. While some policies promote productivity through competition and agglomeration effects, others may hinder it by allowing inefficient firms to survive or by not adequately incentivizing innovation and efficiency.

While it is definitely out of 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 Fact 6 to examine the policy impact on the firm's productivity, revenue, employment, intermediate input, and capital formation. We run the regression first on the policy dummy, and then on the tool set to decompose the effect of different policy tools.

We follow the same routine as above— first examine the dynamic effect of supportive policies and regulatory policies, and then zoom into the supportive policies and decompose the contemporaneous correlation into different policy tools. Figure 25 presents the results of the industrial policy impact on firm productivity (measured by TFP). We examine revenue-based (panels (a) and (b)), output-based (panels (c) and (d)), and value-added-based (panels (e) and (f)) TFP separately. Overall, the results suggest a positive but short-lasting positive impact of supportive policies and a negative impact of regulatory policies. The results show a more robust impact on revenue- and output-based TFP measures as compared to value-added-based TFP measures —- probably because the firms increase the amount of intermediate input significantly in response to supportive policies.

[Figure 25 about here]

Figure 26 presents the results of the industrial policy impact on firm total revenue (panels (a) and (b)), output (panels (c) and (d)), and value-added (panels (e) and (f)). The results are consistent with those for the TFP measures— there is a positive but short-lasting positive impact of supportive policies and a negative impact of regulatory policies.

[Figure 26 about here]

Figure 27 presents the effects of policy on firms' inputs, specifically capital (panels (a) and (b)), labor (panels (c) and (d)), and intermediate input (panels (e) and (f)). The findings indicate that while supportive policies lead to a mild rise in employment and capital investment, they result in considerable increases in intermediate inputs. The impacts of regulatory policies on capital and employment are negative when city-by-industry and year FEs are controlled and turn slightly positive when firm fixed effect are further controlled for. This is probably because regulatory policies deter new firms entry and thus may benefit the incumbent ones in resource allocation due to the decreased competition effect.

[Figure 27 about here]

Tables 23-25 report the horserace results of the contemporaneous correlation between policy tools (focusing on supportive policies only) and the firm outcome variables. The results are mostly consistent with the results on firm benefits as reported in Table 20, from which one can see a clearer quantity-quality trade-off in policy impact. Industrial policy tools that directly provide fiscal subsidies and financial support are the most effective in boosting the value of firm inputs and outputs, with relatively mild impact on firms' value added, and thus productivity. On the other hand, tools that target the production process— the input and R&D related tools are most effective in reducing the cost of input, increasing firms' value-added, and thus boosting firm productivity. Policies to promote firm entry have a consistent negative effect on firm revenue, capital investment, and productivity, reflecting the dominating weaker-screening effect and competition effect— allowing less productive and smaller firms to enter the market, thereby diluting the incumbent firms' access to resources and lowering overall productivity. Tools to foster industrial clusters and demand-based tools exhibit mixed impacts. The former significantly raises firm revenue, but not output and value-added, have positive impact on firm employment and lowers input cost, and the latter have positive effects on capital investment and is negatively associated with all other outcome variables.

[Tables 23-25 about here]

Overall, the results highlight the heterogeneities in policy tools and their different impacts on different dimensions of firm behaviors and outcomes. The overall effect is a combination of different mechanisms such as increased market competition, weakened entry screening, higher market demand, better access to inputs, and so on.

5.5 Policy Diffusion and Spatial Inefficiency

In the last set of empirical analysis, combining policy data and firm data, we take a global view and study the spatial features of local government choices of the policy-targeted sectors. First, we examine the regional correlation of policy choices and its implication on regional trade (Factor 5(a)). Then, we take a dynamic perspective and investigate the efficiency implications if policy diffusion (Fact 5(b)).

Fact 5(a): Increasing inter-regional policy homogeneity is 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 development. However, with strong top-down policy pass-through in China, regional policy choices are becoming increasingly similar, which may lead to overly homogenous industrial structures[12].

When cities and regions adopt similar industrial policies, it diminishes the potential for regional specialization and agglomeration. The result can be local economies that are too similar to one another, fostering competition rather than complementarity between regions. This leads to heightened local protectionism, where cities and regions attempt to shield their industries from external competition to maintain economic control. 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 et al., 2022a; Young, 2000).

There are three possible explanations for the similarities in local governments' policy choices. First, ws we documented in Section 5.2, 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 the local governments as they follow the same upper level policies.

Besides 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 essential to broader supply chains. By attracting and retaining critical industries within their jurisdictions, regions aim to capture the entire supply chain, fostering localized economic growth and securing fiscal revenues. The political incentives for local officials to boost economic performance, combined with fiscal pressures, lead to policy choices that prioritize the development of competitive industries, often at the expense of regional cooperation.

Local protectionism is therefore reinforced by both fiscal and political imperatives. From a fiscal standpoint, 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 region's economic performance, which motivates them to adopt policies that favor local industry retention and growth. This protectionism can manifest as barriers to inter-regional trade and duplication of industrial efforts across cities, contributing to inefficiency in resource allocation on a national scale.

The third contributing factor to policy homogeneity is the learning effect, where cities imitate successful industrial policies from other regions. When a city observes its neighbor benefiting from promoting a particular industry, it may feel compelled to adopt similar policies in order to achieve

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

comparable success. This effect is especially pronounced in high-growth sectors such as technology and renewable energy, where regional officials may see the success of neighboring cities as a blueprint to follow. However, this imitation can further dilute regional specialization, as cities pursue the same industries rather than capitalizing on their unique comparative advantages.

In summary, the increasing similarity of regional industrial policies in China is driven by a combination of top-down directives, local protectionism, and regional competition, all of which are reinforced by fiscal and political incentives. While these forces may help cities achieve short-term economic gains, they also risk long-term inefficiencies by promoting industrial duplication and reducing opportunities for inter-regional specialization. This shift towards policy homogeneity not only reduces the potential for agglomeration benefits but also contributes to local protectionism, which can stifle inter-regional trade and cooperation.

In this fact, we examine the spatial correlation of policy sector choices across cities to assess the degree of policy similarity. We calculate the cosine similarity of sectoral policy choices between city pairs, focusing on intra-province similarities. We then calculate the city-year level policy similarity index as the average similarity for each city with all other cities in the same province. Figure 28 plots the geographical distribution of policy similarity, revealing significant regional variation. For example, areas like Inner Mongolia and the coastal regions exhibit higher levels of policy similarity, while other regions, such as parts of the northwest, show more diversity in policy choices.

[Figure 28 about here]

Combining with the VAT data set, we further investigate the relationship between policy homogeneity and local protectionism. By aggregating the firm-pair transitions to city pair level, we calculate the share of intra-city trade and intra-province trade for each city. Figure 29 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. The figure also shows a positive correlation between policy similarity and the percentage of intra-city trade. Higher policy similarity correlates with a higher share of internal trade within a city, indicating that similar policies may contribute to elevated local protectionism. The stronger correlation for intra-city trade relative to intra-province trade underscores how overly similar policy choices may reduce the incentive for inter-city trade, and the effect is stronger for city pairs within the same province, potentially harming overall economic efficiency.

[Figure 29 about here]

These findings suggest that the over-centralization of industrial policy decisions could undermine the benefits of regional specialization and lead to inefficiencies such as protectionism and duplication of industrial structures across cities. As a result, local policy similarities may contribute to reduced economic dynamism and hinder the development of more efficient regional trade networks.

Fact 5(b): As policies diffuse across regions, it leads to diminishing—and at times counterproductive—policy effectiveness.

The final fact explores the dynamic efficiency implications of regional policy diffusion, focusing on how the effectiveness of industrial policies may diminish as more cities adopt similar strategies. As previously discussed, the competitive and learning incentives often push regions to replicate successful policies implemented by pioneering cities. This dynamic creates a diffusion process where cities rush to promote the same industries. However, this diffusion can lead to inefficiencies, particularly in terms of overcapacity when too many cities target the same industries.

To investigate this, we analyze how the sequence of cities adopting a particular policy affects the entry of new firms, firm size (measured by capital investment), and firm performance. Specifically, we examine whether earlier adopters (pioneers) benefit more than later adopters (followers). We define, for each industry, the order in which cities start to support that industry, allowing us to differentiate between early and late adopters. We estimate the following regression at the city-industry-year level:

$$Y_{sct} = \beta_1 Policy_{sct} + \beta_2 Policy_{sct} \times Order_{cs} + \delta_{sc} + \gamma_t + \eta_s + \epsilon_{sct} \tag{18}$$

where Y_{sct} is the outcome variable (e.g., log number of new firm entries, log value of new capital, or log value of average new 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 adopts a policy for industry s normalized by the total number of cities— 286— with lower values indicating earlier adoption, δ_{sc}, γ_t, and η_s are city-industry, year, and industry fixed effects, respectively, ϵ_{sct} is the error term. 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 outcomes. The interaction term allows us to differentiate the effects on early versus late adopters of the policy.

Table 26 reports the regression results at city-industry-year level. Column (1) reports the results with the log of the number of new firm entries as the dependent variable. The coefficient on $Policy$ is positive and significant, indicating that cities adopting policies do experience an increase in new firm entry. The interaction term ($Policy \times Order$) is also positive, meaning that earlier adopters see even greater increases in firm entry compared to later adopters. Column (2) reports the results for the log of the value of new capital. The effect of $Policy$ is again positive, showing that cities that adopt policies attract more capital investment. However, the interaction term ($Policy \times Order$) is negative, suggesting that while early adopters benefit from increased capital formation, this benefit diminishes significantly for later adopters, potentially due to overcapacity as more cities compete for the same industries and thus followers are applying a lower screening threshold. Column (3) reports the results for log of the value of average new capital per firm: Similarly, the $Policy$ effect is positive, but the interaction term is negative, showing that later adopters attract smaller firms on average.

[Table 26 about here]

At the firm level, we further assess the impact of policy diffusion on firm performance using the following specification:

$$Y_{isct} = \beta_1 Policy_{sct} + \beta_2 Policy_{sct} \times Order_{cs} + \delta_i + \gamma_t + \eta_s + \epsilon_{isct} \tag{19}$$

where Y_{isct} represents firm performance measures such as revenue, profit, or productivity, δ_i includes firm fixed effects to control for time-invariant firm characteristics, all other terms are defined as above.

Table 27 shows the firm-level effects. Early adopters benefit from higher firm revenues and profits, but as more cities adopt similar policies, these gains diminish, and the latecomers experience lower productivity and profit margins. This suggests that later entrants face more intense competition and overcapacity, which erodes the effectiveness of the policy. In summary, while policy diffusion can generate positive effects for early adopters, the increasing number of cities targeting the same industries leads to diminishing and even negative returns.

[Table 27 about here]

There are two possible reasons for the diminishing returns in policy diffusion, particularly for cities that follow in the footsteps of pioneering regions. The first is overcapacity due to 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 infrastructure become stretched, reducing efficiency and productivity for all firms. The table illustrates the negative correlation between policy adoption order and the effectiveness of capital and firm entry.

The second possible reason is the low learning quality in policy implementation: Policy followers are often less capable of executing the policies with the same level of complexity as the early adopters. They may not fully grasp the intricate combinations of policy tools and implementation strategies that lead to success. In particular, followers may be less likely to target industries where they have a comparative advantage, focusing instead on industries that other cities are already targeting. This leads to inefficient allocation of resources. To examine the hypothesis, we run the following regression at city-industry-year level:

$$Policy_{cst} = \beta_1 \cdot RCA_{cst} + \beta_2 \cdot Order_{cs} + \beta_3 \cdot RCA_{cst} \times Order_{cs} + \delta_{st} + \gamma_c + \epsilon_{cst} \tag{20}$$

This equation assesses how the order of policy adoption across cities (denoted by $Order_{cs}$) influences the sectoral choice of industrial policies, particularly when interacting with a city's relative comparative advantage (RCA). It evaluates whether later-adopting cities are less likely to target sectors where they have a comparative advantage.

Table 28 reports the regression results. The table further highlights that regions adopting policies later are less likely to target sectors where they have a comparative advantage. The negative interaction between comparative advantage and policy order suggests that early adopters tend to choose industries aligned with their strengths, while later adopters often target sectors with lower comparative advantages, leading to inefficient industrial development. This pattern reflects the tendency of follower regions to mimic successful policies without considering their own local conditions, further exacerbating inefficiencies and leading to potential overcapacity.

[Table 28 about here]

We also examine the choice of implementation tools for the pioneers and the followers within the same industry. The regression equation is specified as follows:

$$\mathbb{1}(Tool_{ikcst}) = \beta_k \cdot Order_{cs} \times Policy_{cst} + \gamma_{ct} + \epsilon_{ikgst} \tag{21}$$

This equation explores how the timing of policy adoption (denoted by $Order_{cs}$) affects the type of policy tools used. The dependent variable is a binary indicator for each policy tool.

Figure 30 plots the coefficients estimated from the second regression, showing how the timing of policy adoption influences the selection of policy tools. Cities that adopt policies later 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 later adopters. This trend could explain why the performance of follower cities often lags behind early adopters—the tools they select are less likely to drive long-term growth and innovation.

[Figure 30 about here]

To summarize, as more cities target the same industries, resources become stretched, leading to excessive entry and overcapacity, which diminishes overall efficiency. Moreover, follower cities are less capable of sophisticated policy implementation, often selecting industries and tools that do not align with their comparative advantages. They are more likely to rely on subsidies and other quick fixes, rather than adopting policies that could drive sustainable growth. Both channels lead to a significant diminishing return to industrial policies as policy diffuses to more regions across the country.

6 Conclusion and Future Work

This paper provides a comprehensive examination of China's industrial policy landscape by employing a novel large-scale text analysis approach using large language models (LLMs). By analyzing a rich dataset of 3 million government documents from central, provincial, and municipal levels, we uncover important patterns in how industrial policies are formulated, implemented, and diffused across different regions and government levels. Our analysis sheds light on several key aspects of China's industrial policy, including sectoral targeting, tool choice, policy effectiveness, and the political economy behind policy diffusion and persistence.

The comprehensive policy data unveils the multi-faceted nature of industrial policy. Combining the rich policy data and the micro-level firm data, we are able to document both the intricacies and successes of policy choices as well as the potential downside and inefficiencies. One of our key findings is that industrial policies generally align with economic theories by targeting sectors with comparative and absolute advantages, especially at the local level. However, we also document significant heterogeneity in how effective these policies are in driving firm behavior, such as entry, productivity, and investment. Not all tools are equally effective; for example, fiscal subsidies and industrial clusters have positive effects, whereas entry regulation and some environmental policies may hinder new firm entry and productivity.

We further explore the dynamics of policy diffusion and demonstrate that as more cities adopt similar policies, the effectiveness diminishes, often due to overcapacity and less strategic sectoral choices by follower cities. This suggests that policy design needs to be more carefully tailored to regional advantages and economic contexts, rather than simply replicating successful policies from other regions.

Our findings offer critical insights into how industrial policies are formulated and implemented and their varying effects on the broader economy. Moreover, this approach paves the way for future research, demonstrating the potential for using LLMs to decode complex policy environments in other countries and contexts. As global interest in industrial policy continues to grow, understanding the nuances of policy implementation and adaptation at both central and local levels will be crucial for assessing the long-term impact of these policies on economic growth and innovation.

In conclusion, our research using LLMs showcases not only the power of advanced text analysis to glean comprehensive information from complex documents but also the importance of understanding the finer details of policy implementation. By advancing the empirical understanding of industrial policy, this study opens up new avenues for investigating how governments can more effectively design and implement policies to foster long-term economic growth, innovation, and industrial upgrading. If policymakers wish to use industrial policies effectively, they must consider these complexities rather than assuming that what works in one region will necessarily work in another. Overlooking these nuances could lead to misguided conclusions and ineffective interventions.

While our study offers new insights into the mechanisms and effects of industrial policy in China, several important questions remain open for future research. We therefore propose several possibilities. First, although we document the heterogeneous effects of different policy tools, a careful structural model is needed to understand the precise mechanisms through which these tools interconnectedly influence firm behavior. For example, disentangling the relative importance of competition effects, agglomeration, and innovation spillovers in driving productivity growth remains a promising avenue for further inquiry. Second, our findings highlight the importance of policy diffusion and inter-regional correlations in policy choices. Future research could explore both the reason and the long-term consequences of such policy diffusion. As for the driving force of policy diffusion, we discussed the possibilities of top-down directive, regional competition, as well as policy learning as potential mechanisms. More careful empirical work is needed to disentangle these mechanisms. In terms of the consequences, it would be interesting to understand the long-term implications on regional economic convergence or divergence. Do regions that follow pioneering cities eventually catch up, or does the overcapacity problem persist in the long run? We leave these intriguing questions open avenues for exploration in future research.

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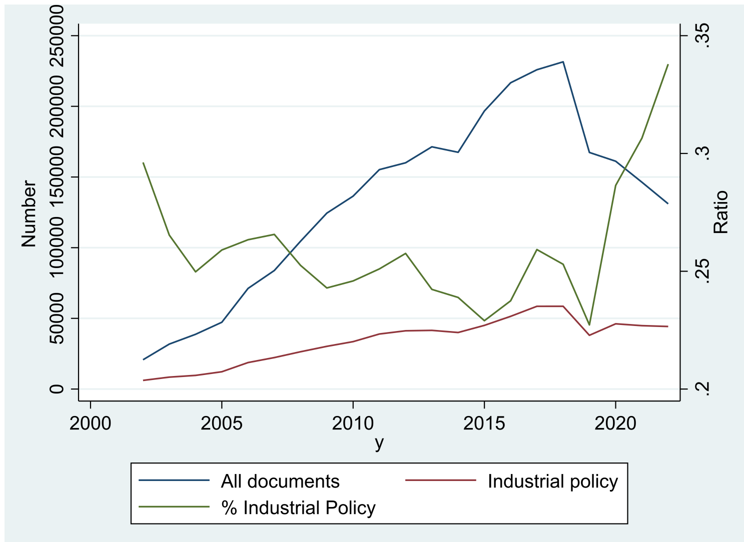
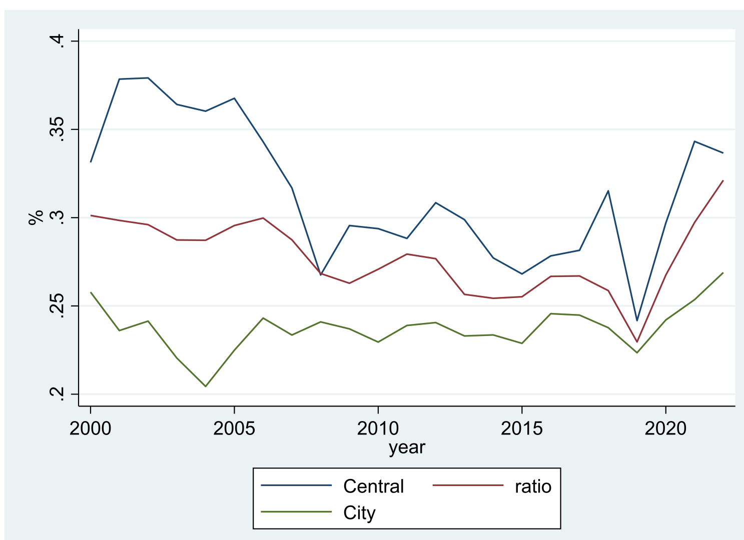
Figure 1: Evolution of the Industrial Policies



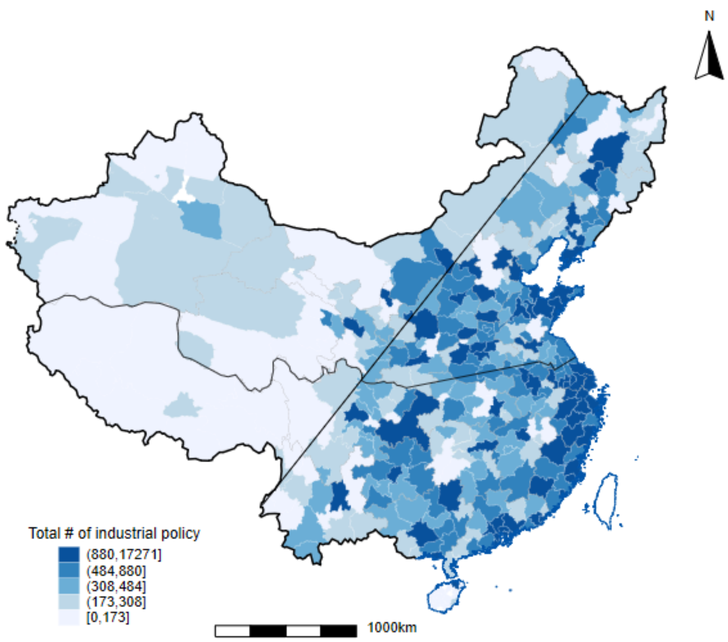
(a) Overall Volume



(b) By Government Level Ratio

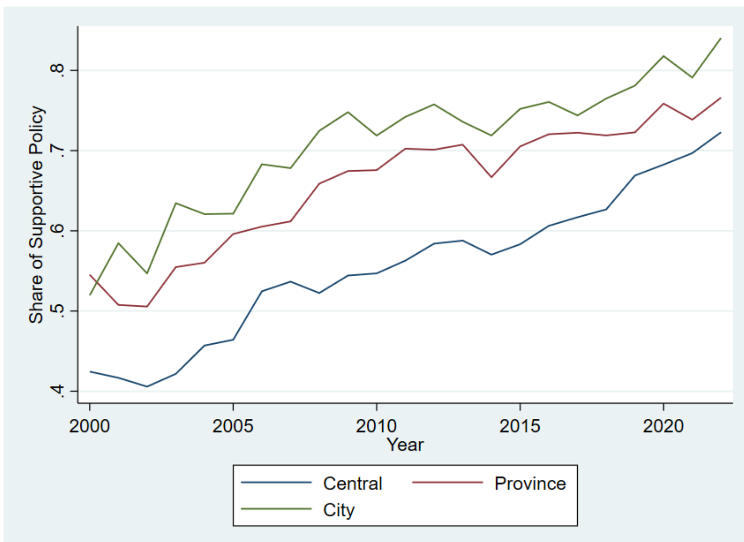
Notes: This figure presents the evolution of the share of industrial policies over time by the level of the issuing government entity. Each level of government includes all affiliated government departments and entities at the same level.

Figure 2: Geographic Distribution of the Industrial Policies



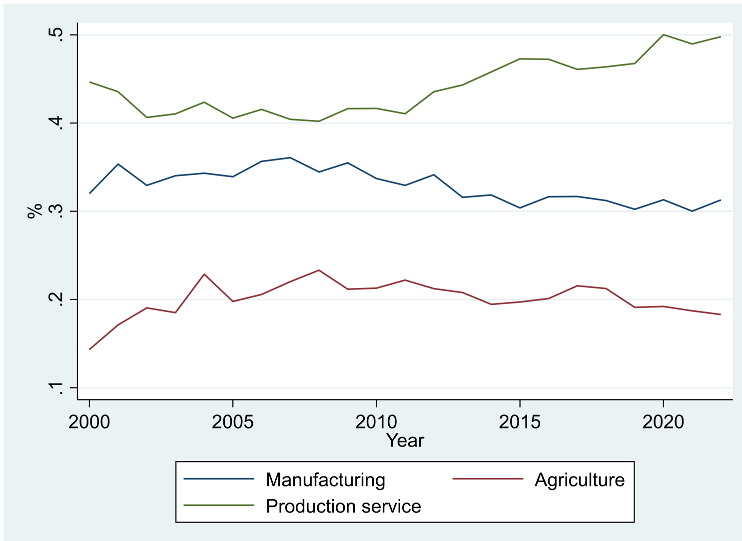
Notes: This figure presents the geographic overview of the distribution of the city-level industrial policies across China.

Figure 3: Evolution of the Direction of Industrial Policies

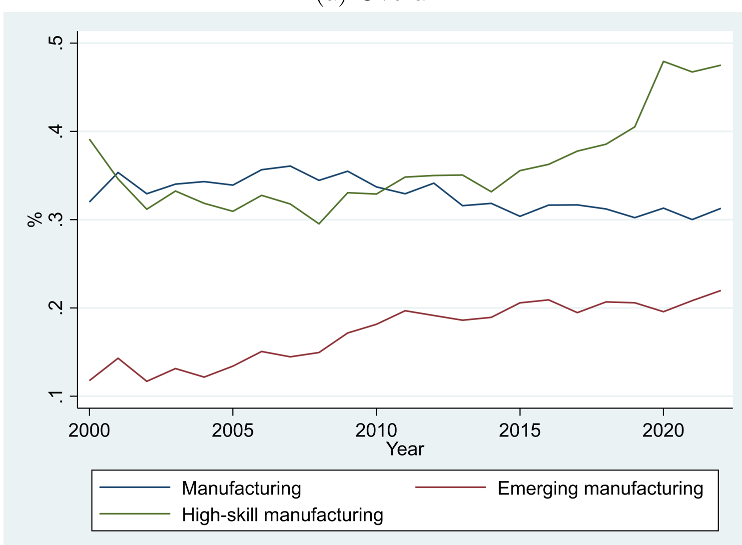


Notes: This figure presents the evolution of the direction of industrial policies over time by the level of the issuing government entity.

Figure 4: Time Trend of Policy-Targeted Industrial Sector



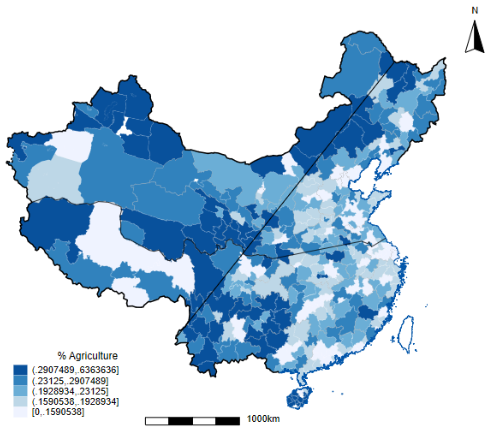
(a) Overall



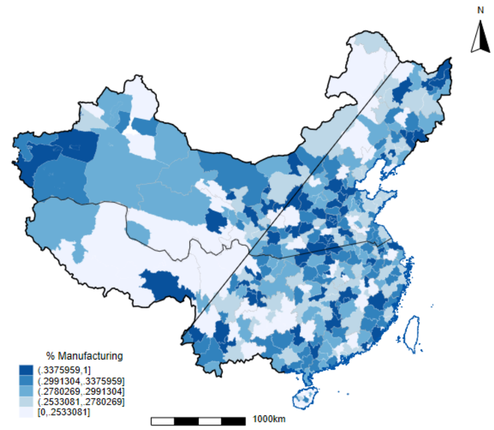
(b) Manufacturing

Notes: This figure presents the trends of the policy-targeted sector at the 2-digit level. The vertical axis represents the proportion of policies that target each sector within each government level.

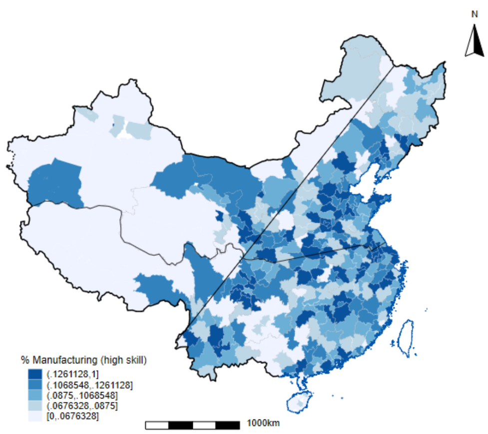
Figure 6: Geographical Distribution of Policy-Targeted Industrial Sector



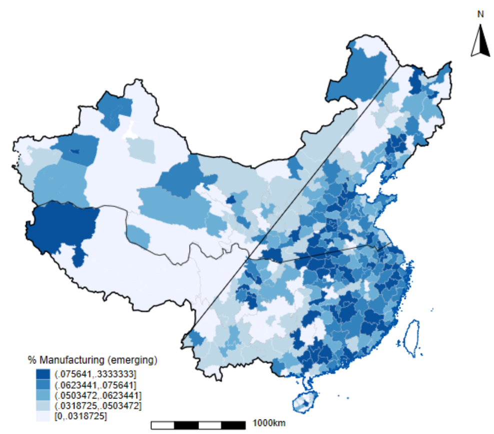
(a) % Agriculture



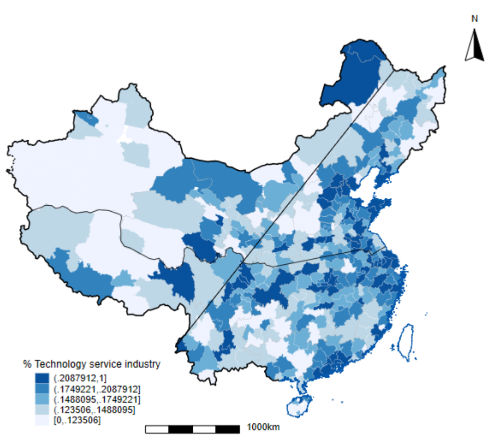
(b) % Manufacturing



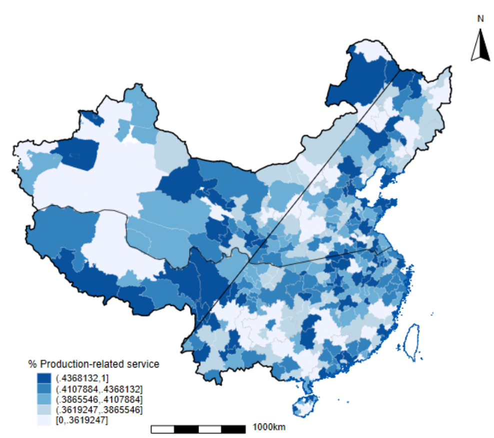
(c) % High-skill Manufacturing



(d) % Emerging New Manufacturing



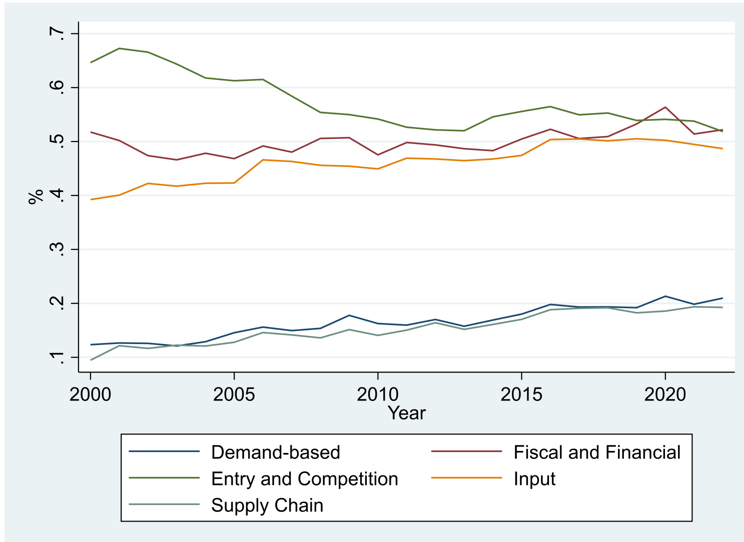
(e) % Technology-related Service



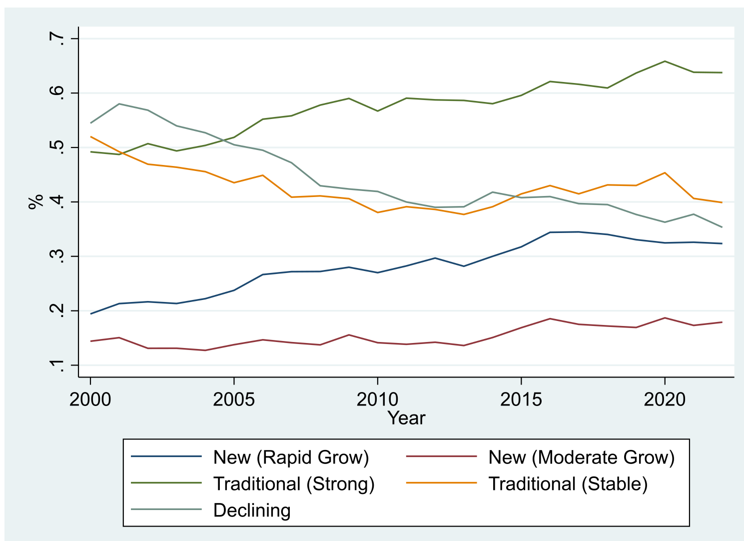
(f) % Production-related Service

Notes: This figure presents the geographical distribution of the targeted industry at 3-digit level for the city-level policies. The darkness of the color represents the proportion of policies that target each sector.

Figure 7: Time Trend of Industrial Policy Tool Usage



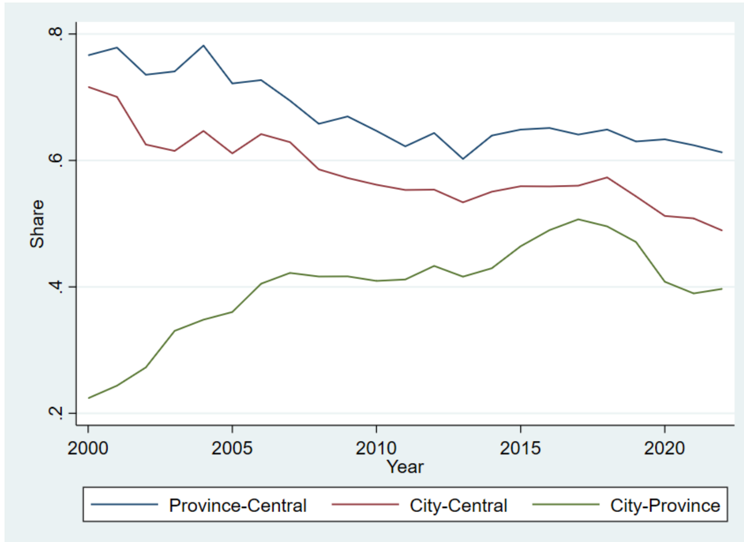
(a) By Tool Category



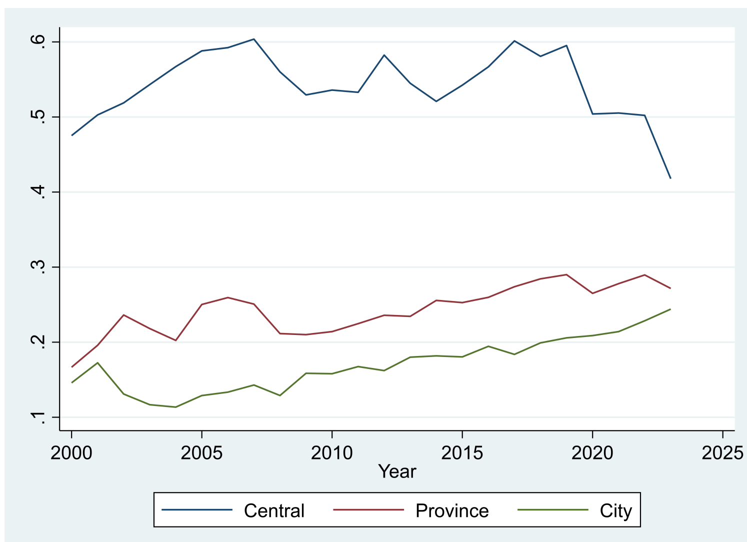
(b) By Usage Growth Pattern

Notes: his figure shows the time trends for the usage of different industrial policy tools. Panel (a) groups the tools by their objective and use, and Panel (b) r groups the tools by their initial usage intensity and growth patterns.

Figure 8: Time Trend of Policy Citation



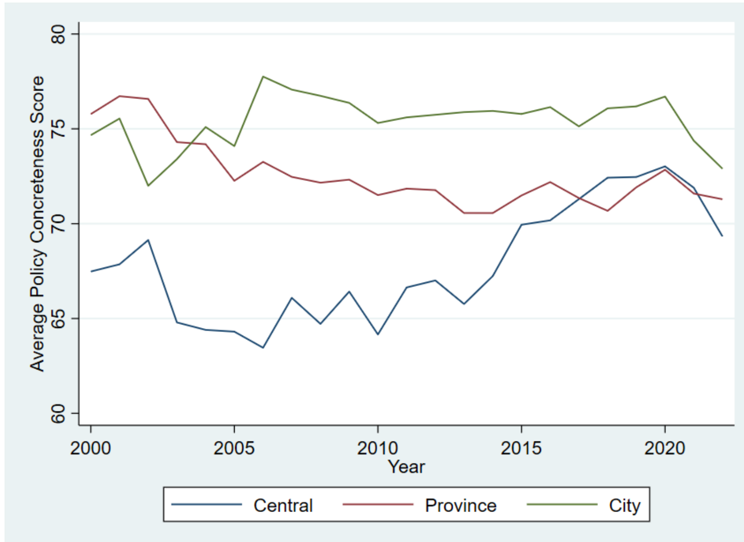
(a) Upper-level Government



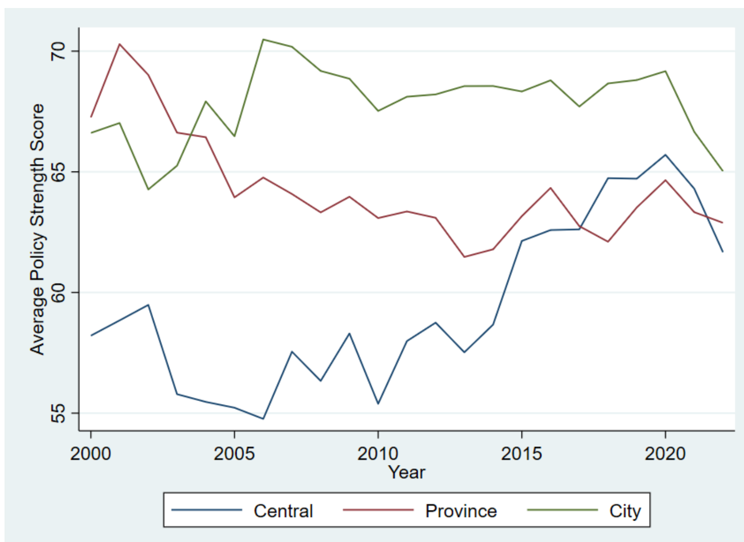
(b) Same-level-government

Notes: This figure plots the policy citation rate over time for industrial policies at different levels of government. Panel (A) plots the share of policy documents citing upper-level government. The green line represents the share of city-level policies citing provincial government policies, the red line for provincial policies citing central government policies, and the blue line for city-level policies citing central government policies. Panel (B) plots the within-government level citation rate over time, representing the share of policies that cite government entities at the same level.

Figure 9: Policy Strength Score



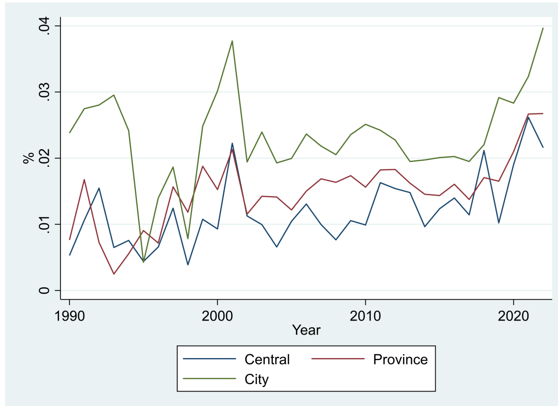
(a) Policy Concreteness



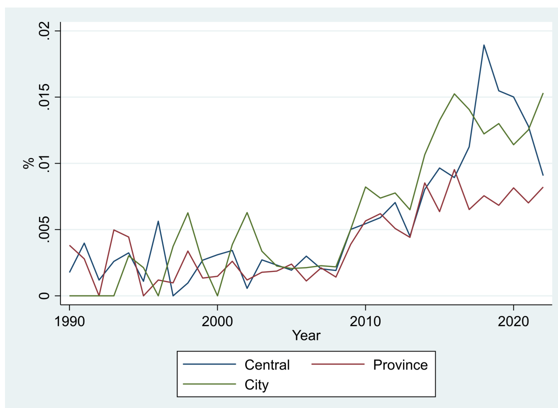
(b) Policy Strength

Notes: This figure plots the average score of policy strength at each government level over time. Panel (a) represents the score for policy concreteness, and Panel (b) represents the score of policy implementation strengths.

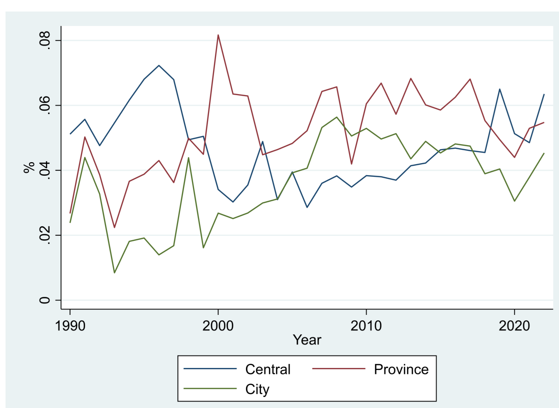
Figure 10: Time Trend of Chip, EV, and Solar Industrial Policy



(a) Chip



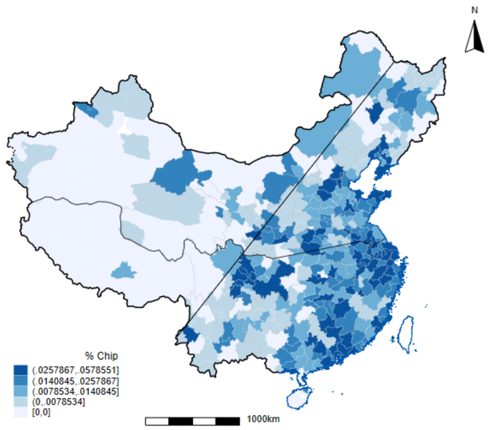
(b) EV



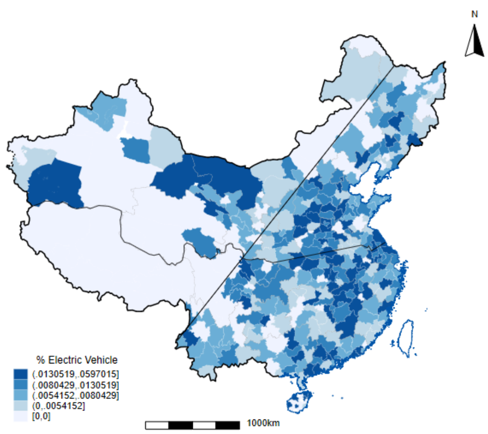
(c) Solar

Notes: This figure plots the time trends of industrial policy activity for three key industries— EV, solar, and semiconductor. These trends highlight the differences in how policy support has evolved across government levels—central, provincial, and city—over time.

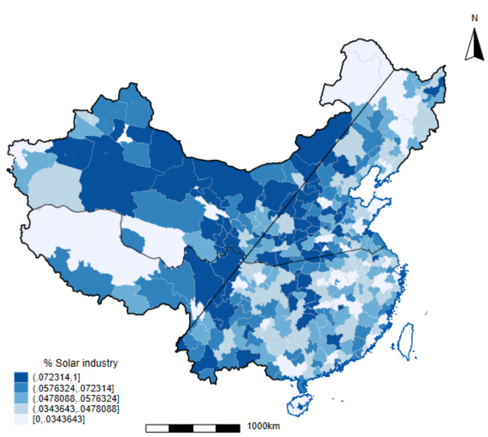
Figure 11: Geographic Distribution of Chip, EV, and Solar Industrial Policy



(a) Chip



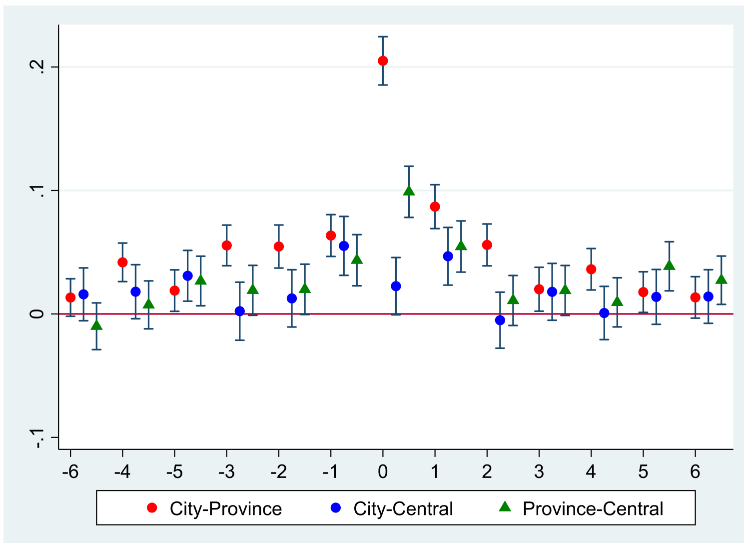
(b) EV



(c) Solar

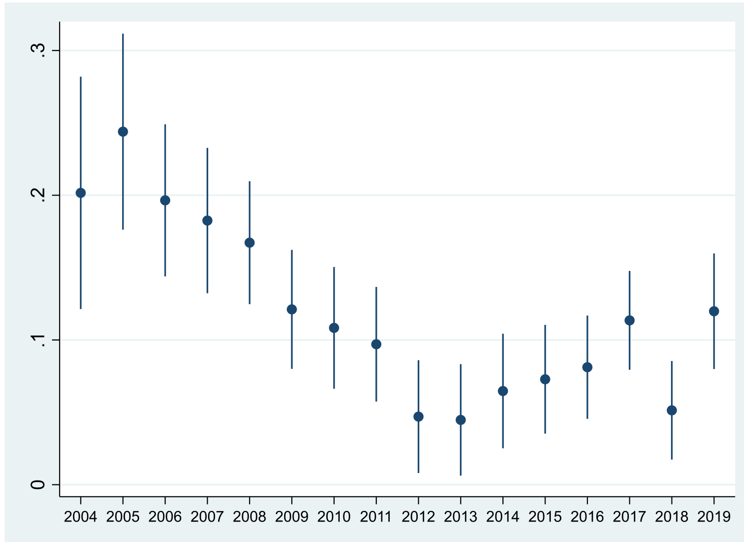
Notes: This figure plots the geographical distribution of industrial policy activity for three key industries— EV, solar, and semiconductor. The darkness of the color represents the proportion of policies that target each sector.

Figure 12: Policy Top-down Pass-through

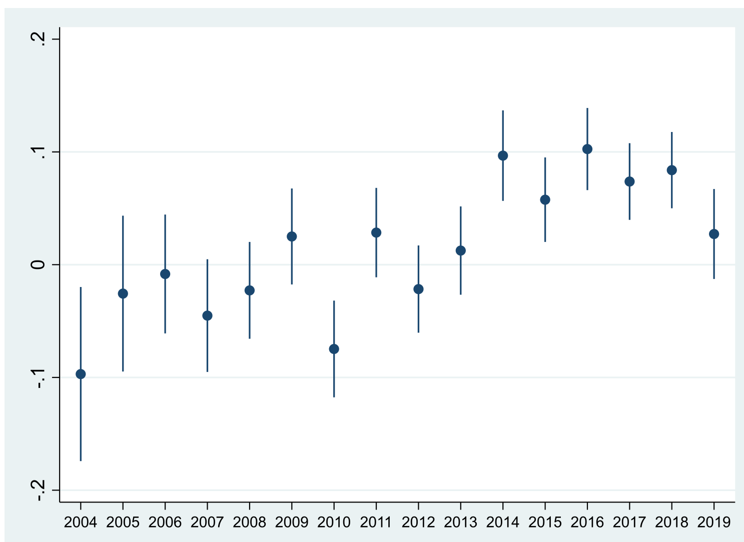


Notes: This figure plots the coefficients and the corresponding 95% confidence intervals of estimating Equations 2 and 3. The red dots represent the coefficients estimated for β_t^p in Equation (2), blue dots for β_t^n in Equation (2), and green triangles for β_t^n in Equation (3). The unit of observation is 4-digit industry-city-year level, and the sample coverage is 2005-2020. Standard errors are clustered at the city-by-industry level.

Figure 13: The Dynamics of Policy Pass-through



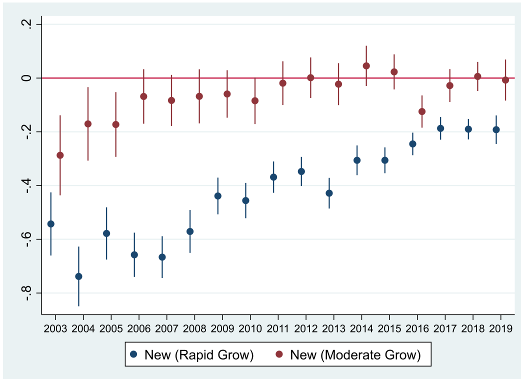
(a) Policy Pass-through (Province)



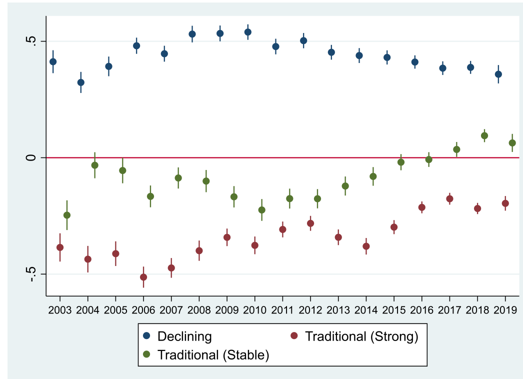
(b) Policy Pass-through (Nation)

Notes: This figure plots the coefficients and the corresponding 95% confidence intervals of estimating Equation 5. The unit of observation is 4-digit industry-city-year level, and the sample coverage is 2005-2020. Standard errors are clustered at the city-by-industry level.

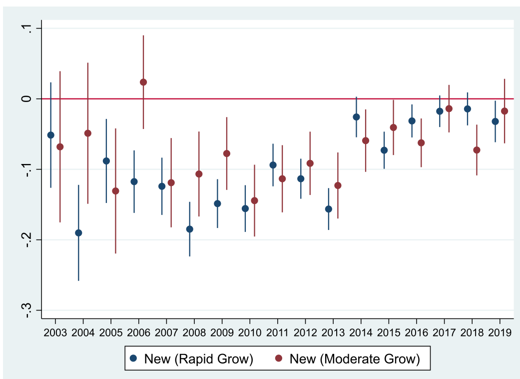
Figure 14: Time Trend of Tool Adoption by Government Level



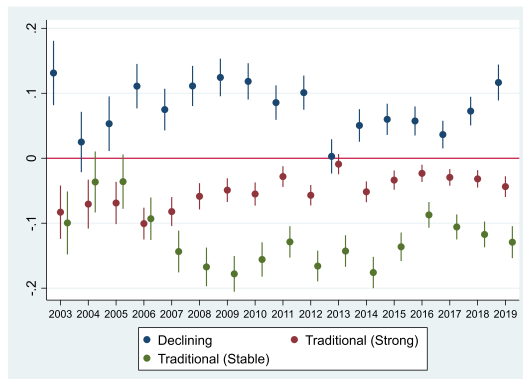
(a) New Tools



(b) Traditional Tools



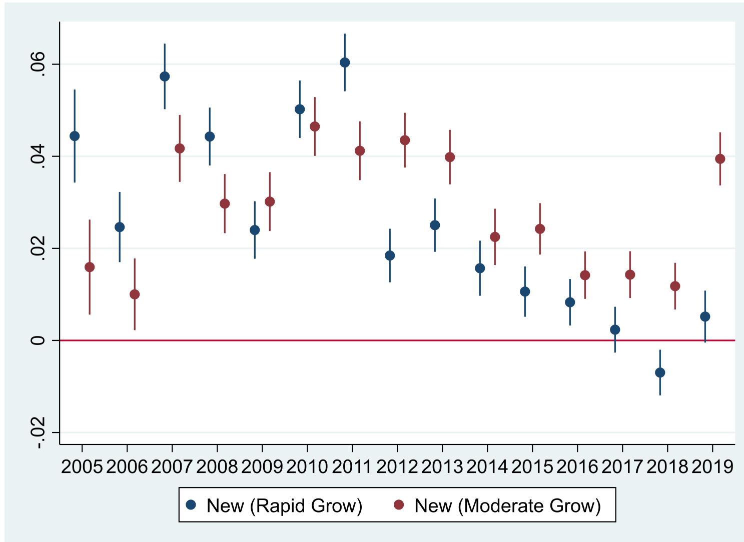
(c) New Tools



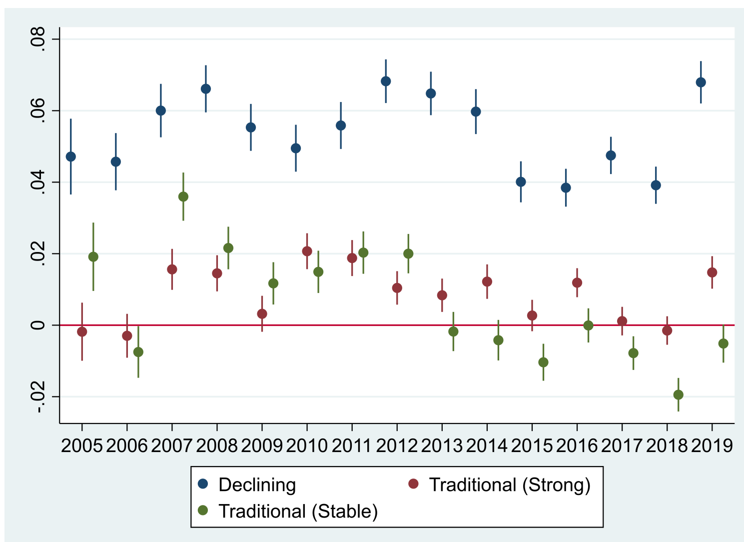
(d) Traditional Tools

Notes: This figure plots the time trend in tool usage across government levels by estimating Equation (7) with PPML. Panels (a) and (b) plot β^ns— the coefficient estimated for the central government— to compare the central government versus the city-level government in tool usage. Panels (c) and (d) compare the provincial-level government and the city-level government by plotting the coefficients for the provincial-level government β^ps.

Figure 15: Time Trend of Tool Adoption By City GDP



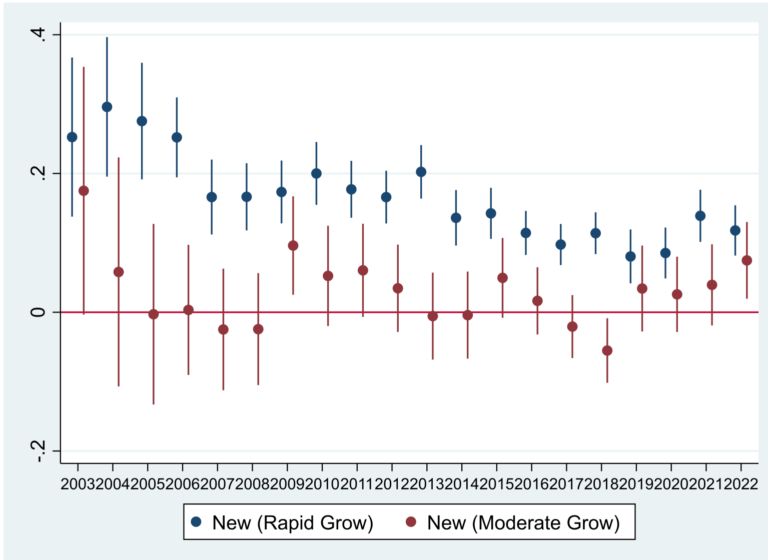
(a) New Tools



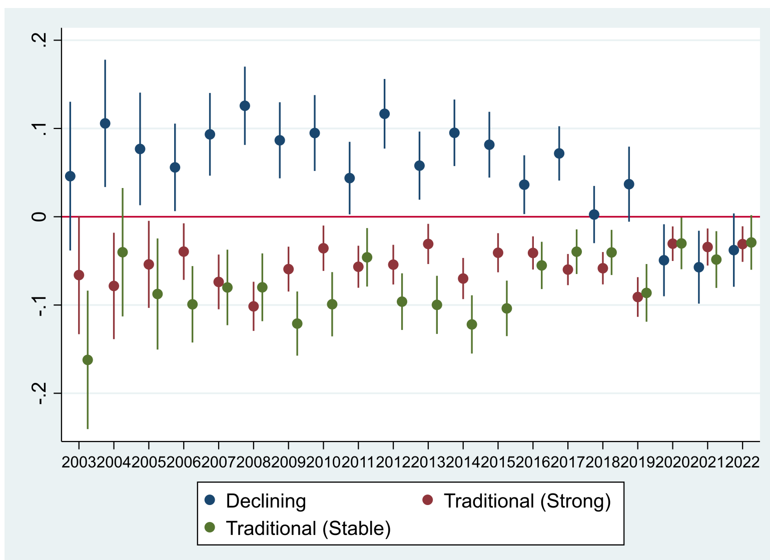
(b) Traditional Tools

Notes: This figure plots the estimated coefficients for β_t by estimating Equation (8) to illustrate the time trend of tool adoption by city development level.

Figure 16: Time Trend of Tool Adoption (Manufacturing)



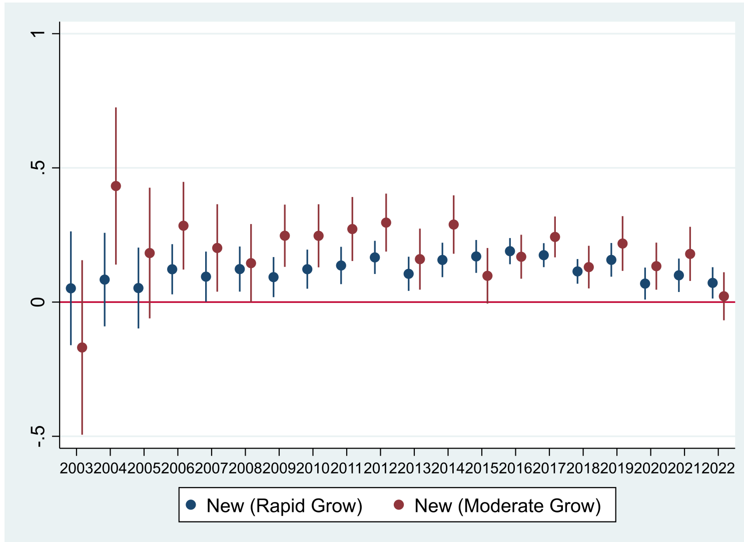
(a) New Tools



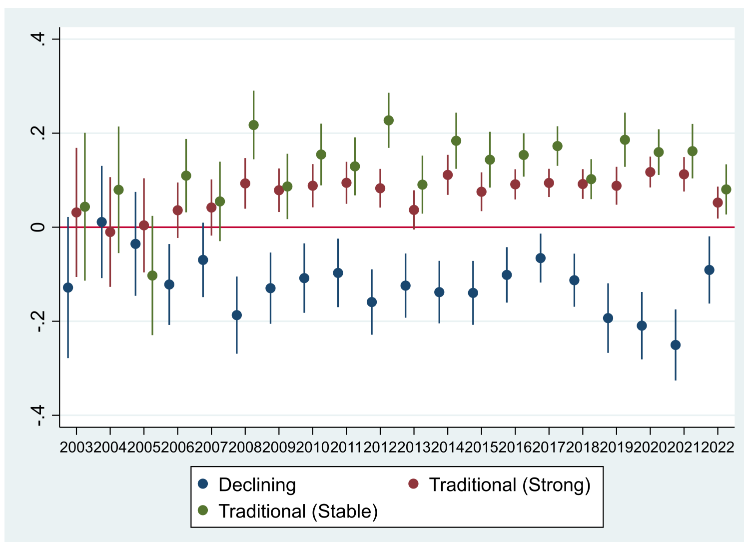
(b) Traditional Tools

Notes: This figure plots the estimated coefficients for β_t by estimating Equation (9) to illustrate the time trend of tool adoption in the manufacturing industry versus other industries.

Figure 17: Time Trend of Tool Adoption (High-skill Manufacturing)



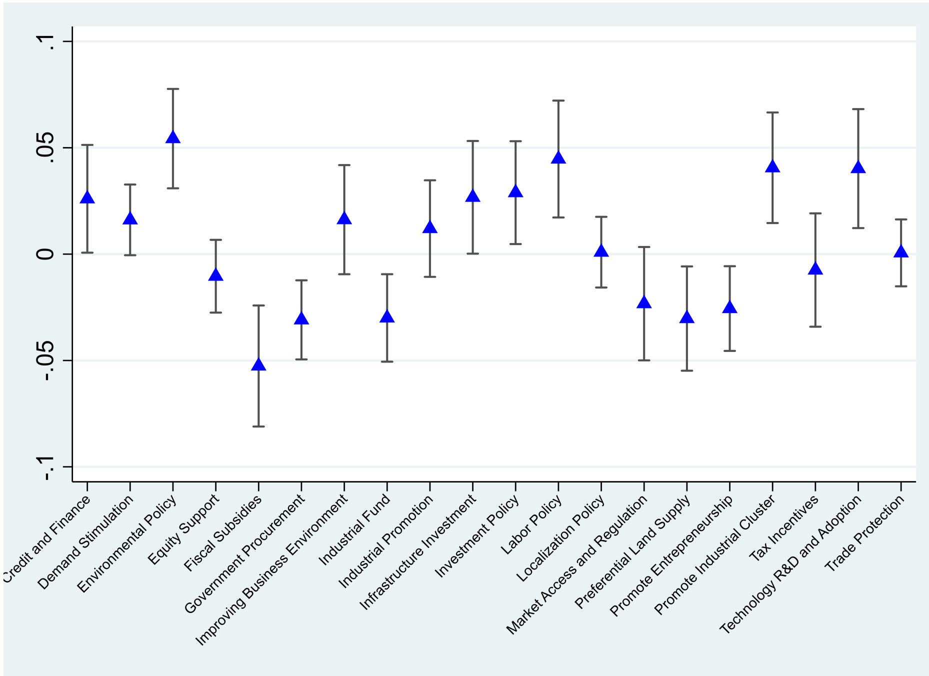
(a) New Tools



(b) Traditional Tools

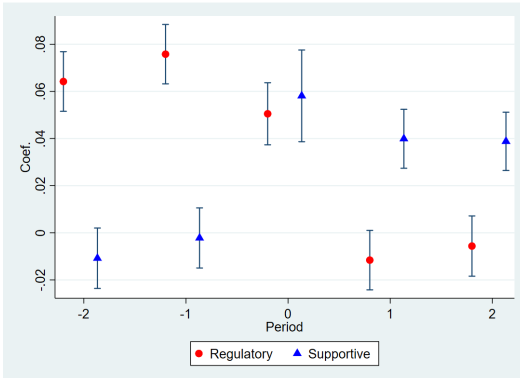
Notes: This figure plots the estimated coefficients for β_t by estimating Equation (9) to illustrate the time trend of tool adoption, within the manufacturing sector, skill-intensive industries versus other traditional industries.

Figure 18: Within-industry Change in Tool Choice

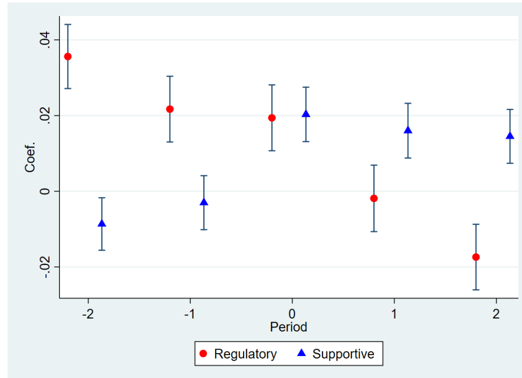


Notes: This figure plots the estimated coefficients for β_k by estimating Equation (10) for various tools, where a positive coefficient indicates an increased likelihood of tool utilization as the industry matures (more years from the initial target year in the city).

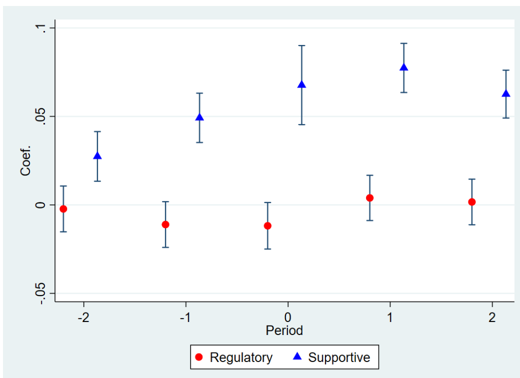
Figure 19: Effect of Industrial Policy: Subsidy and Tax Deduction



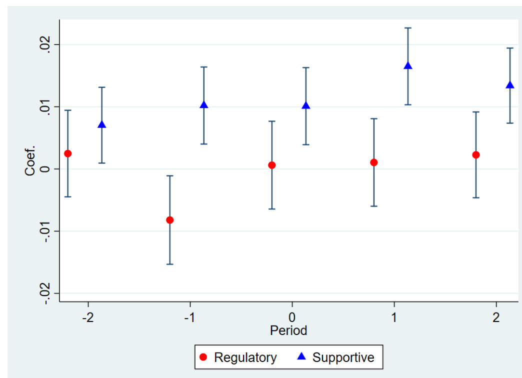
(a) Subsidy (City-by-industry FE)



(b) Subsidy (Firm FE)



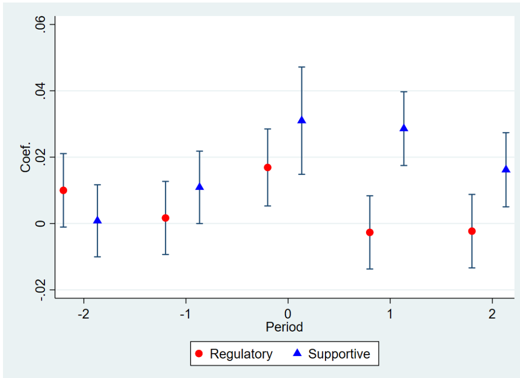
(c) Tax Deduction (City-by-industry FE)



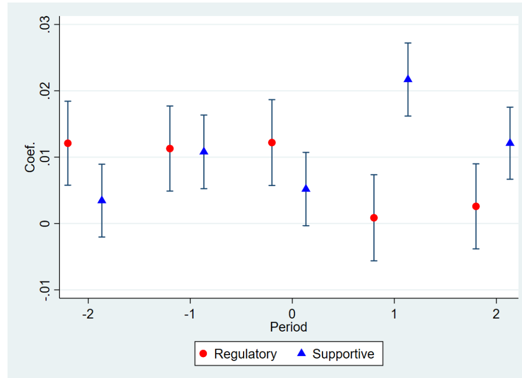
(d) Tax Deduction (Firm FE)

Notes: This figure plots the coefficients and the corresponding 95% confidence intervals of estimating Equation 15. The unit of observation is firm-year level, and the sample coverage is 2008-2020. Panel A and C control for city-by-industry and year fixed effects. Panel B and D control for firm and year fixed effects and city-by-industry trend. Standard errors are clustered at the city-by-industry level.

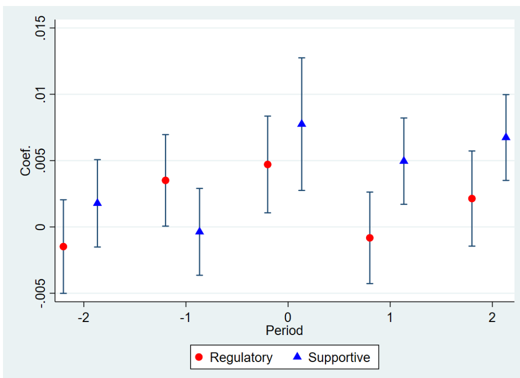
Figure 20: Effect of Industrial Policy: Debt and Leverage



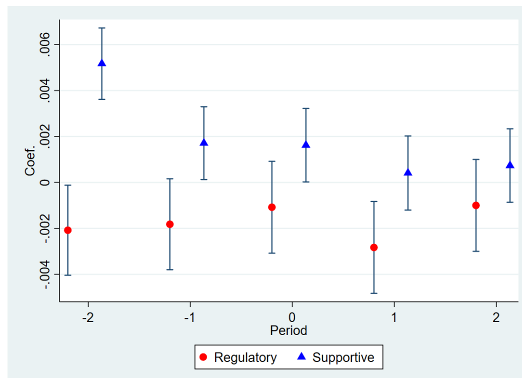
(a) Long Term Debt (City-by-industry FE)



(b) Long Term Debt (Firm FE)



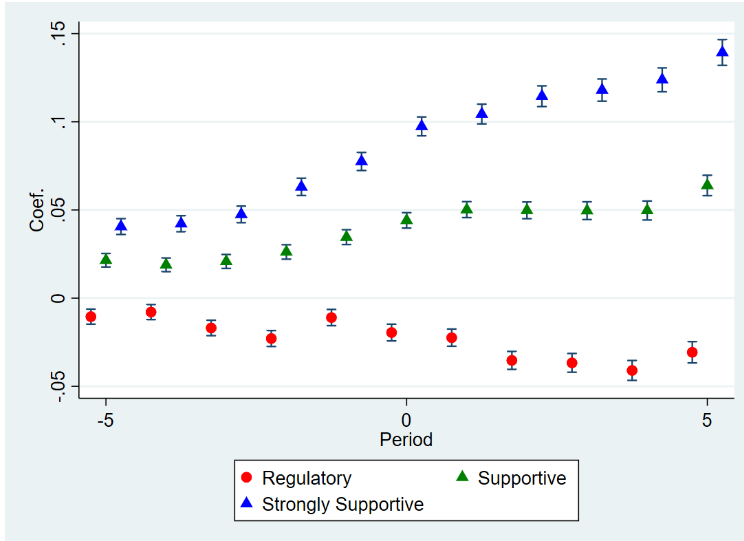
(c) Leverage Ratio (City-by-industry FE)



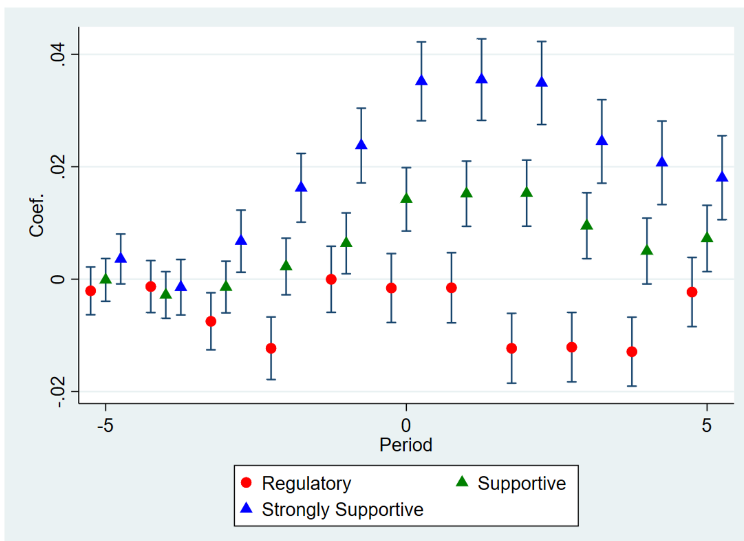
(d) Leverage Ratio (Firm FE)

Notes: This figure plots the coefficients and the corresponding 95% confidence intervals of estimating Equation 15. The unit of observation is firm-year level, and the sample coverage is 2008-2020. Panel A and C control for city-by-industry and year fixed effects. Panel B and D control for firm and year fixed effects and city-by-industry trend. Standard errors are clustered at the city-by-industry level.

Figure 21: Effect of Industrial Policy: New Firm Entry Dynamics



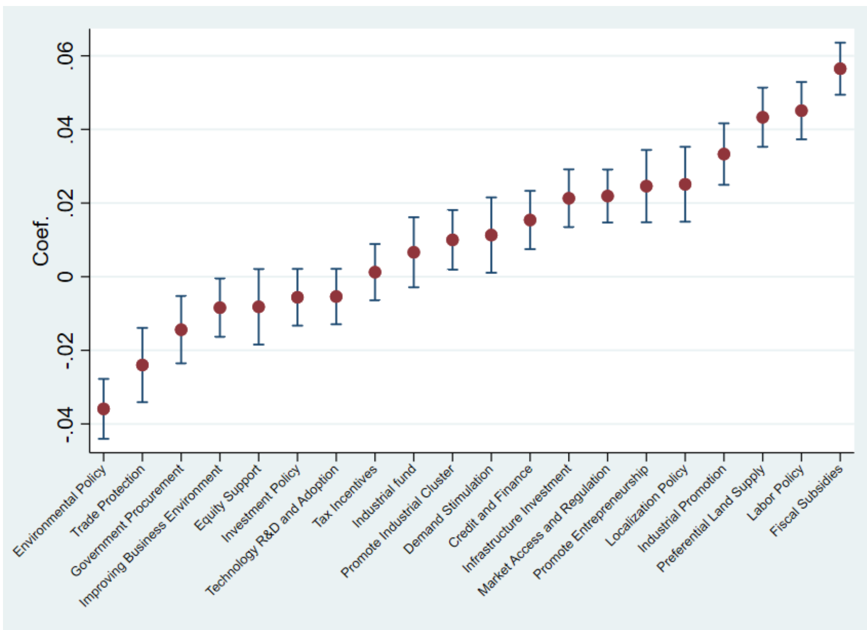
(a) No Trend



(b) City-by-industry Detrend

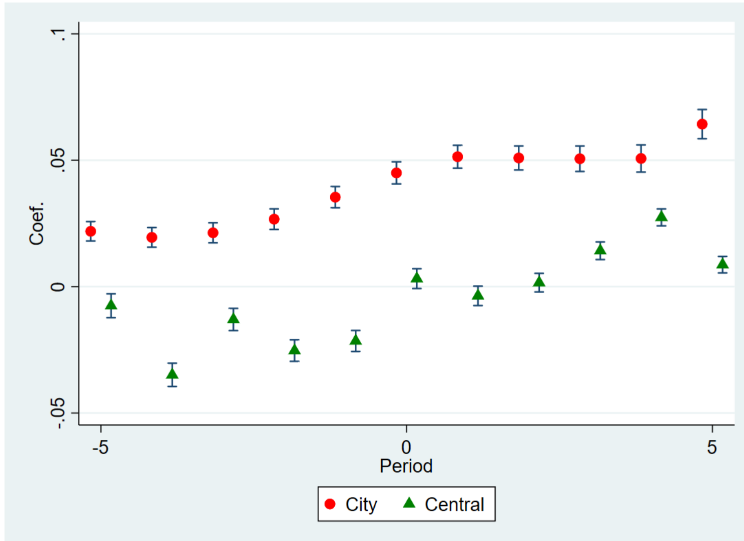
Notes: This figure plots the coefficients and the corresponding 95% confidence intervals of estimating Equation 15. The unit of observation is 4-digit industry-city-year level, and the sample coverage is 2005-2020. Panel A controls for city-by-industry and year fixed effects. Panel A controls for city-by-industry and year fixed effects and city-by-industry trend. Standard errors are clustered at the city-by-industry level.

Figure 22: Effect of Industrial Policy Tools: New Firm Entry

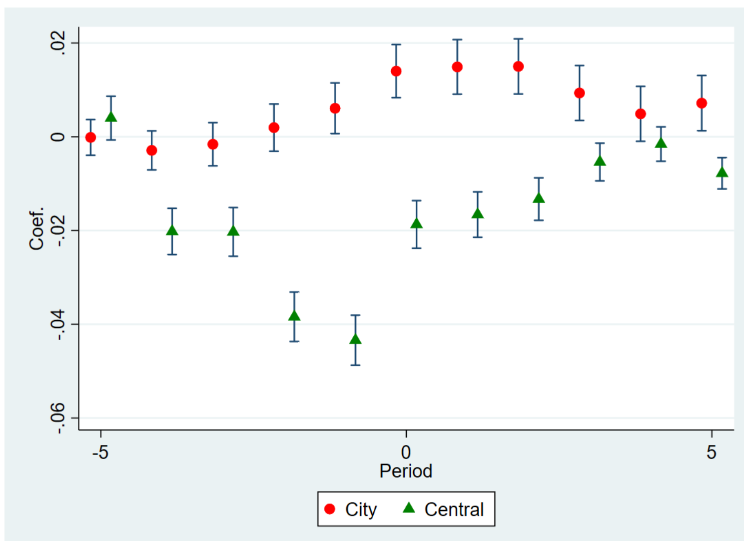


Notes: This figure plots the coefficients and the corresponding 95% confidence intervals of estimating Equation 17 for each industrial policy tool. The unit of observation is 4-digit industry-city-year level, and the sample coverage is 2005-2020. Standard errors are clustered at the city-by-industry level.

Figure 23: Effect of Industrial Policy (Supportive): New Firm Entry Dynamics



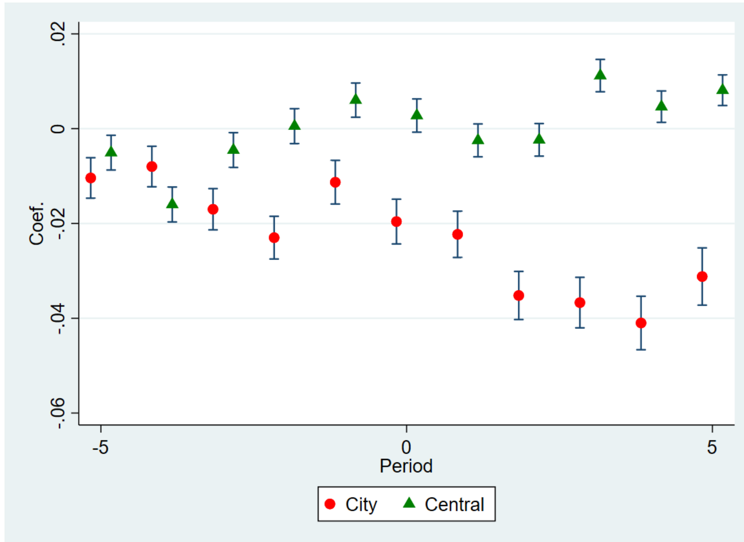
(a) No Trend



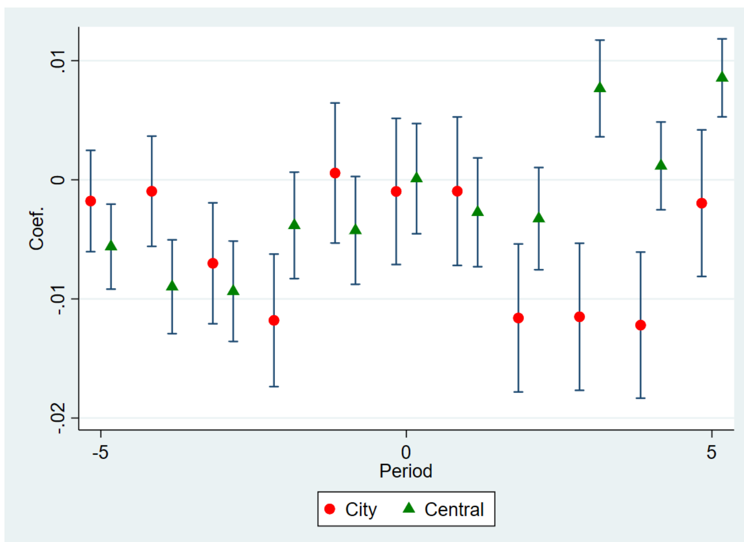
(b) City-by-industry Detrend

Notes: This figure plots the coefficients and the corresponding 95% confidence intervals of estimating Equation 15. The unit of observation is 4-digit industry-city-year level, and the sample coverage is 2005-2020. Panel A controls for city-by-industry and year fixed effects. Panel A controls for city-by-industry and year fixed effects and city-by-industry trend. Standard errors are clustered at the city-by-industry level.

Figure 24: Effect of Industrial Policy (Regulatory): New Firm Entry Dynamics



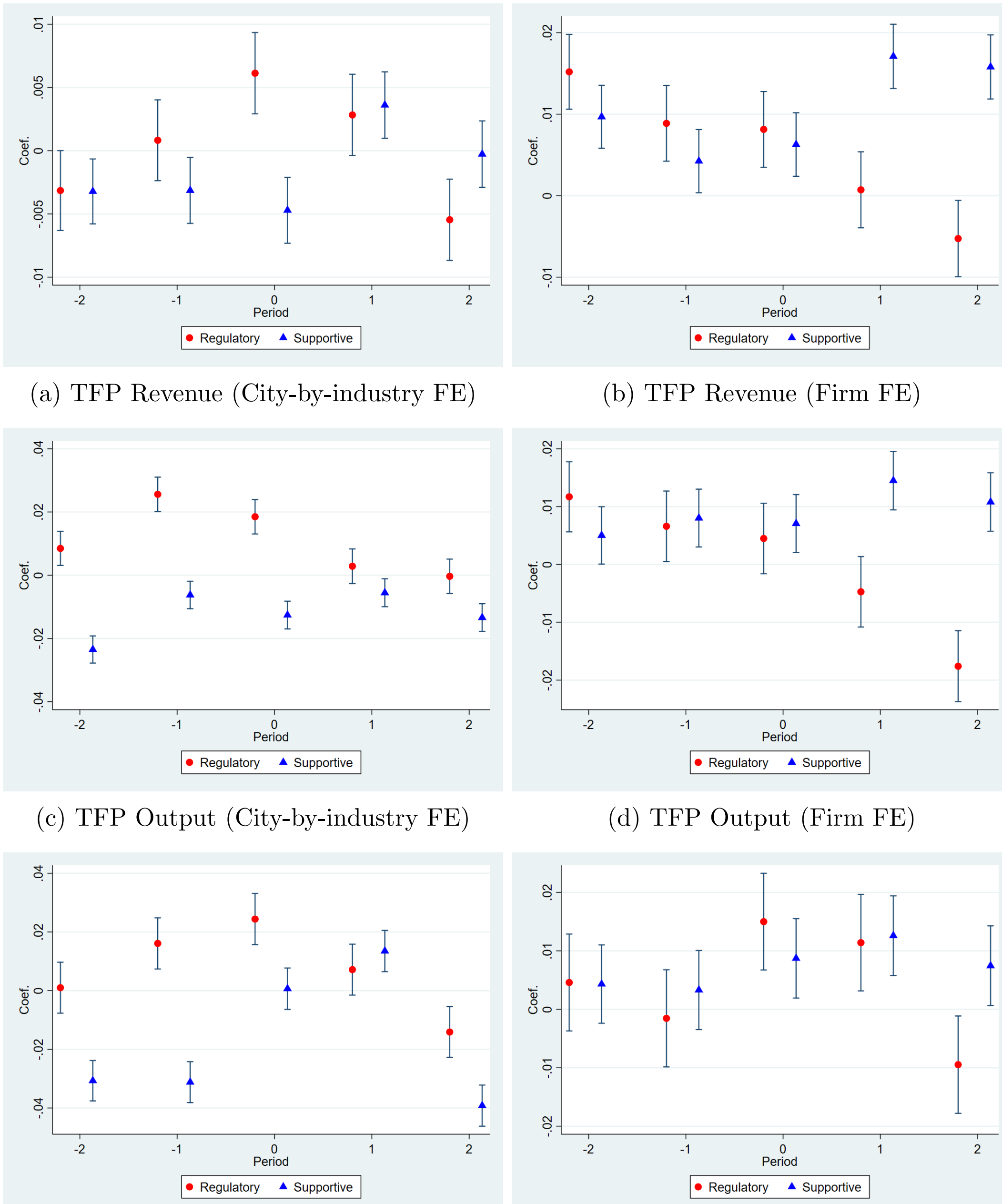
(a) No Trend



(b) City-by-industry Detrend

Notes: This figure plots the coefficients and the corresponding 95% confidence intervals of estimating Equation 15. The unit of observation is 4-digit industry-city-year level, and the sample coverage is 2005-2020. Panel A controls for city-by-industry and year fixed effects. Panel A controls for city-by-industry and year fixed effects and city-by-industry trend. Standard errors are clustered at the city-by-industry level.

Figure 25: Effect of Industrial Policy: TFP



(a) TFP Revenue (City-by-industry FE)

(b) TFP Revenue (Firm FE)

(c) TFP Output (City-by-industry FE)

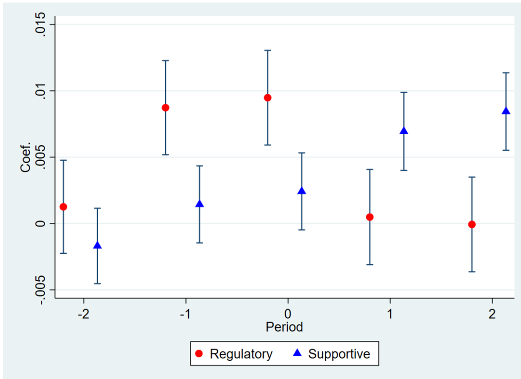
(d) TFP Output (Firm FE)

(e) TFP Value-added (City-by-industry FE)

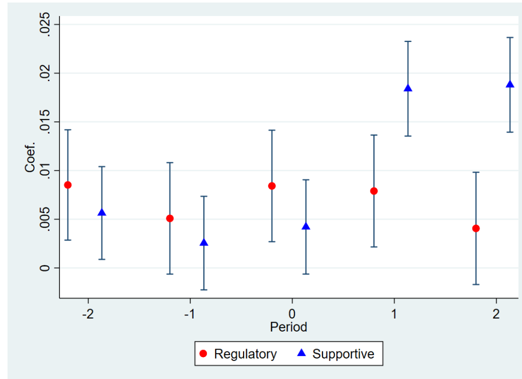
(f) TFP Value-added (Firm FE)

Notes: This figure plots the coefficients and the corresponding 95% confidence intervals of estimating Equation 15. 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 and city-by-industry trend. Standard errors are clustered at the city-by-industry level.

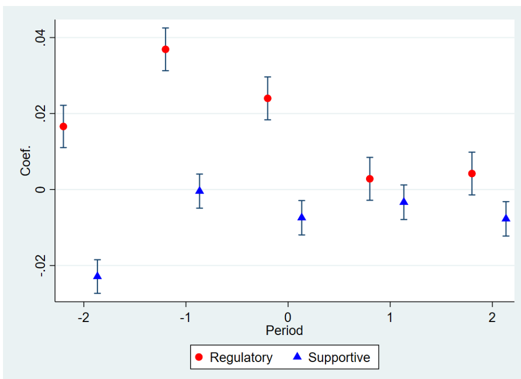
Figure 26: Effect of Industrial Policy: Revenue, Output, and Value-added



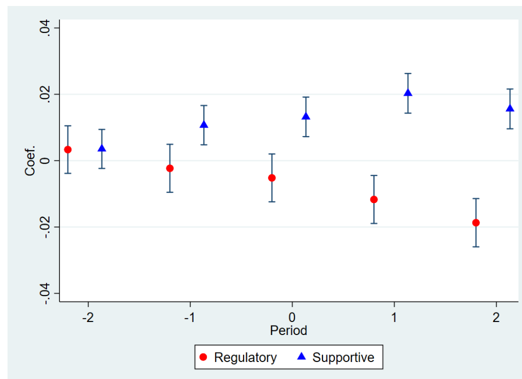
(a) Revenue (City-by-industry FE)



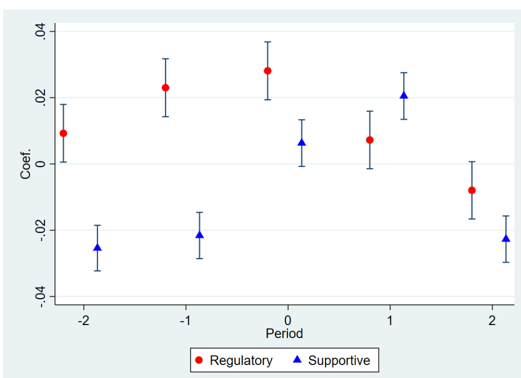
(b) Revenue (Firm FE)



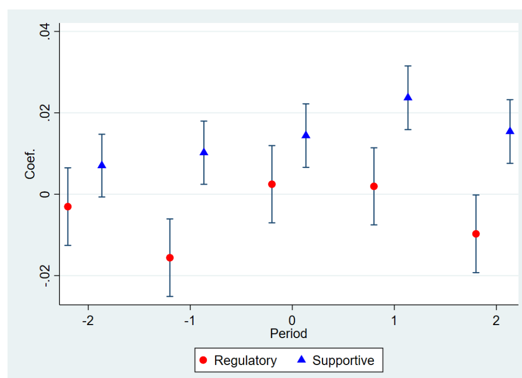
(c) Output (City-by-industry FE)



(d) Output (Firm FE)



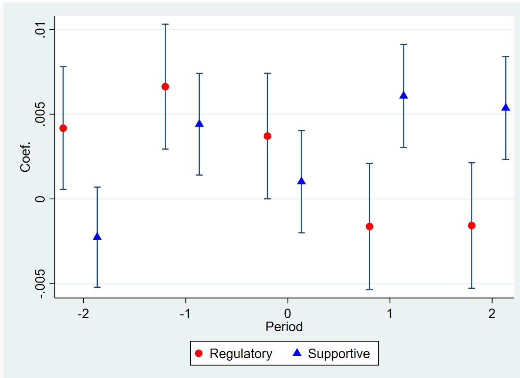
(e) Value-added (City-by-industry FE)



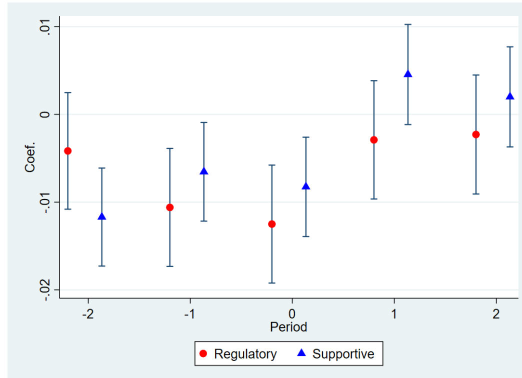
(f) Value-added (Firm FE)

Notes: This figure plots the coefficients and the corresponding 95% confidence intervals of estimating Equation 15. 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 and city-by-industry trend. Standard errors are clustered at the city-by-industry level.

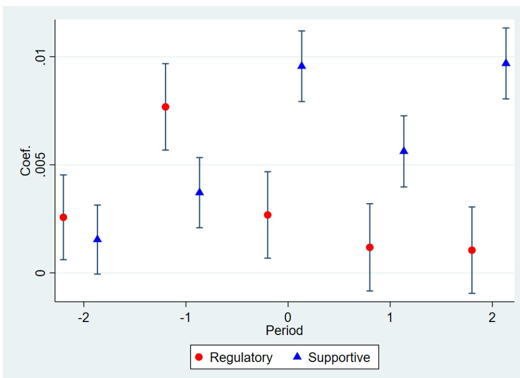
Figure 27: Effect of Industrial Policy: Input



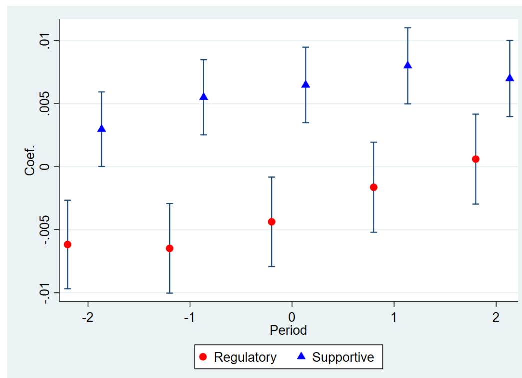
(a) Capital (City-by-industry FE)



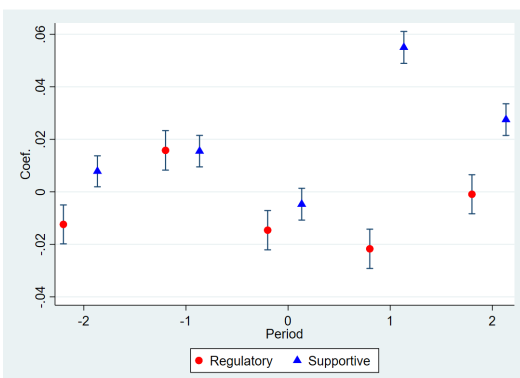
(b) Capital (Firm FE)



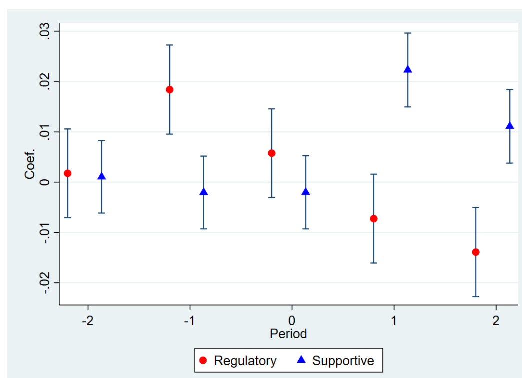
(c) Labor (City-by-industry FE)



(d) Labor (Firm FE)



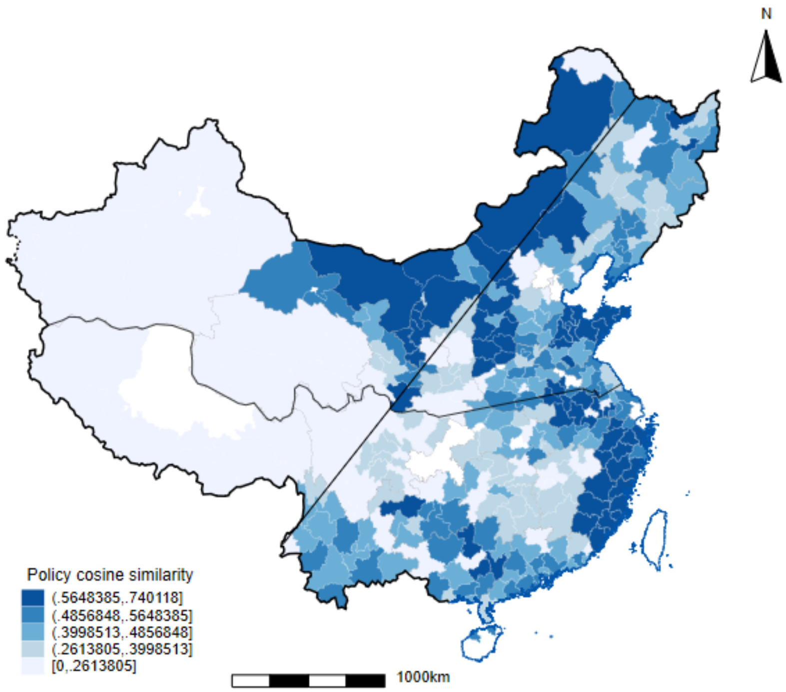
(e) Intermediate Input (City-by-industry FE)



(f) Intermediate Input (Firm FE)

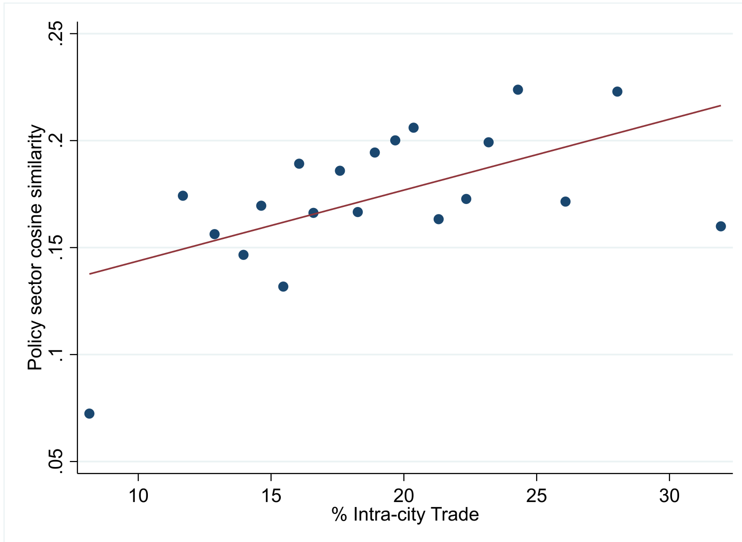
Notes: This figure plots the coefficients and the corresponding 95% confidence intervals of estimating Equation 15. The unit of observation is firm-year level, and the sample coverage is 2008-2020. Panel A, C, and E control for city-by-industry and year fixed effects. Panel B, D, and F control for firm and year fixed effects and city-by-industry trend. Standard errors are clustered at the city-by-industry level.

Figure 28: Geographical Distribution of Policy Sector Similarity

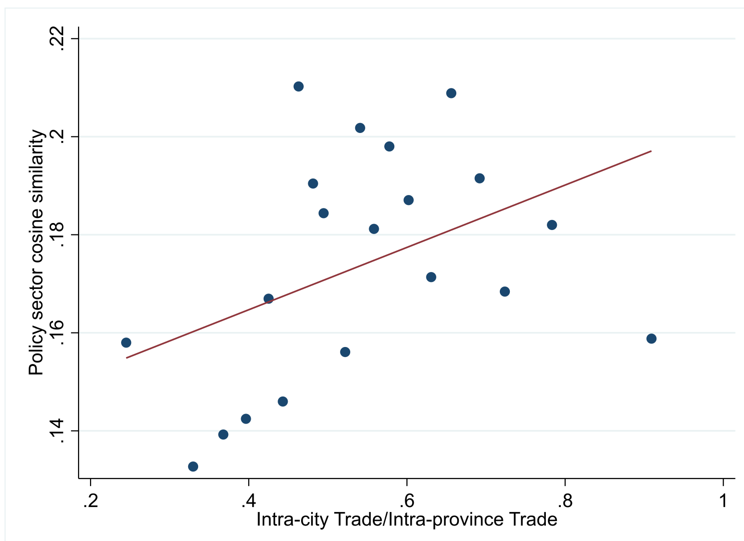


Notes: This figure plots the geographical distribution of policy similarity. Policy similarity is calculated as the cosine similarity of industry-level policy vector between city pairs, focusing on intra-province similarities. We then calculate the city-year level policy similarity index as the average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

Figure 29: Policy Sector Similarity and Local Protectionism



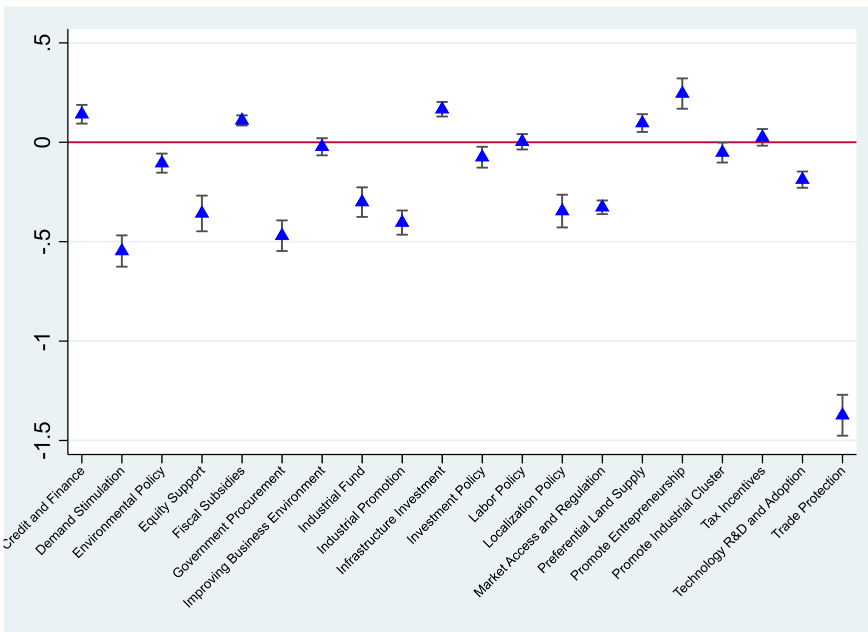
(a) % Intra-city Trade



(b) 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. We then calculate the city-year level policy similarity index as the average similarity for each city with all other cities in the same province.

Figure 30: Policy Diffusion and Policy Tool



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 policy level, and the sample coverage is 2005-2020. 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 Share 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 Direction by Government Level

	Support		Suppress		Regulate	
	#	%	#	%	#	%
Central	57,272	56.81	3,168	3.14	40,365	40.04
Province	238,708	69.62	3,923	1.14	100,254	29.24
City	220,069	74.69	4,152	1.41	70,407	23.90

Note: This table presents the distribution of the direction of industrial policies by the level of the issuing government entity.

Table 4: Summary Statistics: Number of Industrial Policy Documents

Variable	Obs	Mean	Std. dev.	Min	Max
Panel A: City-Industry-Year Level					
# of Policy	2,896,320	0.32	1.43	0	106
# of Supportive Policy	2,896,320	0.25	1.13	0	75
# of Regulatory Policy	2,896,320	0.08	0.52	0	66
Panel B: Province-Industry-Year Level					
# of Policy	267,220	3.60	7.93	0	320
# of Supportive Policy	267,220	2.61	6.28	0	295
# of Regulatory Policy	267,220	0.98	2.50	0	101
Panel C: Nation-Industry-Year Level					
# of Policy	8,620	11.70	19.17	0	235
# of Supportive Policy	8,620	6.44	12.06	0	185
# of Regulatory Policy	8,620	5.26	9.04	0	129

Note: This table presents the summary statistics of the number of policy documents at region-industry-year level by the level of the issuing government entity.

Table 5: Industrial Policy Target Sector by Government Level

	All	Central	Province	City
Agriculture	0.20	0.15	0.21	0.20
Manufacturing	0.32	0.38	0.31	0.32
Manufacturing (emerging)	0.06	0.05	0.05	0.08
Manufacturing (high skill)	0.12	0.13	0.12	0.12
Service	0.52	0.40	0.45	0.56
Service (high skill)	0.19	0.16	0.20	0.21
Technology related service	0.22	0.22	0.22	0.24
Production related service	0.45	0.44	0.44	0.48
Life service	0.23	0.20	0.20	0.27
Observations	688227	93708	310984	257686

Note: This table presents a breakdown of the target sectors (by 2-digit industry code or key industry characteristics for the standards of the classifications of these industry labels.) of industrial policies, categorized by government level. Each cell reports the share of the government documents within the same government level that targets the sector.

Table 6: Industrial Policy Tool Classification

	All	Central	Province	City
Subsidy and Finance				
Credit and Finance	0.15	0.11	0.13	0.18
Tax Incentives	0.20	0.20	0.17	0.24
Equity Support	0.05	0.04	0.04	0.06
Fiscal Subsidies	0.43	0.26	0.41	0.49
Entry and Regulation				
Industrial Fund	0.07	0.04	0.06	0.09
Promote Entrepreneurship	0.06	0.04	0.05	0.08
Investment Policy	0.14	0.11	0.12	0.16
Improving Business Environment	0.19	0.14	0.16	0.23
Market Access and Regulation	0.37	0.44	0.36	0.36
Trade Protection	0.09	0.20	0.08	0.07
Input				
Labor Policy	0.23	0.16	0.22	0.28
Preferential Land Supply	0.13	0.06	0.11	0.18
Infrastructure Investment	0.19	0.12	0.16	0.23
Technology R&D and Adoption	0.25	0.21	0.24	0.28
Environmental Policy	0.14	0.09	0.13	0.16
Demand-side				
Demand Stimulation	0.05	0.04	0.05	0.07
Government Procurement	0.07	0.05	0.07	0.08
Industrial Promotion	0.11	0.07	0.10	0.13
Supply Chain				
Promote Industrial Cluster	0.14	0.08	0.13	0.18
Localization Policy	0.05	0.03	0.04	0.07
Observations	745727	97891	332711	286632

Note: This table presents the share of usage (defined as the percentage of policy documents that report using the tool) for each industrial policy tool with a breakdown into different government levels.

Table 7: Industrial Policy Objective by Government Level

	All	Central	Province	City
Key industry				
Promote strategic industry	0.56	0.58	0.55	0.56
Promote pillar industry	0.11	0.07	0.10	0.12
Promote emerging industry	0.17	0.13	0.15	0.20
Support traditional advantageous industry	0.10	0.09	0.10	0.10
Upgrade traditional industry	0.14	0.11	0.13	0.15
Support green industry	0.06	0.05	0.06	0.07
Promote other key industry	0.19	0.18	0.19	0.19
Innovation				
Promote innovation	0.23	0.23	0.23	0.24
Promote new technology adoption	0.10	0.08	0.09	0.11
Social welfare				
Urbanization	0.08	0.05	0.06	0.10
Stimulate employment	0.19	0.16	0.17	0.21
Promote social equity and welfare	0.33	0.30	0.32	0.33
Other social goal	0.06	0.07	0.06	0.06
Observations	473402	56390	210120	187561

Note: This table presents the distribution of government objectives of industrial policies, categorized by government level. Each cell reports the proportion of the government documents within each government level that states the policy objective.

Table 8: Industrial Policy Requirement by Government Level

	All	Central	Province	City
Firm Location	0.48	0.40	0.48	0.50
Specific Firms	0.25	0.25	0.24	0.26
R&D Technology/Investment	0.29	0.24	0.28	0.32
Firm Age	0.15	0.12	0.14	0.17
Firm Ownership Type	0.20	0.25	0.18	0.21
Firm Scale	0.52	0.44	0.51	0.57
Other Conditions	0.35	0.33	0.34	0.37
Observations	548541	71525	244463	211791

Note: This table presents the distribution of the requirements that firms must meet to be eligible for policy support, categorized by government level. Each cell reports the proportion of the government documents within each government level that specifies the requirement.

Table 9: Industrial Policy Implementation by Government Level

	All	Central	Province	City
Political KPI	0.04	0.02	0.04	0.06
Positive incentive	0.09	0.12	0.09	0.06
Negative incentive	0.22	0.25	0.21	0.19
Setting target	0.79	0.67	0.79	0.81
Encouraging experimentation	0.20	0.15	0.19	0.21
Coordination	0.39	0.45	0.39	0.37
Local adaptation	0.30	0.19	0.29	0.34
Observations	770819	101339	344411	295788

Note: This table presents the distribution of the methods of policy implementation and organizational details, categorized by government level. Each cell reports the proportion of the government documents within each government level that specifies the implementation method.

Table 10: Industrial Policy Tool: Chip, EV, and Solar Energy

	Chip	EV	Energy
Fiscal and Financial	0.63	0.64	0.55
Credit and Finance	0.23	0.22	0.20
Tax Incentives	0.34	0.31	0.26
Equity Support	0.11	0.09	0.07
Fiscal Subsidies	0.52	0.55	0.46
Entry and Competition	0.55	0.60	0.57
Industrial Fund	0.20	0.16	0.10
Promote Entrepreneurship	0.16	0.11	0.07
Market Access and Regulation	0.24	0.35	0.36
Investment Policy	0.21	0.21	0.20
Improving Business Environment	0.26	0.25	0.21
Trade Protection	0.09	0.11	0.09
Input	0.57	0.57	0.55
Labor Policy	0.32	0.25	0.20
Preferential Land Supply	0.17	0.20	0.18
Infrastructure Investment	0.22	0.31	0.28
Technology R&D and Adoption	0.43	0.39	0.31
Environmental Policy	0.14	0.22	0.28
Demand-based	0.23	0.34	0.19
Consumer subsidy	0.07	0.18	0.08
Industrial Promotion	0.16	0.17	0.09
Government Procurement	0.12	0.17	0.11
Supply Chain	0.31	0.28	0.19
Promote Industrial Cluster	0.29	0.25	0.17
Localization Policy	0.08	0.09	0.06
Observations	15,073	5,903	38,402

Note: This table presents the distribution of industrial policy tool usage for three key industries— EV, solar, and semiconductor. Each cell reports the proportion of the government documents within each government level that employs the tool.

Table 11: Industrial Policy Implementation: Chip, EV, and Solar Energy

	Chip	EV	Energy
Political KPI	0.03	0.03	0.04
Positive incentive	0.12	0.10	0.08
Negative incentive	0.18	0.19	0.23
Setting target	0.80	0.81	0.84
Encouraging experimentation	0.27	0.29	0.22
Coordination	0.46	0.44	0.42
Local adaptation	0.28	0.31	0.30
Observations	15,073	5,903	38,402

Note: This table presents the distribution of the methods of policy implementation and organizational details for three key industries— EV, solar, and semiconductor. Each cell reports the proportion of the government documents within each government level that specifies the implementation method.

Table 12: Summary Statistics for Firm Registration

Variable	Obs	Mean	Std. dev.	Min	Max
New registration capital (billion RMB)	2,165,775	191.28	14,226.42	0	16,057.89
New registration # of firms	2,165,775	26.83	381.76	0	118,629.00
Cumulative registration capital (billion RMB)	2,165,775	1,425.19	40,109.63	0	16,238.90
Cumulative registration # of firms	2,165,775	229.16	2,330.35	0	535,472.00
RCA^p	2,165,775	1.29	4.21	0	455.78
RCA^n	2,165,775	1.55	14.50	0	3,975.96
AA	2,165,775	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 2005-2020.

Table 13: Sector Choice and Regional Advantage

	(1)	(2)	(3)	(4)
l.RCA^n	0.00155***			0.000674***
	(8.23e-05)			(8.60e-05)
l.RCA^p		0.0176***		0.0155***
		(0.000618)		(0.000634)
l.AA			2.980***	2.349***
			(0.148)	(0.143)
Industry-by-year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Observations	1,962,840	1,962,840	1,962,840	1,962,840

Note: This table reports the PPML estimation results of Equation (1). 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 2005-2020. Standard errors are clustered at the city-by-industry level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 14: Sector Choice and Regional Advantage (by GDP)

	(1)	(2)	(3)	(4)
l.RCA^n	-0.00679***			-0.00631***
	(0.000880)			(0.000878)
l.RCA^n*log(GDP)	0.00155***			0.00140***
	(0.000155)			(0.000157)
l.RCA^p		-0.000579		-0.00686*
		(0.00361)		(0.00374)
l.RCA^p*log(GDP)		0.00289***		0.00368***
		(0.000595)		(0.000606)
l.AA			5.584***	5.355***
			(0.467)	(0.471)
l.AA*log(GDP)			-0.397***	-0.436***
			(0.0706)	(0.0707)
log(GDP)	-0.110***	-0.107***	-0.101***	-0.102***
	(0.0217)	(0.0217)	(0.0217)	(0.0217)
Industry-by-year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Observations	1,870,717	1,870,717	1,870,717	1,870,717

Note: This table reports the PPML estimation results of Equation (1). 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 2005-2020. Standard errors are clustered at the city-by-industry level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 15: Policy Pass-through from Central to Local

	(1)	(2)	(3)	(4)	(5)	(6)
Policy^p	0.156***	0.0887***	0.0784***	0.364***	0.0523	0.305***
	(0.00831)	(0.00749)	(0.00733)	(0.0461)	(0.0452)	(0.0636)
Policy^n		0.0299***	0.0276**	-0.0539	-0.0170	-0.0764
		(0.0113)	(0.0110)	(0.0565)	(0.0452)	(0.0671)
Policy^p*log(GDP)				-0.0385***		-0.0396***
				(0.00590)		(0.00599)
Policy^n*log(GDP)				0.0110		0.0106
				(0.00706)		(0.00717)
Policy^p*log(# Cities)					0.0118	0.0303**
					(0.0203)	(0.0137)
Policy^n*log(# Cities)					0.0202	0.0114
					(0.0203)	(0.0218)
Industry-by-Year FE	Yes	No	No	No	No	No
City-by-Industry FE	No	Yes	Yes	Yes	Yes	Yes
City-by-Year FE	No	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes
Observations	1,942,864	717,660	662,958	649,004	662,958	649,004

Note: This table reports the results of estimating Equation 4. The unit of observation is 4-digit industry-city-year level, and the sample coverage is 2005-2020. Standard errors are clustered at the city-by-industry level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 16: Policy Pass-through and Local Politician Connection

	(1)	(2)	(3)	(4)
Policy^p	0.133***	0.136***	0.136***	0.140***
	(0.00630)	(0.00634)	(0.00616)	(0.00635)
Policy^n	0.0292***	0.0292***	0.0292***	0.0292***
	(0.00620)	(0.00620)	(0.00620)	(0.00620)
Connection_{mg}	-0.0287**			
	(0.0127)			
$\text{Policy}^p\text{*Connection}_{mg}$	0.0210			
	(0.0169)			
Connection_{sg}		0.0228*		
		(0.0120)		
$\text{Policy}^p\text{*Connection}_{sg}$		0.000552		
		(0.0162)		
Connection_{ms}			0.0414***	
			(0.0158)	
$\text{Policy}^p\text{*Connection}_{ms}$			-0.0367**	
			(0.0184)	
Connection_{ss}				0.0330***
				(0.0121)
$\text{Policy}^p\text{*Connection}_{ss}$				-0.0345**
				(0.0161)
City, Year, Industry FE	Yes	Yes	Yes	Yes
Observations	2,375,750	2,375,750	2,375,750	2,375,750

Note: This table reports the results of estimating Equation 4. Connection_{mg} is the indicator for political connection between city mayor and provincial governor, Connection_{sg} for city party secretary and provincial governor, Connection_{ms} for city mayor and provincial party secretary, and Connection_{ss} for city party secretary and provincial party secretary. The unit of observation is 4-digit industry-city-year level, and the sample coverage is 2005-2020. Standard errors are clustered at the city-by-industry level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 17: Policy Persistence and the Change of Local Politician

	(1)	(2)	(3)
Policy^p	0.141***	0.136***	0.117***
	(0.00593)	(0.00594)	(0.00762)
Policy^n	0.0294***	0.0275***	0.0195**
	(0.00614)	(0.00615)	(0.00779)
l.Policy		0.367***	0.368***
		(0.00888)	(0.00893)
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)
City, Year, Industry FE	Yes	Yes	Yes
Observations	2,803,600	2,663,420	2,663,420

Note: This table reports the results of estimating Equation (6). 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 2005-2020. Standard errors are clustered at the city-by-industry level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 18: Policy Persistence and the Local Politician Persistence

	(1)	(2)	(3)
Policy^p	0.136***	0.105***	0.108***
	(0.00594)	(0.0199)	(0.0238)
Policy^n	0.0275***	0.0158	0.00229
	(0.00615)	(0.0213)	(0.0255)
l.Policy	0.346***	0.276***	0.252***
	(0.00711)	(0.0240)	(0.0300)
l.Policy (same politician)		0.0910***	0.135***
		(0.0271)	(0.0328)
l.Policy (neighbor)			0.0352
			(0.0320)
City, Year, Industry FE	Yes	Yes	Yes
Observations	2,663,420	153,162	153,162

Note: This table reports the results of estimating Equation (6). We 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. The unit of observation is 4-digit industry-city-year level, and the sample coverage is 2005-2020. Standard errors are clustered at the city-by-industry level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 19: Effect of Industrial Policy: Subsidy, Tax, and Debt

	log(Subsidy)		Tax deduction rate		1(Long-term debt)		Leverage ratio	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Policy$^+$	0.0603***	0.0184***	0.0543***	-0.00386	0.0283***	0.000186	0.00744***	-0.000437
	(0.00986)	(0.00349)	(0.0113)	(0.00291)	(0.00821)	(0.00260)	(0.00254)	(0.000758)
Policy$^-$	0.0467***	0.0159***	-0.00898	-0.00318	0.0178***	0.00675**	0.00491***	-0.000104
	(0.00668)	(0.00429)	(0.00666)	(0.00334)	(0.00582)	(0.00304)	(0.00185)	(0.000954)
log(Register capital)	0.331***		-0.0830***		0.274***		-0.0333***	
	(0.00127)		(0.00144)		(0.00119)		(0.000380)	
Constant	-0.915***	1.191***	-1.485***	-0.623***	-3.870***	-0.523***	-0.194***	-0.184***
	(0.0132)	(0.00150)	(0.0145)	(0.00130)	(0.0132)	(0.00131)	(0.00372)	(0.000355)
City-by-industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,055,403	3,174,825	1,649,263	1,228,368	1,713,689	1,066,831	6,697,233	6,326,495

Note: This table reports the results of estimating 11 and 12. 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.

Table 20: Effect of Industrial Policy: Subsidy, Tax, and Debt

	log(Subsidy)		Tax deduction rate		1(Long-term debt)		Leverage ratio	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Industrial cluster	0.0184***	0.0131**	-0.0485***	-0.0135***	0.0134**	0.0141***	-0.00144	-0.00292**
	(0.00673)	(0.00534)	(0.00708)	(0.00420)	(0.00567)	(0.00370)	(0.00178)	(0.00116)
Demand stimulation	-0.0564***	-0.0243***	0.0243***	0.00528	0.00591	0.0112***	0.00323*	0.00422***
	(0.00635)	(0.00503)	(0.00678)	(0.00397)	(0.00543)	(0.00355)	(0.00168)	(0.00110)
Entry and regulation	-0.00893	-0.00275	-0.00208	0.00510	-0.0108	-0.0111***	-0.00384*	-0.00376***
	(0.00753)	(0.00583)	(0.00816)	(0.00483)	(0.00662)	(0.00424)	(0.00201)	(0.00130)
Input and R&D	-0.00382	-0.0171***	-0.0104	-0.0197***	0.0202***	0.0136***	0.000297	0.00142
	(0.00795)	(0.00620)	(0.00869)	(0.00515)	(0.00709)	(0.00447)	(0.00214)	(0.00137)
Fiscal and finance	0.0514***	0.0430***	0.0509***	0.0132***	0.00286	-0.0103**	0.00287	0.000977
	(0.00767)	(0.00570)	(0.00867)	(0.00485)	(0.00685)	(0.00421)	(0.00205)	(0.00125)
log(Register capital)	0.331***		-0.0830***		0.274***		-0.0333***	
	(0.00127)		(0.00144)		(0.00119)		(0.000380)	
Constant	-0.856***	1.194***	-1.457***	-0.623***	-3.855***	-0.524***	-0.186***	-0.184***
	(0.00991)	(0.00134)	(0.0108)	(0.00117)	(0.0109)	(0.00115)	(0.00293)	(0.000316)
City-by-industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,055,403	3,174,825	1,649,263	1,228,368	1,713,689	1,066,831	6,697,233	6,326,495

Note: This table reports the results of estimating 11 and 12. 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.

Table 21: Effect of Industrial Policy: Heterogeneity by Size

	log(Subsidy)		Tax deduction rate		1(Long-term debt)		Leverage ratio	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Policy^{+}	-0.366***	-0.0280**	-0.0144	-0.0107	-0.0302***	-0.00921	0.0260***	0.00962***
	(0.00997)	(0.0130)	(0.0111)	(0.00962)	(0.0117)	(0.0100)	(0.00317)	(0.00283)
log(Register capital)	0.270***		-0.0921***		0.271***		-0.0295***	
	(0.000851)		(0.00106)		(0.000931)		(0.000274)	
Policy^{+}*log(Register capital)	0.0627***	0.00732***	0.00734***	0.000877	0.00358***	0.00139	-0.00410***	-0.00147***
	(0.00144)	(0.00189)	(0.00166)	(0.00144)	(0.00137)	(0.00118)	(0.000443)	(0.000396)
Constant	-0.528***	1.287***	-1.460***	-0.656***	-3.830***	-0.515***	-0.225***	-0.228***
	(0.00559)	(0.00161)	(0.00657)	(0.00137)	(0.00759)	(0.00126)	(0.00185)	(0.000351)
City-by-industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,075,274	2,663,526	4,699,474	1,060,915	4,581,836	969,078	5,845,828	5,423,393

Note: This table reports the results of estimating Equations 11 and 12. 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.

Table 22: Effect of Industrial Policy: New Firm Entry

	log(# of New Firm Registration)			log(New Capital Registration)		
	(1)	(2)	(3)	(4)	(5)	(6)
Policy	0.133***	0.131***	0.0219***	0.325***	0.319***	0.0753***
	(0.00219)	(0.00219)	(0.00181)	(0.00757)	(0.00757)	(0.00717)
Policy^p		0.0250***	0.00225**		0.101***	0.0151***
		(0.00114)	(0.000935)		(0.00392)	(0.00370)
Policy^n		0.00450***	0.00809***		0.0139***	0.00968***
		(0.000919)	(0.000754)		(0.00317)	(0.00299)
City-by-industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City-by-industry Trend	No	No	Yes	No	No	Yes
Observations	2,896,320	2,896,320	2,896,320	2,896,320	2,896,320	2,896,320
R-squared	0.790	0.790	0.875	0.649	0.649	0.726

Note: This table reports the results of estimating Equation 14. The unit of observation is 4-digit industry-city-year level, and the sample coverage is 2005-2020. Standard errors are clustered at the city-by-industry level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 23: Effect of Industrial Policy: TFP

	TFP (Revenue)		TFP (Output)		TFP (Value-added)	
	(1)	(2)	(3)	(4)	(5)	(6)
Industrial cluster	0.00175	0.00122	-0.0119***	-0.00718**	-0.0224***	-0.00621
	(0.00302)	(0.00196)	(0.00398)	(0.00322)	(0.00556)	(0.00512)
Demand stimulation	-0.00463	0.00436**	-0.0263***	-0.0104***	-0.0102*	-0.00910*
	(0.00287)	(0.00186)	(0.00375)	(0.00303)	(0.00519)	(0.00478)
Entry and regulation	-0.0140***	-0.0106***	-0.0299***	-0.0255***	0.00802	-0.00373
	(0.00332)	(0.00216)	(0.00440)	(0.00357)	(0.00616)	(0.00570)
Input and R&D	0.00985***	9.09e-05	0.0156***	0.0139***	0.00154	0.0107*
	(0.00350)	(0.00227)	(0.00460)	(0.00373)	(0.00642)	(0.00595)
Fiscal and finance	0.00377	0.00555***	0.0187***	0.0107***	0.0115*	0.00346
	(0.00322)	(0.00208)	(0.00424)	(0.00343)	(0.00594)	(0.00550)
log(Register capital)	0.216***		0.186***		0.113***	
	(0.000382)		(0.000519)		(0.000726)	
Constant	4.731***	6.135***	4.761***	5.953***	2.504***	3.265***
	(0.00259)	(0.000528)	(0.00355)	(0.000918)	(0.00504)	(0.00152)
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
Observations	5,046,662	5,412,868	3,191,051	3,216,183	2,176,250	2,086,792
R-squared	0.301	0.780	0.242	0.653	0.179	0.542

Note: This table reports the results of estimating Equations 11 and 12. 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.

Table 24: Effect of Industrial Policy: Revenue, Output, Value-added

	log(Revenue)		log(Output)		log(Value-added)	
	(1)	(2)	(3)	(4)	(5)	(6)
Industrial cluster	0.0142***	0.00848***	-0.00274	-0.00394	-0.0135**	-0.00163
	(0.00375)	(0.00220)	(0.00466)	(0.00332)	(0.00626)	(0.00512)
Demand stimulation	-0.0194***	0.00667***	-0.0196***	-0.00714**	0.000925	-0.0107**
	(0.00357)	(0.00210)	(0.00439)	(0.00313)	(0.00586)	(0.00479)
Entry and regulation	-0.0161***	-0.0118***	-0.0453***	-0.0289***	-0.0141**	-0.00823
	(0.00411)	(0.00242)	(0.00514)	(0.00367)	(0.00693)	(0.00570)
Input and R&D	0.0184***	-0.00558**	0.0275***	0.0182***	0.0191***	0.0176***
	(0.00433)	(0.00255)	(0.00537)	(0.00384)	(0.00722)	(0.00594)
Fiscal and finance	0.00323	0.0106***	0.0200***	0.00870**	0.00324	0.00303
	(0.00398)	(0.00234)	(0.00494)	(0.00353)	(0.00667)	(0.00549)
log(Register capital)	0.605***		0.568***		0.571***	
	(0.000470)		(0.000603)		(0.000811)	
Constant	5.503***	9.357***	5.856***	9.556***	4.032***	7.910***
	(0.00311)	(0.000591)	(0.00407)	(0.000943)	(0.00557)	(0.00151)
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
Observations	5,840,617	6,404,485	3,427,147	3,474,246	2,305,886	2,216,758
R-squared	0.434	0.850	0.422	0.796	0.385	0.733

Note: This table reports the results of estimating Equations 11 and 12. 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.

Table 25: Effect of Industrial Policy: Capital, Labor, Input

	log(Capital)		log(Employment)		log(Input)	
	(1)	(2)	(3)	(4)	(5)	(6)
Industrial cluster	0.00137	0.00432*	0.00968***	0.00519***	-0.0214***	-0.0198***
	(0.00432)	(0.00223)	(0.00230)	(0.00126)	(0.00590)	(0.00452)
Demand stimulation	0.0147***	0.000941	-0.00125	0.00406***	-0.0255***	-0.0176***
	(0.00410)	(0.00212)	(0.00219)	(0.00120)	(0.00557)	(0.00427)
Entry and regulation	-0.0304***	-0.00467*	0.00303	0.00325**	-0.0128**	0.000523
	(0.00475)	(0.00246)	(0.00252)	(0.00138)	(0.00649)	(0.00501)
Input and R&D	0.00683	-0.000966	-0.00306	-0.00752***	-0.0354***	-0.0551***
	(0.00500)	(0.00259)	(0.00266)	(0.00146)	(0.00680)	(0.00525)
Fiscal and finance	0.00398	0.00330	0.00431*	0.00415***	0.0777***	0.0641***
	(0.00460)	(0.00238)	(0.00244)	(0.00133)	(0.00627)	(0.00484)
log(Register capital)	0.724***		0.368***		0.582***	
	(0.000546)		(0.000288)		(0.000749)	
Constant	2.280***	7.035***	0.961***	3.321***	4.838***	8.632***
	(0.00371)	(0.000605)	(0.00191)	(0.000338)	(0.00502)	(0.00124)
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
Observations	5,134,236	5,513,313	5,959,639	6,550,089	3,248,157	3,303,677
R-squared	0.519	0.904	0.505	0.889	0.430	0.774

Note: This table reports the results of estimating Equations 11 and 12. 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.

Table 26: Policy Diffusion and Overcapacity: Entry and Capital

	log(# New Entry)	log(Value of New Capital)	log(Value of Average New Capital)
Policy	0.0597***	0.134***	0.0872***
	(0.00364)	(0.0144)	(0.0124)
Policy*Order	0.0210	-0.162***	-0.248***
	(0.0128)	(0.0507)	(0.0435)
Constant	0.967***	2.631***	1.871***
	(0.000409)	(0.00162)	(0.00139)
City-by-Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
City-by-industry Trend	Yes	Yes	Yes
Observations	2,896,320	2,896,320	2,896,320
R-squared	0.875	0.726	0.604

Note: This table reports the results of estimating Equation (18). 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 2005-2020. Standard errors are clustered at the city-by-industry level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 27: Policy Diffusion and Overcapacity: Firm Performance

	Revenue		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 (19). 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 2005-2020. Standard errors are clustered at the city-by-industry level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 28: Policy Diffusion and Sector Choice

	(1)	(2)	(3)	(4)
RCA^n	0.00194***	0.00113**		
	(0.000197)	(0.000481)		
RCA^p			0.0145***	0.00891***
			(0.000773)	(0.00186)
Order	-2.738***		-2.702***	
	(0.0188)		(0.0192)	
RCA^n*Order	-0.00430***	-0.00321*		
	(0.000634)	(0.00177)		
RCA^p*Order			-0.0264***	-0.0214***
			(0.00341)	(0.00655)
Constant	-1.447***	-1.632***	-1.464***	-1.638***
	(0.00488)	(0.00249)	(0.00496)	(0.00291)
City, Industry FE	Yes	No	Yes	No
City-by-Industry FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,844,600	1,001,660	2,844,600	1,001,660

Note: This table reports the results of estimating Equation (20). 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 2005-2020. Standard errors are clustered at the city-by-industry level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Online Appendix (Not For Publication)

Appendix A Additional Figures and Tables

Figure A1: Word Cloud: Industrial Policy vs. Non-Industrial Policy

(a) Industrial Policy

(b) Non-Industrial Policy

Notes: This figure presents the word clouds based on keywords in titles of industrial policies vs non-industrial policies.

Figure A2: Word Cloud: Electric Vehicle

(a) Title

(b) Full Text

Notes: This figure presents word clouds for the EV industry based on extracted industry names and the full policy texts.

Figure A3: Word Cloud: Electricity Production

(a) Title

(b) Full Text

Notes: This figure presents word clouds for the electricity production industry based on extracted industry names and the full policy texts.

Figure A4: Word Cloud: Industrial Policy Tools

(a) Tax Incentive

(b) Fiscal Subsidy

(c) Credit and Finance

(d) Industrial Fund

Notes: This figure presents word clouds based on a list of policy tool keywords extracted regarding four types of policy tools: tax incentives, fiscal subsidies, credit policies, and industrial funds, respectively.

Figure A6: Time Trend of Industrial Policy Tool (New)

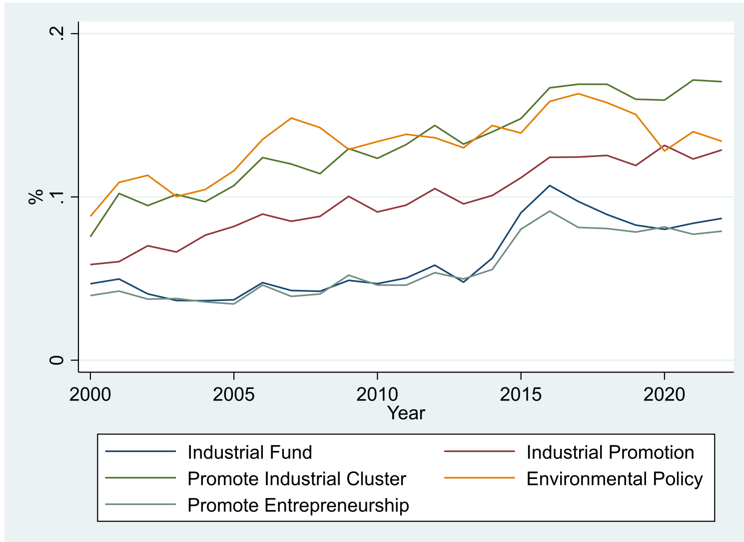


Figure A7: Time Trend of Industrial Policy Tool (New)

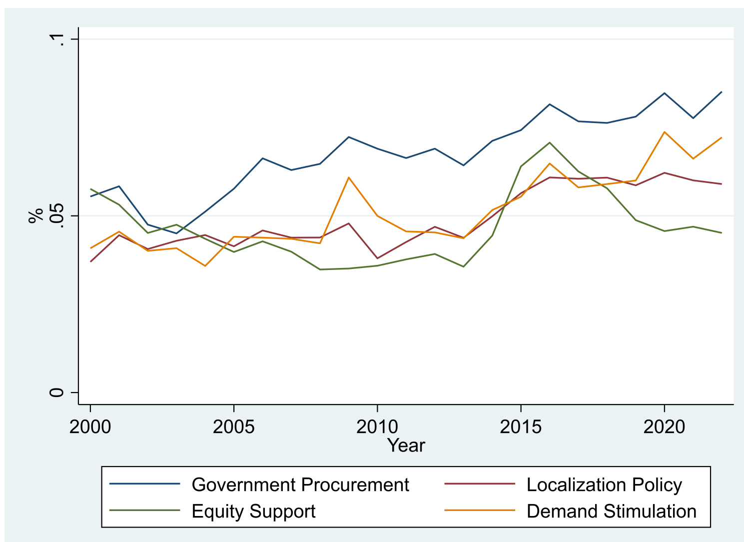
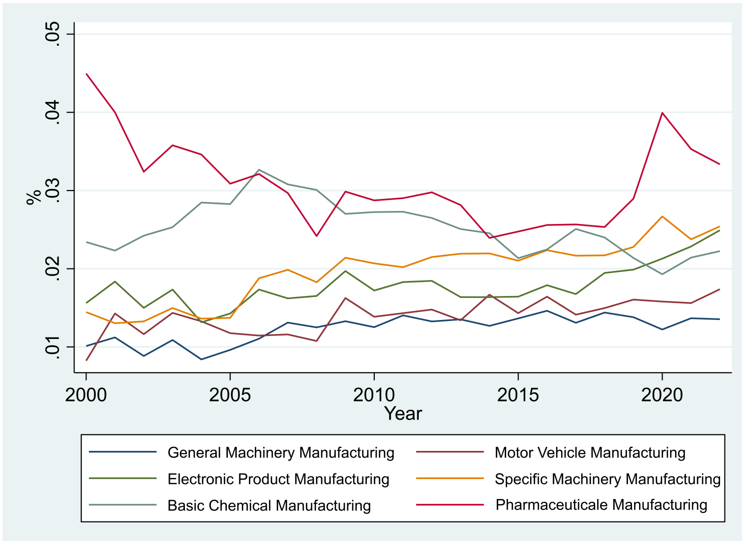
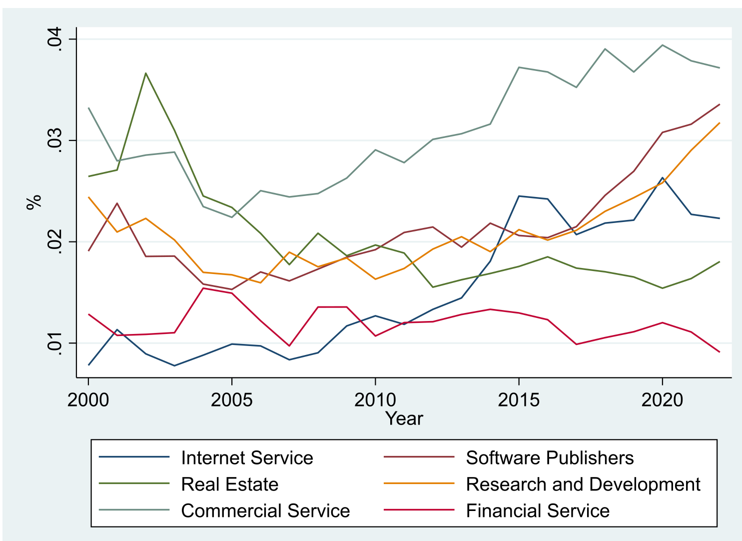


Figure A5: Time Trend of Policy-Targeted Industrial Sector (Breakdown)



(a) Overall



(b) Manufacturing

Notes: This figure presents the trends of a breakdown of the targeted industry at 3-digit level for the most frequently targeted within the manufacturing and the service sector. The vertical axis represents the proportion of policies that target each sector within each government level.

Figure A8: Time Trend of Industrial Policy Tool (Traditional)

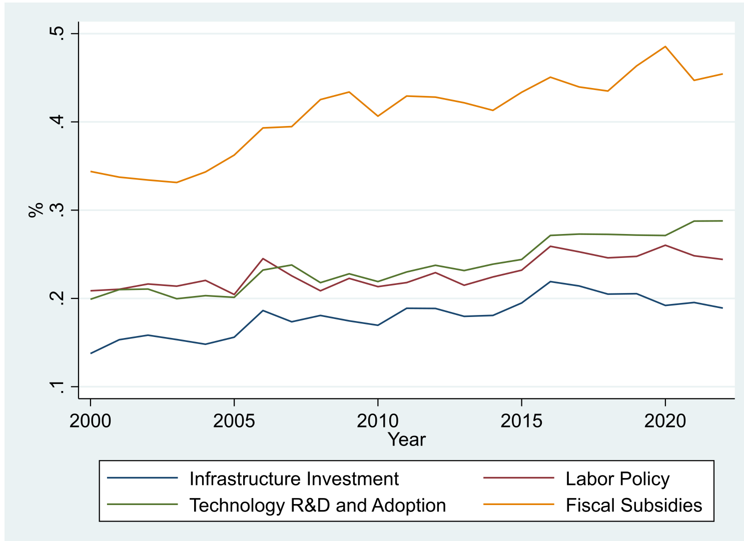


Figure A9: Time Trend of Industrial Policy Tool (Traditional)

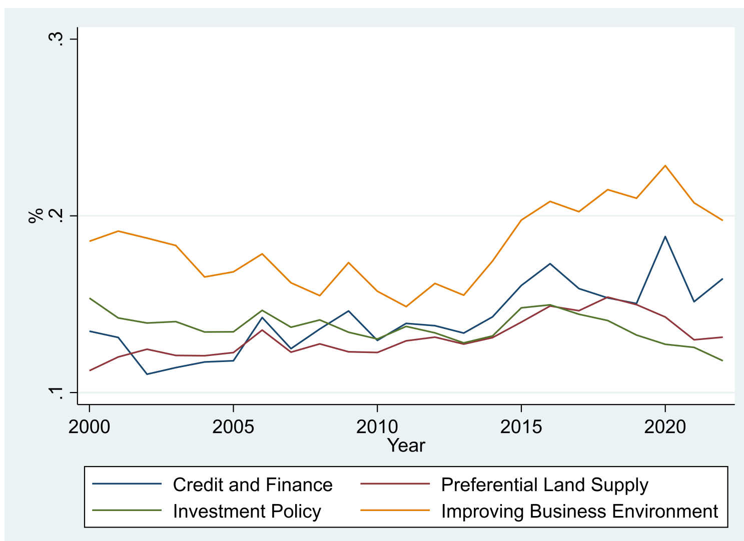


Figure A10: Time Trend of Industrial Policy Tool (Declining)

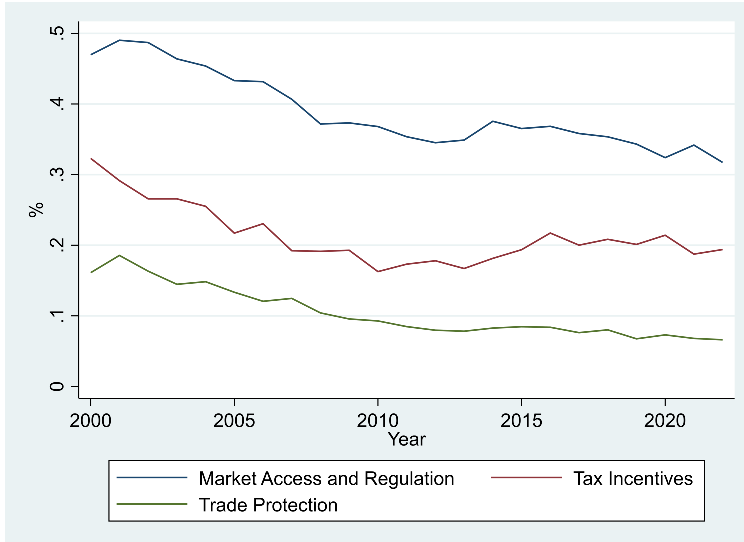


Table A1: Random Sample of Industrial Policies and non-Industrial Policies

Panel A: Random titles of industrial policies
Several Opinions of the Guangdong Provincial People's Government on Implementing the State Council's Opinions on Accelerating the Development of the Tourism Industry
Audit Pre-announcement (2014) No. 2: Pre-announcement by Zhoushan City Audit Bureau on Conducting a Special Audit Investigation into the Effectiveness of Municipal Financial Subsidies to Enterprises in 2013
Notice of the Jiangsu Provincial Development and Reform Commission on Organizing the Final Evaluation of China Clean Development Mechanism Fund Grant Projects
Notice of the Chongqing Poverty Alleviation and Development Office on Issues Related to Conducting 2015 Entrepreneurship Training for Leaders in Poverty Alleviation
Notice of the China Banking and Insurance Regulatory Commission, the National Intellectual Property Administration, and the National Copyright Administration on Further Strengthening Intellectual Property Pledge Financing Work
Notice of the Fuzhou Municipal People's Government on Forwarding the "Approval of the Fujian Provincial People's Government on the Implementation Plan for the Ninth Batch of Agricultural Land Conversion and Land Acquisition in Fuzhou City in 2015"
Notice of the Office of the People's Government of Changping District, Beijing Municipality, on Issuing the "Implementation Plan for Further Deepening Key Tasks in Streamlining Administration and Decentralization, Combining Delegation with Regulation, and Optimizing Services Reform in Changping District"
Notice of the Henan Provincial Department of Science and Technology on Applications for the First Batch of Academician Workstations in Henan Province in 2011
Notice of the National Energy Administration on Issuing the Administrative Measures for Completion Acceptance of Coal Mine Construction Projects
Notice of the Office of the People's Government of Anqing City on Supporting Large Commercial Circulation Enterprises in Carrying Out Pilot Projects for the Construction of Modern Rural Circulation Systems
Panel B: Random titles of non-industrial policies
Letter of the Anhui Provincial Department of Science and Technology on Collaborative Opinions Regarding Proposal No. 0090 at the Fifth Session of the 12th Provincial CPPCC
Notice of the Teacher Resources Division of the Jiangxi Provincial Department of Education on Holding Training Classes on Teacher Ethics and Conduct for Rural Compulsory Education Primary and Secondary School Teachers Across the Province
Notice of the Party Group of the Wuxi Water Resources Bureau on Issuing the "Specific Measures of the Wuxi Water Resources Bureau on Further Improving Work Style"
Reply Letter from the Municipal Civil Affairs Bureau on the Scope Change of Ronghe Garden and Yuanyong Commercial Plaza

Announcement of the Fujian Provincial Department of Justice on Matters Regarding On-site Verification for Applications for Legal Professional Qualifications
Approval of the China Securities Regulatory Commission on Approving Hubei Kailuo Technology Co., Ltd. to Issue Shares to Shanghai Zhuofan Investment Co., Ltd. and Others to Purchase Assets and Raise Supporting Funds
Announcement of the Haikou Municipal Bureau of Land and Resources on Restoring the Legal Effectiveness of State-owned Land Certificate No. 609 (2003) in Laocheng
Notice of the Taizhou Municipal People's Government on the Removal of Comrade He Rusong from His Position
Approval of the China Banking Regulatory Commission on the Entrusted Application by Jiangxi Rural Credit Union for a Unified Government Procurement Card Brand
Approval of the China Insurance Regulatory Commission on the Head of the Finance Department of Taiping Life Insurance Co., Ltd.

Note: This table presents a random selection of 10 titles from the texts identified as industrial policies and 10 titles from those not identified as such.

Table A2: Random Samples of Filtered-out and Filtered-in Policies

Titles of Filtered-out Policies
Notice from the General Office of the People's Government of Guigang City on Issuing the 2012 Geological Disaster Prevention Plan of Guigang City
Administrative Measures for Township Ferry Terminals in Suzhou City (2004 Revision)
Response from the Anhui Provincial Department of Education to Proposal No. 468 of the First Session of the 13th Provincial People's Congress
Second Announcement of Bidding for Survey and Design of the Three-Year Improvement Project for County and Township Highways in Dinghai District
Response from the Anhui Provincial Department of Housing and Urban-Rural Development to Proposal No. 0674 of the First Session of the 11th Provincial Committee of the Chinese People's Political Consultative Conference
Notice from the People's Government of Ziyuan County on Issuing the Compensation Measures for Expropriation of Houses on State-Owned Land for the Shantytown Redevelopment Project in Ziyuan County
Letter from the China Banking Regulatory Commission Approving the Adjustment of Registered Capital and Change of Shareholders of Defutai Bank Co., Ltd.
Notice from the General Office of the Guangzhou Municipal People's Government Forwarding the Guiding Opinions of the Municipal Information Office on Informatization Work in Districts and County-Level Cities
Response from the Ministry of Human Resources and Social Security to Proposal No. 3848 (Social Management Category No. 377) of the Fifth Session of the 12th National Committee of the Chinese People's Political Consultative Conference
Notice from the Ningbo Municipal Bureau of Housing and Urban-Rural Development on Publishing the List of the First Batch of Pilot Villages for Village Design Implementation in 2021
Titles of Filtered-in Policies
Notice from the Xiamen Municipal Bureau of Commerce on Issuing the "Implementation Plan for Creating Green Shopping Malls in Xiamen City (2020-2022)"
Notice from the Hunan Provincial Department of Science and Technology on Publishing the Results of the Regular Evaluation of Provincial Key Laboratories and Engineering Technology Research Centers in 2022
Notice from the Beijing Municipal Commission of Housing and Urban-Rural Development on Commending the "Beijing Civilized and Safe Construction Sites" and "Beijing Civilized and Safe Model Construction Sites" of the Construction System in 2011
Notice from the Anhui Provincial Department of Science and Technology on Focusing on Connecting and Encouraging the Development of a Batch of Provincial Science and Technology Innovation Think Tanks

Notice from the Shandong Provincial Department of Agriculture and Rural Affairs on Conducting Investigation and Rectification Work on the Operation and Maintenance Management of High-Standard Farmland
Notice on Issuing the "Opinions of the Chengdu Municipal Economic Commission on Regulating the Development of Industrial Industry Associations (Trial Implementation)" by the Chengdu Municipal Economic Commission
Notice from the Fujian Provincial Economic and Information Commission, Fujian Provincial Department of Finance, Fujian Provincial State Taxation Bureau, and Fujian Provincial Local Taxation Bureau on Recognizing Products Produced by Longyan Zhongfu Wood Industry Co., Ltd. and 29 Other Enterprises as Resource Comprehensive Utilization Products
Notice from the Jiangsu Provincial Department of Science and Technology on Organizing the Application for Jiangsu Provincial High-Tech Products in 2017
Interpretation of the "Opinions on Accelerating the Cultivation and Development of Agricultural Innovators"
Notice from the General Office of the People's Government of Fuzhou City on Issuing Measures for Promoting Commercial Consumption Growth in Response to the Epidemic

Note: This table presents random samples of the policies that were filtered out and filtered in with an additional round of LLM analysis.

Table A3: Common Types of Misclassifications on Four Example Policy Tools

Policy Tool Category	Type of excluded misclassifications	Examples of keywords from first-round LLM
Tax Incentives	Fiscal Support and Subsidies	Introduce local fiscal subsidy policies for the transfer of yak industry grasslands
Tax Incentives	Mention of Taxes, Rewards/Penalties, or Numbers without Incentives	Enterprises must legally pay taxes and register their business operations
Tax Incentives	Fee and Price Adjustments	Implement a paid usage system for plastic shopping bags
Tax Incentives	General Policy Support	Encourage the promotion and application of new technologies
Fiscal Subsidies	Tax incentives and Fee Reductions	Enjoy equal treatment with state-owned enterprises in taxes, loans, and business startups
Fiscal Subsidies	General Policy Support	Promote the construction of the Yangpu railway branch project
Fiscal Subsidies	Administrative Management and Procedures	Organize the collection, use, and management of water resource fees
Fiscal Subsidies	Enterprise Self-Funding	Expenses are self-funded
Credit Policies	Fiscal Support and Subsidies	Apply for central special funds
Credit Policies	Market Mechanisms and Industry Operations	Encourage venture capital investments
Credit Policies	Infrastructure Construction	Support enterprises investing in infrastructure construction
Industrial Funds	Fiscal Support and Subsidies	Use 60% of local retention from new taxes to subsidize construction in new dairy farms
Industrial Funds	Other Financial Support	Support enterprises in issuing bonds for financing
Industrial Funds	Infrastructure and Public Project Construction	Increase funding efforts for park construction
Industrial Funds	Enterprise Policies and Support	Encourage enterprises to invest overseas, focusing on cooperation with ASEAN
Industrial Funds	Project-Related Support	Funding support for excellent entrepreneurial projects

This table illustrates the second-round refinement based on LLM's self-critique and summary. It presents the common types of misclassifications on four major policy tool categories that the second-round LLM analysis excludes from the first-round results.

Table A4: Top Title Keywords and Full Text Keywords from LLM-identified Industrial Policies

Top Title Keywords	Top Full Text Keywords
Industry	Industry Chain
Special Funds	Leading Enterprises
Small and Medium-sized Enterprises	Key Enterprises
Service Industry	Technology-Based
High-Tech	Supply Chain
Support	Leading Industries
Modern	Core Technology
Cultivate	Sales Revenue
High Quality	Incubator
Industrialization	Main Business
Transformation	Venture Capital
Research and Development	Deep Processing
Encourage	Logistics and Distribution
Manufacturing	Value-Added
Power Generation	Advanced Processing
Integration	Famous Brands
E-commerce	High Yield
Logistics	High Performance
Breeding	Brand-Name Products
Mechanization	Market Share

Note: This table presents the top 20 keywords from the LLM-identified industrial policies by their frequency in titles and full texts, respectively.

Table A5: Random Sample of Documents with Keywords

Title	Informative keyword in title
Excellent Case No. 5 of the "Ten Projects of Ten Million Square Meters"—Qingdao M6 Virtual Reality Industrial Park	Industrial Park
Letter from the Shaanxi Provincial Bureau of Surveying, Mapping, and Geoinformation on Holding a Training Course on Technical Standards for Surveying and Mapping Geoinformation, Promotion and Application of the 2000 National Geodetic Coordinate System, and Quality Management	Promotion and Application
Notice from the Fuzhou Real Estate Registration and Transaction Center on Continuing Volunteer Service Activities for Civilized Guidance at Metro Stations to Support Urban Construction and Management Work	Guidance
Notice from the Department of Agriculture and Animal Husbandry of Inner Mongolia Autonomous Region on Conducting Research on the Work of Stabilizing Pork Production and Supply in 2020 and the Implementation of Related Policies	Live Pigs
Notice from the Price Bureau of Guangxi Zhuang Autonomous Region on the Feed-in Tariff for Tianhu Hydropower Station	Electricity Price
Notice from the Department of Finance of Inner Mongolia Autonomous Region on Allocating Interest Subsidies for Long-term Policy Loans for Relocation-based Poverty Alleviation and Income from Special Construction Funds in the First Quarter of 2018	Interest Subsidy
Notice from the General Office of Hulunbuir Municipal People's Government on Adjusting the Leading Group for the Resource Utilization of Livestock and Poultry Manure in Hulunbuir City	Manure
Announcement from the Shanghai Stock Exchange on Approving China Galaxy Securities Co., Ltd. to Provide Primary Liquidity Services for the E Fund CSI Biomedicine ETF	Biopharmaceuticals
Notice from the Audit Division of Jiangsu Provincial Department of Education on Holding a Symposium on Auditing the Construction Project of Superior Disciplines in Provincial Universities	Advantage
Forwarding the Notice from the Ideological and Political Work Department of the Ministry of Education on Cultivating and Building High-Quality Projects in University Ideological and Political Work by the Hunan Provincial Department of Education	Cultivation
Title	**Most informative keyword in full text**

Notice of the Xinxiang Municipal People's Government on Issuing the "Interim Measures for Commissioned Loans of Personal Housing Provident Fund in Xinxiang City"	Collateral
Notice of the General Office of Yinchuan Municipal People's Government on Issuing the "Guiding Opinions on the Standards and Cost Estimation for the Separation, Transfer, Maintenance, and Renovation of 'Three Supplies and One Industry' in Staff Family Areas of Yinchuan State-owned Enterprises"	Copper Rod
Notice of the Office of the People's Government of Wuchuan Gelao and Miao Autonomous County on Issuing the "Trial Measures for the Management and Use of Special Funds and Materials for Civil Affairs in Wuchuan Autonomous County"	Agricultural Subsidy Network
Reply from the Hangzhou Municipal Bureau of Agriculture and Rural Affairs Regarding Recommendation No. 13 from Yuhang District at the First Session of the 14th Municipal People's Congress	Market Share
Notice of the Office of Binzhou Municipal People's Government on Issuing the "Regulations on Functional Allocation, Internal Institutions, and Staffing of Binzhou Municipal Construction Bureau"	Introduction of Technology
Approval for the Adjustment of Construction Tasks for the Xiangshuiba Reservoir Project in Jinping County	Multiple Cropping Index
Notice of the Deyang Municipal People's Government on Announcing the Projects for the 12th Exhibition of Philosophical and Social Science Research Achievements in Deyang City	Chain Method
Letter from the Department of Agriculture of Guangxi Zhuang Autonomous Region Submitting Collaborative Handling Opinions on Proposal No. 20160090 at the Fourth Session of the 11th CPPCC of the Autonomous Region	Business Model
Notice of the Guangzhou Municipal Science and Technology Bureau on Issuing the Application Guide for the 2023 Municipal Innovation Environment Plan—Science Popularization Theme (Science Popularization Brand Projects)	Yanhe
Implementation Opinions of the Sichuan Bureau of Surveying and Mapping on Strengthening Surveying and Mapping Culture Construction	High Added Value

Note: This table 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.

Table A6: Random Sample of LLM-identified Industrial Policies without Keywords

Title of Identified Industrial Policies without Informative Title Keyword
Opinion from the Hebei Provincial Development and Reform Commission on Renewing the Approval of Pesticide Formulation Production Qualifications for Enterprises such as Xingtai Haiyuan Agrochemical Technology Co., Ltd.
Notice from the General Office of Jieyang Municipal People's Government on Establishing the Jieyang PM2.5 Pollution Control Working Group
Announcement from the Guangxi Zhuang Autonomous Region Market Supervision Administration on Issuing the "Catalogue of Electric Bicycles Approved for Registration in Guangxi Zhuang Autonomous Region" (23rd Batch)
Notice from the Dongguan Municipal Real Estate Administration Bureau on Carrying Out the Application for Evaluation of the "2011 Dongguan City Model Residential Communities (Buildings, Industrial Areas) in Property Management" Projects
Announcement No. 13 of 2018 by the National Energy Administration—Approval of 15 Industry Standards Including the "Welding Procedure Qualification Code for Conventional Islands of Nuclear Power Plants"
Notice from the State Administration of Radio and Television on Issuing the Measures for Rewarding Technical Quality of Radio and Television Programs
Notice from the Department of Housing and Urban-Rural Development of Hubei Province on Organizing the Application for the 2010 Hubei Provincial Construction Industry New Technology Application Demonstration Projects
Notice from the Department of Transportation of Guizhou Province on Issuing the "14th Five-Year Plan for Energy Conservation and Environmental Protection Development in Transportation of Guizhou Province"
Notice from the Jiangsu Provincial Sports Bureau on Issuing the "Jiangsu Province Fitness Club Promotion Plan (2016–2020)"
Notice from the Department of Finance of Henan Province on Issuing the Budget of Project Funds for the 2013 International Cooperation Plan
Title of Identified Industrial Policies without Informative Full Text Keyword
Notice of the Suzhou Municipal Agriculture Committee on Summarizing 2015 Work in Leisure and Sightseeing Agriculture and Analyzing Typical Cases
Notice from the Zhejiang Provincial Department of Land and Resources Forwarding the "Notice from the General Office of the Ministry of Land and Resources on Further Promoting Matters Related to Establishing Model Counties (Cities) for Economical and Intensive Use of Land and Resources"
Notice of the Ningbo Municipal Government on Carrying Out Work to Integrate Mineral Resource Development

Notice of the Office of Xiufeng District People’s Government of Guilin City on Issuing the Implementation Plan for the ”Xiufeng Residents Tour Xiufeng” Activity in Xiufeng District, Guilin City
Notice of the Guangdong Provincial Price Bureau and the Guangdong Provincial Department of Transportation on Issuing the ”Measures for Motor Vehicle Maintenance Price Management by the Guangdong Provincial Price Bureau and Department of Transportation”
Notice of the Departments of Science and Technology, Education, Finance, and Human Resources and Social Security of Fujian Province on Issuing the ”Seven Measures for Further Promoting the Implementation of Policies on Innovative Development of Universities and Provincial Research Institutes”
Notice of the Guizhou Provincial Price Bureau and the Guizhou Provincial Department of Construction on Establishing Standards for Transaction Fees of Non-Residential Real Estate in Our Province
Approval on Recognizing Ningbo Galaxy Pile Co., Ltd. and Cixi City Building Components Co., Ltd. as Resource Comprehensive Utilization Enterprises
Decision of the General Office of the Fujian Provincial People’s Government on Amending the ”Notice Forwarded by the General Office of the Fujian Provincial People’s Government on Several Measures by the Provincial Administration for Industry and Commerce to Promote Trademark Brand Work” (2018)
Circular on Commending the Model Enterprises and Advanced Enterprises in Energy Conservation and Emission Reduction in Ningbo City for the Year 2008

Note: This table presents ten randomly selected policy titles that the LLM identifies as industrial policies but that do not contain any title or full-text keyword meeting the same informativeness threshold.

Appendix B x

B.1 Industrial Policy Tool

1. Tax incentives: Implementing industrial policies through tax reductions, tax credits, accelerated depreciation, etc.

2. Fiscal subsidies: The government subsidizes companies or industries through direct fiscal subsidies, government guarantees, fiscal allocations, in-kind grants, production subsidies, etc., as a form of industrial policy.

3. Credit policies: The government guides financial institutions to provide low-interest loans, interest subsidies, loan guarantees, development bank loans, policy-directed lending by financial institutions, and priority bank credit to industries or enterprises as a form of industrial policy.

4. Equity support: State-owned enterprises, governments, local government financing platforms, etc., support the development of specific industries or enterprises through equity injections.

5. Industrial funds: The government establishes industrial funds or government investment funds to provide venture capital support, invest through industrial funds, guide government investments, prioritize government venture capital support, and provide quota support to support and guide investment in specific industries.

6. Trade protection measures: The government implements industrial policies through export bans, export licensing requirements, export quotas, export taxes, export subsidies, export tax incentives, export credit agencies, export-related non-tariff measures, other export incentives, import bans, import licensing requirements, import monitoring, import quotas, import tariffs, import-related non-tariff measures, internal taxes on imports, technical barriers to imports, technical matching or technology transfer requirements related to imports, anti-dumping measures, countervailing measures, and other import incentives. Similar policies may also be used to target enterprises from other regions rather than foreign enterprises.

7. Investment policies: The government attracts and guides foreign investment by imposing entry restrictions on foreign or out-of-region enterprises, shareholding ratio restrictions on foreign or out-of-region enterprises, preferential policies for foreign or out-of-region investments; establishing specialized investment promotion agencies to provide investment consulting, project matchmaking, policy interpretation, and other services for specific industries or enterprises.

8. R&D and technology adoption: The government encourages enterprises to conduct R&D through R&D subsidies, funding coordination, technology innovation funds, additional deductions for R&D expenses, support for technology transfer, industry-university-research cooperation alliances, establishment or support of public research institutions, etc.; or encourages enterprises to adopt specific technologies or high-tech through subsidies, funding coordination, tax and fee reductions, and other measures.

9. Public procurement policies: The government supports the development of domestic enterprises by prioritizing procurement of goods and services from the industry by the government or state-owned enterprises, procurement quotas, etc.

10. Labor policies: The government provides human resource assurance for industrial development through technical training programs, providing training subsidies, establishing or supporting training institutions, establishing skills committees, labor market access policies, migration policies and quotas, talent attraction supporting policies (such as priority household registration for talents, preferential housing for talents), wage tax credits, talent subsidies, etc.

11. Infrastructure investment: The government provides basic support for industrial development by constructing transportation infrastructure, information and communication technology infrastructure, energy infrastructure, and other areas.

12. Industrial cluster policies: The government promotes industrial agglomeration and development by constructing economic zones or industrial parks, supporting innovation clusters, industrial chain collaboration, etc. Additionally, the government plays the leading role of key enterprises through policy guidance and funding support, encourages the development of key nodes in the industrial chain, provides upstream and downstream industry support, or simultaneously encourages the joint input and development of upstream and downstream industries to drive the entire industry.

13. Environmental protection policies: The government guides enterprises toward green development through environmental protection subsidies, energy conservation and emission reduction policies, green credit, etc.

14. Market access and competition policies: The government regulates market competition behavior by formulating product standards, industry access standards, implementing anti-monopoly policies, and maintaining fair competition policies.

15. Demand-side: The government encourages industrial development through product subsidies, consumer stimulus subsidies, licensing support, and other measures. For example, but not limited to, encouraging trade-in of old products for new ones, promoting products in rural areas, issuing consumption vouchers, and providing supportive policies for electric vehicle licensing.

16. Land: The government ensures land use needs for industrial development through preferential allocation of industrial land, land purchase discounts, rent subsidies, assisting enterprises in land consolidation, provision of utilities (such as water, power, roads), etc.

17. Localization policies: The government promotes local supply chains and economic development by requiring enterprises to employ local labor, operate locally, procure locally, etc.

18. Entrepreneurship support: The government fosters emerging industries and innovative enterprises by building entrepreneurial service platforms such as incubators and accelerators, providing startups with facilities, funding, consulting, training, and other support.

19. Industry promotion: The government provides display platforms for specific industries or enterprises by organizing or supporting trade exhibitions, product promotion events, etc., to expand product visibility and promote market development.

20. Improving the business environment: The government reduces institutional transaction costs for enterprises by streamlining administration and delegating power, combining deregulation with enhanced supervision, optimizing services, reducing administrative approvals, decentralizing approval authority, optimizing approval processes; or by building a service-oriented government, enhancing the awareness and efficiency of government services for enterprises; or by improving the legal environment, increasing judicial efficiency, providing a fair business environment for enterprises, reducing transaction costs for enterprises; or by improving intellectual property protection mechanisms to enhance enterprises' motivation for R&D.

B.2 conditionality

1. Scale or Strength: Policies often specify the size of enterprises eligible for support, which can be determined by conditions like asset size, registered capital, number of employees, profitability, or tax contributions. For example, some policies may only target large-scale enterprises or restrict eligibility to small and medium-sized enterprises (SMEs).

2. Years of Operation: Certain policies are designed to either support startups or, alternatively, target enterprises that have been operating for a specified number of years. This condition ensures that only firms at a certain stage of their lifecycle benefit from the policy.

3. R&D and Technology: Many policies require that firms have a certain level of R&D investment or possess specific technological qualifications (e.g., patents, R&D platforms, or high-tech capabilities). This condition incentivizes innovation and the adoption of advanced technologies.

4. Region: Some policies are region-specific, meaning that only firms operating in a particular geographical area, paying taxes locally, or sourcing materials regionally are eligible. This type of condition is commonly used to promote local economic growth or regional industrial specialization.

5. Ownership Nature: Policies may also distinguish between different types of ownership. For instance, some policies favor state-owned enterprises (SOEs), while others may prioritize domestic private firms, foreign-invested enterprises, or specific ownership structures based on shareholding ratios.

6. Specific Enterprises: Certain policies explicitly support a limited number of designated enterprises. For example, a policy might be aimed at national champions or industry leaders, offering them preferential treatment to drive sector-wide growth. These policies often name the supported firms directly.

7. Other Conditions: In addition to the above, some policies set eligibility based on additional factors such as credit ratings, tax credit qualifications, environmental protection credentials, and other certifications. These conditions aim to ensure that only enterprises meeting high standards of corporate governance or sustainability receive support.

B.3 stated goal

The common objectives of government policies and their examples include but are not limited to the following:

1. Promote the Development of Strategic Industries: Policies aimed at fostering sectors deemed critical for national development, such as advanced manufacturing or aerospace.

2. Promote the Development of Emerging Industries: Supporting nascent sectors like new energy vehicles (NEVs) or artificial intelligence (AI) that are expected to drive future economic growth.

3. Promote the Development of Pillar Industries: Supporting the traditional sectors that form the backbone of the economy, such as steel, machinery, or textiles.

4. Support the Transformation and Upgrading of Traditional Industries: Encouraging traditional sectors to modernize and adopt new technologies in order to remain competitive in a globalized market.

5. Support the Development of Green Industries: Prioritizing sectors involved in environmental sustainability, renewable energy, and green technologies to foster a low-carbon economy.

6. Promote Technological Innovation: Policies aimed at developing technologies that address critical technological challenges, such as"choke point" technologies or frontier tech advancements.

7. Promote the Application of New Technologies: Encouraging firms to adopt cutting-edge technologies, such as digitization or artificial intelligence, to enhance productivity and competitiveness.

8. Stabilize the Economy and Stimulate Employment: Industrial policies that focus on stimulating labor-intensive industries, mitigating unemployment, and providing a safety net for displaced workers.

9. Promote Social Equity and Improve People's Livelihood: Policies that prioritize inclusive development, poverty alleviation, rural revitalization, or improving social welfare.

10. Urbanization: Supporting policies that promote urban development, integrate rural and urban areas, and manage the challenges associated with rapid urbanization.

11. Other Social Goals: This could include initiatives aimed at improving the living environment, such as environmental conservation efforts or projects to enhance public health and safety.

B.4 implementation

1. Inclusion in performance evaluation: This refers to using the assessment results of policy implementation as a crucial basis for the comprehensive evaluation of lower-level governments and relevant departments, or their principal leaders and leadership teams. The assessment results are incorporated as key criteria for the selection, appointment, promotion, rewards, and punishments of government officials. These results are submitted to the government's organizational and personnel departments, serving as important references for government cadre management, among others. Note: The subjects included in policy assessment are the implementation performance of lower-level governments, departments, and officials. Enterprises or other market entities cannot be classified into this category.

2. Supervision and Inspection: Conducting special supervision, regular oversight and inspection, organizing on-site verification, establishing supervision and notification systems, requiring lower-level governments and departments to regularly report work progress, periodic work summaries, etc., to higher-level departments during policy implementation.

3. Performance Evaluation: For example, formulating performance evaluation indicator systems, conducting annual performance evaluations, introducing third-party evaluation agencies.

4. Positive incentives: For example, commending and promoting exemplary models, providing financial rewards, giving preferential treatment in evaluations and selections, prioritizing support in project approvals, fund allocation, and linking with land quota allocations, etc.

5. Accountability and Punishment Mechanisms: For example, specifying responsible units or individuals, issuing public criticisms to units with unsatisfactory assessment results, establishing an accountability system, strictly holding accountable those who are ineffective in their work, severely punishing those with acts of dereliction of duty or misconduct, and implementing a"one-vote veto" system, etc.

6. Setting Specific Goals: For example, setting clear and specific targets with indicators and numerical values, developing timeline, creating work logs, and breaking down and delegate tasks.

7. Other Categories Definition: Other categories related to assessment, punishment, and incentive that do not belong to Categories 1-6.

B.5 innovation

1. Encouraging Experimentation. For example, in policy implementation, selecting specific regions or units to carry out pilot projects, encourage pioneering and experimentation, supporting the construction of innovative demonstration bases, conduct reform and innovation trials, etc.

2. Granting Discretion. For example, delegating approval authority to lower-level governments or relevant departments, granting decision-making discretion, encouraging them to formulate implementation plans independently, and encouraging their adjustments based on actual situations, etc.

3. Encouraging Exploration and Innovation. For example, encouraging lower-level governments or relevant departments to engage in bold exploration during policy implementation, allowing them to independently innovate in the process of policy execution, and promoting the development of innovative mechanisms and models.

4. Tolerance For Failure. For example, during policy implementation and execution, establishing fault tolerance mechanisms for lower-level governments or relevant departments, exempting relevant responsibilities, showing leniency towards mistakes, and excluding such errors from negative evaluations or performance assessments.

5. Summarization and Promotion of Experience Encouraging or requiring lower-level governments or relevant departments to summarize their practices in policy implementation and promotion, disseminate successful cases, exchange innovative achievements, and form replicable and scalable models, etc.

6. Other Innovation Categories. Other categories that indicate the government encourages relevant government policy execution departments or lower-level governments to carry out policy innovation, but are not included in Categories 1-5.

B.6 scope

1. Financial Support: Includes specific financial support (such as subsidies, incentives with concrete amounts) and financial guarantee measures (such as allocating special funds, increasing fiscal expenditure, broadening financing channels, securing matching funds, enhancing fund management, etc.).

2. Mandatory Enforcement Emphasizes the absolute necessity of policy implementation (e.g., resolute enforcement), employing mandatory measures (such as strict enforcement, prohibitions, cancellations, orders for rectification, etc.).

3. Set Up Organizational Coordination Mechanism This includes specifying the intensity of organizational implementation (such as establishing specialized working bodies, conducting

research and evaluations, formulating detailed implementation rules, specifying procedures and processes, clarifying departmental responsibilities and functions, proposing work requirements, outlining key focus areas, prioritizing projects, developing work plans, deploying tasks, scheduling work progress, etc.), as well as setting up coordination and implementation mechanisms (such as integrated planning, establishing inter-departmental coordination mechanisms, holding regular coordination meetings, jointly conducting inspections, building information-sharing platforms, collaboratively addressing key and challenging issues, etc.).

4. Supporting Policies and Institutional Development Includes supporting policies (such as simplifying approval procedures, giving priority support, improving supporting infrastructure, strengthening talent cultivation, etc.); capacity building (such as conducting professional training for relevant government staff, enhancing their professional capabilities, organizing experience exchanges, holding specialized seminars, strengthening the talent pool within government departments, etc.); and institutional development (such as establishing and improving systems, reforming and perfecting mechanisms, standardizing management, etc.).

5. Other Measures

B.7 local adaptation

1. Grounded in Local Conditions

   Emphasizes independently formulating policies based on the actual circumstances and specific needs of the locality, or developing supporting plans and detailed implementation measures for higher-level government policies by adapting policy to local conditions.

2. Leveraging Advantages in Factor Endowments Leverage the region's advantages in factors such as geographical location, natural resources, labor force, capital, technology, business environment, and supply chain advantages to formulate policies and develop related industries.

3. Exploiting Local Industrial Strengths

   Relying on the local industrial foundation, existing local leading and specialized industries, key fields, advantageous industries, and leading backbone enterprises to develop related industries or to build regional characteristic industrial clusters.

4. Differentiated Policies Emphasizes formulating policies by region and level, providing classified guidance, and implementing policies by enterprise, formulating differentiated support policies according to the actual conditions of different industries.

5. Other Adaptations to Local Conditions: Does not belong to Categories 1-4 but can reflect that the government formulates policies by adapting to local conditions.

B.8 intergovernmental

1. Implementing higher-level policies. For example, implementing the deployments, work requirements, meeting spirits, or document spirits of higher-level governments, departments, or leaders.

2. Citing higher-level laws and policies as the basis. For example, according to, in accordance with, following the laws and documents of higher-level governments or departments as the basis for policy formulation.

3. Executing according to higher-level requirements. For example, executing according to the requirements of higher-level governments, departments, or leaders.

4. Forwarding higher-level documents. Such as forwarding the policy contents of higher-level governments or departments.

5. Responding to higher-level Initiatives. Such as responding to the calls of higher-level governments or departments, cooperating with higher-levels to carry out work, etc.

6. Receiving Guidance from Higher Levels. Such as carrying out work under the guidance of higher-levels, receiving business guidance from higher-levels, etc.

7. Reporting for approval or authorization. Such as reporting to, requesting instructions from higher-level governments, departments, or leaders for review and approval, etc.

8. Designating Pilot Programs.

9. Promoting policy experiences.

10. Policy applicability. The government in 7.2 is within the scope of policy application, key areas, designated to cooperate with policy implementation, or specific targets and indicators are set for them.

11. Commendation and rewards.

12. Criticism and punishment.

13. Other categories.

B.9 citation

1. Forwarding and Issuance. For instance, forwarding or distributing a particular document to relevant governments or departments.

2. Implementation. Such as implementing according to the spirit, provisions, or regulations of a certain document.

3. Basis for Policy. For example, formulating detailed implementation rules based on specific laws or regulations.
4. Policy Continuation or Abolition. For instance, continuing to execute a certain policy, taking further measures based on it, or if this policy document replaces a previous policy, leading to its abolition.
5. Policy Coordination. Such as linking or aligning with certain policies.