Decoding China's Industrial Policies*

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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 a set of key facts about China's industrial policy that explore the following critical questions. What are the economic and political foundations of the targeted industries? What policy tools are deployed? How do policy tools vary between different levels of government and between regions, as well as over the development phases of an industry? What is the impact of these policies on firm behavior, including entry, production, and productivity growth? 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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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.

underplay our contribution (?)

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 its sectoral development and technological capabilities (Naughton, 2021; Naughton, Xiao, and Xu, 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 de-

terminants 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. Understanding China's industrial policy is key to understand the success and pitfalls of the Chinese economy in the last two decades.

Despite the importance of studying China's industrial policy, significant gaps remain in the literature, mainly due to data constraints. Scholars have limited access to detailed and systematic information on the implementation of these policies, 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 microlevel 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 it should exist; 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 such detailed multidimensional data

on China's industrial policy landscape in a structured form. To our knowledge, we are the first to assemble this comprehensive dataset of China's industrial policy at this granular level, which allows us to answer many questions that could not be addressed in the previous literature (see Section 2.1).

LLMs, while increasingly popular as a powerful research aid in social science studies, are particularly challenging to use in our context, where they are tasked with analyzing excessively long documents and answering 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. Our strategies include: 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 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 government's 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 four 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, the dynamic choice of policy tools and implementation methods over the industry's development stages, policy diffusion across regions and the local government's choice of policy tools and implementation methods and policy diffuses, 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 set of empirical facts examines the economic and political economic determinants 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, Lane, and Rodrik (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(a)). To the extent that more developed regions have stronger administrative and fiscal capacity, the results also highlight the importance of this 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 1(b)). 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 1(c)). In addition, we also examine the persistence in sector choice, an important issue in policy implementation (Juhász and Lane, 2024). We find that the targeted sectors in a city exhibit a certain degree of persistence over time; but interestingly, we find that the targeted sectors in a city are shifted when there is a change of local politicians and tend to mimic previous policies of the new politician in the city he previously served (Fact 1(d)). The result confirms the rotation of politicians as an important mechanism for policy learning and diffusion.

The second 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 in

more developed regions are early users of new policy tools, which are later spread throughout the country and adopted by higher-level governments (Facts 2(a) and 2(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 2(c)). We then examine, within each industry, how local governments are evolving their industrial policy tools and implementation methods over time to accommodate each industry's developmental phase. Interestingly, consistent with the idea of industry policies as customized public services (Juhász, Lane, and Rodrik, 2023), we find that within each individual industry, local governments are evolving their industrial policy tools and implementation methods over time to accommodate the development phase of the industry. The policy tool bundles evolve 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 2(d)). The policy implementation starts with local governments' emphasis on strict enforcement combined with local adaptation, to encouraging policy innovation and learning with more concrete and comprehensive organizational supports (Fact 2(e)).

The third set of facts turns the attention to the within-industry across-region diffusion of policies. We demonstrate a trend of increasing interregional policy homogeneity and that the level of homogeneity is strongly correlated with local protectionism in trade (Fact 4(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 4(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 4(a) and 4(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.

In the fourth set of empirical analysis, we associate policy information with various firm data sources to evaluate the effectiveness of 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 5(a)), and thus significantly boost entry (Fact 5(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 5(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.

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, Lane, and Rodrik (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, Monga, and Stiglitz, 2013). The earlier empirical literature on industrial policy focuses mainly on describing what happens to the policy-targeted industries, most of which find that industrial policies have been generally ineffective or counterproductive (Baldwin and Krugman, 1986; Head, 1994; Luzio and Greenstein, 1995; Irwin, 2000; Hansen, Jensen, and Madsen, 2003). More recent literature zooms into specific settings with a careful identification design to assess whether industrial policy elicited the desired 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 focus on whether an industrial policy should be implemented and which sectors should be targeted, Barwick, Kalouptsidi, and Zahur (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 fronts. First, the existing literature often examines industrial policy within a specific context, which can contribute to 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 period of time, 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 complex industrial policies in a large and diverse economy with regional decentralization in economic development (Xu, 2011). The unprecedented data set created through our analysis serves as a basis 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 the central and the local levels will be crucial to 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 passthrough, 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.

Our paper also contributes to the literature on China's industrial policy. Naughton (2021) provides a detailed overview of the evolution of China's industrial policy over the past 20 years. DiPippo et al. (2022) provide an estimate of Chinese industrial policy spending as of 2019. Aghion et al. (2015) use firm-level data and find that subsidies and tax holidays promote productivity when directed at more competitive industries; tariffs and loans do not. Barwick, Kalouptsidi, and Zahur (2023) use a dynamic structural model of the shipbuilding industry to recover government subsidies to Chinese shipyards, and then uses the estimated model to assess the welfare consequences of different subsidy policies. Branstetter, Li, and Ren (2023) document negative impact of government subsidies on firms' ex-post productivity growth.[1]. Liu (2019) demonstrates the importance of taking into account the input-output linkages in optimal choosing the sector to be targeted by industrial policy.

Our research offers by far the most comprehensive description of China's industrial policy landscape, spanning over 20 years and granular at the city level, as previous research has generally been limited to national or provincial analyses relying on specific policy documents, e.g., the Five-Year Plans. 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. 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, Kelly, and Taddy, 2019; Goldstein, Spatt, and Ye, 2021), especially those employ LLM to analyze text data (e.g. Li et al., 2024b; Lopez-Lira and Tang, 2023; Li, Tu, and Zhou, 2024; Kim, Muhn, and Nikolaev, 2024; Bai et al., 2023; Bybee, 2023; Jha et al., 2024). For example, Korinek (2023) introduces LLMs and their potential applications in various research tasks. Eisfeldt, Schubert, and Zhang (2023) measure the exposure of each occupation to generative AI based on 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.

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

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 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 presents a detailed description of the industrial policy data canonicalized using LLM, categorized by key thematic dimensions. Section 4 describes several additional data sets on firms and Chinese politicians that we will use in combination with the industrial policy data set created by the LLM approach. Section 5 documents a set of 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

Several approaches have been proposed in the existing literature to measure industrial policies. These approaches rely primarily on structured policy documents, such as national or provincial five-year plans, or specific policy announcements, or *de facto* measures based on government subsidies firms received. There is also a more recent emerging effort to apply text-based methods to official government documents to code industrial policies. We group existing measures into three broad categories and compare them with our proposed LLM-based method.

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

The second group of studies employs a data-driven approach, combining policy interventions with firm-level administrative data to measure the intensity of industrial policy. For example, Aghion et al. (2015) use the Annual Survey of Industrial Firms (ASIF) data set to construct policy support intensity measures at the city-industry level by aggregating firm-level information, by city-industry, on subsidies, tax holidays, interest payments, and tariffs. Similarly, Branstetter and Li (2023) analyze the total subsidies received by public firms using data from the China Stock Market & Accounting Research (CSMAR) Database to assess the impact of government subsidies on firm performance. DiPippo et al. (2022) compare industrial policy expenditures across countries and use firm-level data to evaluate the effectiveness of policy interventions. Compared to the first approach, this approach only focuses on the industries or firms that actually receive government subsidies, thus it may fail to capture the policies that were not well implemented, or those that mainly utilize

other implementation tools such as consumer subsidy, government procurement, government equity fund, etc.

The third group of studies uses government documents as a source for policy analysis, which has become increasingly prominent. For example, Sinclair and Zhang (2023) scrape 444 official policy documents issued by China's State Council after 2008 and focus on those relevant to industry-specific policies. Their analysis focuses on policies with positive tones and attempts to identify policies using keywords such as "promote" and "develop." Recent advances in text-based methods have enabled the analysis of industrial policy using machine learning techniques. For example, Juhász et al. (2022) use the Global Trade Alert (GTA) database to analyze industrial policies across countries, industries, and time periods. They manually classify a subset of policies and then apply the BERT model to classify the entire data set, 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 around the world. This text-based method relies on the monitoring and reporting of 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 GTA database is manually collected and labeled by a team of observers in each country and Juhász et al. (2022) further labeled the documents with a refined definition of industrial policies, 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, the existing 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. However, 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 do not capture the multidimensional complexity of industrial policies. Second, current measures operate predominantly 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 the implementation of policies at more granular levels, such as cities or districts. In addition, understanding the dynamics of policy passthrough from the central government to local governments, along with the patterns of local policy learning and experimentation, also requires detailed local-level analysis, which has been largely absent in the existing literature. This is where newer methods, such as LLMs, can enable a deeper analysis of

complex, unstructured text data and offer the potential to overcome these limitations.

2.2 Policy Documents

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

We identify and remove duplicate documents based on the title of the document, the issuing entity, and the publication date. After deduplication, the final data set contains 3.1 million unique policy documents for the years 2000 to 2022. Each document provides detailed information on the issuing government body, the effective period of the policy, and its objectives.

2.3 Coding Policy Documents Using LLMs

The government documents provide a wealth of information on policy. In this section, we outline how we leverage LLMs to systematically extract and organize the multidimensional complexity of industrial policies from policy documents.

2.3.1 Overview: What Can We Learn from Policy Documents

We categorize the insights that can be systematically extracted from government documents into four broad categories. First, we identify industrial policies from the near universe of government policy documents described above. This involves determining whether a particular document can be classified as an industrial policy document following a clear and consistent definition (see below). Second, we determine the tone of each policy document (e.g. supportive, regulatory, or discouraging) 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 documents on the scope and operation of the policy, 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 to understanding how the policy is intended

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

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 have been extensive discussions on the exact definition of what constitutes an industrial policy among scholars and practitioners. In trying to identify industrial policies from the Global Trade Alert database, Juhász et al. (2022) apply a relatively narrow definition as policies with: 1) stated goal of changing 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 extr-anational, 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."

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

In this project, we follow Juhász et al. (2022) and Naughton (2021) to use a relatively narrow definition of industrial policy. Specifically, 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 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.

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

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

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

1. The subject of industrial policy must be the government, including various levels of government and subordinate departments. If the text involves company development or collaboration between non-governmental entities, it is not an industrial policy.

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

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

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

Targeted Industry. Because we require an industrial policy to target specific industries, we can identify the industries targeted in each industrial policy document. We identify the industry at the most granular 4-digit industry level. 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 enjoy the spillover effect of the policy target. For example, an industrial policy promoting the long-run growth of electronic vehicles may also benefit battery manufacturers; we do not include battery manufacturing in the definition of "directly targeted industry" unless the document specifically mentions policies for the battery industry.

Policy Tone. We examine the "tone" or intent behind the policy, whether it aims to supportive, regulate, or suppress a certain industry. Notice that even according to our narrow definition of industrial policy, it does not have to be supportive of an industry or a sector. Supportive policies aim to advance sectors through initiatives such as promoting technological innovation, industrial upgrading, attracting and training labor, improving the business environment, coordinating regional development, infrastructure investment, encouraging openness to foreign investment and lowering entry barriers. Regulatory policies, while potentially beneficial in the long term, are more focused on immediate 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 standards. Suppressive policies seek to limit or phase out certain sectors, including actions such as restricting overproduction, supporting market clearing, eliminating outdated production capacity, controlling real estate speculation, or limiting energy-intensive industries.[2]

Policy Implementation Tools. 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 to categorize these tools. For example, the Multi-Agency Support Team (MAST) of the United Nations Conference on Trade and Development (UNCTAD) has developed a coding system for trade-related policy measures that includes 12 categories, ranging from capital control to subsidies, tariffs, migration measures, and others. Similarly, Juhász et al. (2022) used the more detailed taxonomy used by the Global Trade Alert (GTA) project to track various policy interventions around the world. These approaches, while comprehensive for measures related to imports and exports, tend to focus predominantly on national-level policies with a specific emphasis on trade-related interventions.

Our approach builds on the existing frameworks but extends it to account for the unique characteristics of domestic industrial policy, especially at the local government level. We retain several categories of policy tools relevant to trade and international competitiveness, such as entry subsidies, import/export controls, financing tools, and fiscal subsidies, as they remain relevant within China's broader industrial strategy. However, to accurately reflect the distinctive features of China's domestic industrial policies, we incorporate additional policy tools that local governments frequently use. These include labor subsidies, preferential land allocation, industrial funds, and policies promoting industrial clusters - tools that are more tailored to regional economic development and

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

reflect China's decentralized industrial governance structure.

In this extended framework, we classify policy tools into five broad categories:

1. The first category is a group of traditional financial measures that align with international frameworks, such as credit and finance provisions, tax incentives, equity support, and fiscal subsidies. These tools are critical in reducing the financial burden on companies, stimulating investment, and encouraging sectoral growth.

2. 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.

3. The third category includes tools that subsidize inputs in different stages of production, covering 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). In addition, 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.

4. 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 shows to increase product visibility and market access.

5. 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 example, 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 organizing industrial policy tools into these five categories, we significantly advance the literature by capturing the comprehensive toolkits of China's industrial policies both at the national and local level. Such a granular industrial policy dataset is certainly more appropriate for the analysis of industrial policy at the subnational level; it also 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 dynamics, and broader economic goals.

Other 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 effective duration of the policy, the objectives, the 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 more nuanced understanding of industrial policies beyond the implementation tools.

First, we examine the conditionality of policy support, which refers to the requirements or conditions that firms must meet in order to qualify for policy support. These criteria serve as filters through which governments target specific types of firms, ensuring that the policy benefits are allocated according to the intended objectives. Based on the extracted information, the common conditions found in Chinese industrial policies can usually be categorized by the following dimensions: firm 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 that 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, as well as social goals such as employment, equity, or urbanization, etc.

By extracting and categorizing both the conditionality and the stated goals of industrial policies, we can develop a deeper understanding of how government strategies are formulated and structured. These dimensions add crucial layers of complexity to the analysis, providing new 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 policy strength and the government's effort in executing industrial policies, particularly in terms of organizational arrangements within different levels of government. These details give us a clearer picture of how effectively policies are carried out and the administrative measures used to ensure their success.

To assess the strengths of the policy, we evaluate the content of the policy documents in two dimensions. First, we consider how substantive the policy measures are: Does the policy contain vague and broad statements, or does it include highly specific and actionable measures with clear

goals, supervision, punishment, and incentive mechanisms? Second, we assess the intensity of the following measures: Are 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?

To extract information about governments' organizational arrangements related to policy implementation, we guide LLM to read through the documents and evaluate the following four aspects. First, performance evaluation, punishment, or incentives. 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 government agencies, governments, and officials are encouraged to engage in policy innovation. This reflects the government's willingness to allow local experimentation and adaptation to achieve policy goals. We can track how and to what extent lower-level actors are given the freedom or incentives to innovate within the policy framework. Third, methods of policy enforcement. Policy documents may also contain specific measures or arrangements designed to advance the implementation of the policy. This can include task forces, cross-departmental collaborations, 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. This adaptation could involve tailoring goals to local economic strengths, adjusting implementation timelines, or accommodating specific regional challenges. By identifying these local adaptations, we can better understand the flexibility and responsiveness of the policy to the unique local needs and conditions.

By systematically extracting these details using LLMs, we can 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 different levels of government.

First, we extract information on the citation of policies within the documents, revealing how

policies influence and evolve across different government levels.[3] Citations can be categorized into several types. "Forwarding and issuance" citation refers to distributing the policy to other government levels or departments for implementation; "implementation" citation involves citing policies as the basis for specific actions, highlighting their continued influence; "basis for policy" citation occurs when a policy is formulated based on higher-level laws or frameworks; "policy continuation or abolition" citation captures whether a policy continues or replaces a previous one, leading to its abolition; lastly, "policy coordination" citation 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 according to their purpose. Mentions of upper-level government often relate to implementing higher-level policies, citing higher-level laws or policies as a basis, executing specific requirements, forwarding central policies for local action, responding to national initiatives, receiving technical guidance, or seeking approval or authorization from upper authorities. In contrast, references to lower government typically involve directing policy implementation, directing lower government coordination, designating pilot programs, promoting successful policy experiences, defining where the policy is applicable, recognizing commendation or rewards for effective implementation, or issuing criticisms and punishments for non-compliance. In addition, there are miscellaneous mentions of lower government relevant to policy enforcement and governance.

By analyzing both explicit mentions of government levels and the policy citation network, we can better understand the hierarchical coordination of policies in China's multilevel 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 central directives and local innovations contribute to the broader industrial policy landscape.

2.3.2 Details of LLM Implementation: Overcoming Hallucination

Large Language Models. LLMs are advanced deep learning algorithms with billions of parameters, making them ideal tools for analyzing texts to perform 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

[3] 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.

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

Given the complexity of our tasks —-which require 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 tokens (or about 4.9 trillion words), equivalent to the word count of millions of books. Thus, it 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 queries. 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 document 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 structure. 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 direction. It could take hours to explain to human research assistants. Providing clear definitions and guidance, along with counterexamples, is therefore crucial to the quality of the output. However, both the full

texts and the definitions and guidance are necessarily lengthy. In particular, the median length of our policy documents is 1,160 words, with the 90th percentile reaching 5,461 words. Furthermore, 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 the Processes. We conduct two major rounds of LLM queries using both the titles and the full texts of policy documents. The first round covers all policy documents in our sample. The second round focuses on a subset tentatively identified as industrial policies, determined by combining the industry policy scores from the first round LLM query with an orthogonal assessment from a different LLM model on policy titles. We separated the queries into two rounds because the performance of the LLM model deteriorates with excessively long questions, despite the strong performance of the model in processing long texts. Furthermore, based 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, in addition to 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 and evaluating, incentives and punishment for 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 the main components of the prompts we query the LLM.

Major Prompts. To mitigate 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 example, we included a detailed 2,406-word definition of industry policy and policy tool categories based on the existing literature, equipping the LLM with a 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 of policy documents to increase sampling coverage.

In addition, we provide structured and clear guidelines in the prompts for the LLM to analyze the text, and, when necessary, we decompose complex problems to guide the LLM's analytical process step by step. For example, before determining whether a policy constitutes an industrial

policy, we require the LLM to answer eleven specific questions pertaining to multiple aspects of industrial policy.

In addition, we adopt several general prompt strategies that have been found to be useful in different applications in the literature: we set the temperature parameter to zero to obtain more consistent outputs;[4] 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 scores (0-100), concise reasoning, and all relevant text extracted directly from the original text. Including confidence scores 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 number of erroneous policy citations. Furthermore, the inclusion of relevant text and reasoning allows for continual improvement by employing another LLM to critically review 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 (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 a stronger capability to perform complex tasks than `Gemini-1.5-flash-001`. Due to cost concern, we only query it with the policy titles, which are the most informative component 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

[4] In artificial intelligence (AI) and machine learning, temperature is a parameter for adjusting the output of large language models (LLMs). Temperature controls the randomness of text that is generated by LLMs during inference.

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 documents 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 counterexamples, 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 documents are comprehensively captured and that misclassifications are minimized. We adopt a conservative approach and only maintain obvious counterexamples to reduce the likelihood of misclassification in the additional-round LLM analysis.

Finally, we combine the LLM score from the first round, which evaluates the full text of the document, with the LLM score from the second round, which focuses on the document title, to classify whether a document constitutes an industrial policy. Specifically, our criteria are: 1) the first-round score regarding "the document is an industrial policy" must exceed 60 (out of 100); 2) the second-round score regarding "the document is definitely not an industrial policy" should be under 60 (out of 100); and 3) the score difference must be greater than 15. That is, we only tag a policy document as industrial policy if the LLM assesses it strongly suggesting industrial policy status based on the full text, and the LLM does not assess it to be strongly indicative of non-industrial policy based on the document title; moreover, the positive indication based on the full text needs to exceed the negative indication based on the title by a set margin.[5] Through these procedures, we identify 768,387 industrial policies out of a total of 3.1 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 improve the quality of LLM output. Specifically, we extract lists of target industry-related text in the two major rounds of LLM queries using the full policy texts. Although 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, while 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

[5] In principle, we can adjust the thresholds in the two rounds. The current thresholds are based on our experiments using random samples of documents through several iterations.

mentioned industries. Our results indicate that this step primarily serves 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 multistep 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 allows 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 that encompasses any instruments not captured by the predefined classes. To enhance accuracy, we provide detailed definitions in the prompt. Importantly, we design two sets of questions within the first round of LLM prompt: one set of questions specifically asks 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 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 the relevant text from the policy text along with the classification.

We manually checked a randomly selected subset of the output of the LLM responses in the first round, all relevant texts regarding policy tools in the policy document are almost always extracted by the LLM, and there are few false positives in the list. However, 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 counterexamples of misclassifications. We obtain counterexamples by asking another LLM model to summarize misclassifications from a random sample of 10,000 responses related to each category of policy tools from the first-round LLM analysis. We then manually review and further condense the

LLM's summaries. This two-step strategy ensures that all common misclassifications are captured in a comprehensive and accurate way. We adopt a conservative approach and only maintain obvious counterexamples to reduce the likelihood of misclassification in the additional-round LLM analysis. Table D in Appendix D presents an example list of counterexamples we provide to the additional round of LLM.

Finally, we combine the scores of the first round LLM response with the scores of the second round critical review to arrive at the final classification. Figure 1 illustrates the broad roadmap of our LLM approach to decode China's industry policy from government policy documents.

In Appendix A, we also describe the results of several verification checks that we use to evaluate the quality of the LLM outputs, based on word clouds, manual checks, and time series evidence.

2.4 LLM Approach vs. Keyword Search Approach

To assess the efficacy of our LLM approach, we compare it with a hypothetical scenario in which a researcher relies on keyword searches. In particular, certain textual analyses performed by the LLM are inherently infeasible using keyword-based methods. For example, identifying the main 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, or identified as one of the policy targets, or discussed with details such as local industry conditions, key enterprises, and detailed policy measures. Furthermore, mapping these major target industry names to the 432 unique standardized industry names presents significant challenges to the traditional approach. The sheer number of potential combinations between names extracted from policy texts and standardized industry classifications renders the task computationally overwhelming, and fuzzy matching techniques are impractical. For example, keywords such as "new energy", "clean technology", "intelligent", "digital", "power battery", "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 government documents as industrial policies, a critical component of our textual analysis, where a keyword approach might be potentially feasible. To implement the keyword search approach, we first need to come up with a "bag of keywords." We begin by selecting informative keywords from both policy titles and full texts. One option is to define the bag of keywords as keywords that appeared with sufficient frequency, say at least 100 times, in the titles or full texts of policy documents judged by our LLM as industrial policy documents. However, such an approach would result in a vast number of such keywords, in total 12,002 unique keywords from policy titles and 141,199 from full texts, which makes it challenging to thoroughly verify their informativeness manually within a reasonable timeframe. We choose an alternative option. We define and rank the informativeness of each keyword by the proportion of policy titles (full texts, respectively) that our LLM approach identifies as industrial policies among all the titles (full texts, respectively) that contain the keyword. We then select keywords based

on the rankings. The approach is justified as long as our LLM approach can reasonably classify industrial policy, even with some noise. In Table A4 , we present the top 20 keywords by their frequency in titles and full texts, respectively. All of them are arguably related to industrial policies.

In Table 1, we present the number of unique keywords based on policy title (full text, respectively) under different informativeness threshold, as well as the number of policy documents that contain at least one title (full text, respectively) keyword above the threshold. The results involve many keywords to identify a decent number of industrial policies. For example, there are 239 (651, respectively) unique title (full text, respectively) keywords whose informativeness measure exceeds the threshold 80%, that is, at least 80% of the appearance of these keywords are from industrial policy documents identified by our LLM approach, either in title or in full text depending on whether the keywords are tile or full text keyword. Using this bag of keywords, only 168,309 (116,057, respectively) policies at least contain one such keyword in their title (full text, respectively), much smaller than the 768,387 industrial policies that we identify from the LLM approach. Lowering the informativeness threshold to 70% to be included in the bag of keywords would result in 518 (3,602, respectively) unique title (full text, respectively) keywords. The high numbers of unique keywords imply that a substantial amount of effort is required to manually identify them, especially when it comes to full text. The length of the full texts, with a median length of 1,160 words, further adds to the challenge. Yet, even with this informativeness threshold of 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. We find that while the policies identified by the keyword methods contain informative keywords by construction, closer examination reveals that they often pertain to topics such as the reporting of exemplary cases, social and public affairs, public projects, universities, approvals from securities exchanges, poverty alleviation measures, responses to proposals, proposals by the Chinese People's Political Consultative Conference, and internal government governance, which would not have meet our definition of industrial policy.

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.

In contrast, the policies identified by the LLM do not contain very high-frequency informative keywords by design. Thus, if the LLM approach contains classification errors, there may be instances in which the LLM model is most likely to exhibit such errors. However, these policies are arguably related to industrial policy in one way or another. 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, but will be missed in keyword searches. These findings underscore the importance of contextual understanding and confirm the advantages of the LLM approach.[6]

3 Description of Industrial Policies

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

3.1 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, 30.9% of government documents are industrial policies, accounting for 13% of all industrial policies identified by LLMs; at the provincial level, 26.8% of government documents are industrial policies; and at the city level, only 23.5% of the government documents are identified as industrial policies. It is also interesting to note that, first, industry policy documents issued by the central government include significant more than five-year plans that are often used in the existing literature; second, the industrial policy documents issued by the central government only accounts for 13.2% of all industrial policy documents, suggesting the importance of provincial and city level policies in China. Due to the significantly smaller volume of government policies at the county or township level, our analysis below focuses only on the central, provincial, and city level industrial policies, resulting in a total of 741,269 policy documents.

[Table 2 about here]

A notable trend observed in the LLM-analyzed data is the increasing prevalence of industrial policy in government documents at all administrative levels, central, provincial, and municipal. During the past 20 years, there has been a marked increase in both the volume and complexity

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

of industrial policies, reflecting the growing importance of government intervention in shaping economic development.

Figure 2 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 2 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 in South and East China. 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 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.

3.2 Policy Tones

Table 3 presents the distribution of policy tones 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 aim to regulate the targeted industry; at the provincial level, the ratio

is 30%; and at the city level only 24% of the government documents are identified as regulatory industrial policies. The fact that a significant fraction of industrial policies have regulatory tones, and some small percentage even have suppressive tones, suggests that focusing only on supportive policies such as subsidies is likely to paint an incomplete picture of China's industrial policy landscape.

[Table 3 about here]

Figure 4 then plots the evolution of industrial policy tones over time by the level of the issuing government entity, highlighting the growing prominence of supportive industrial policies at all levels of government.

[Figure 4 about here]

3.3 Distribution of Targeted Industries

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 provides a breakdown of the target sectors of industrial policies for the 2-digit industry code and key industry characteristics, by government level.[7] The proportion of policies targeting each sector is listed for all levels of government combined, as well as separately for each government level.

[Table 4 about here]

The agriculture industry, while primarily rooted in traditional sectors, draws substantial attention from all levels of government, with local governments representing a greater share of this attention. Manufacturing and production-related services receive the highest overall focus, accounting for 29% and 49% of all policies, suggesting a close link between traditional manufacturing and the services supporting production processes. In particular, the central government emphasizes manufacturing even more, with 38% of its policies targeting this sector. The focus of the central government on manufacturing highlights the national strategy to strengthen industrial production and competitiveness; in contrast, the city-level government emphasizes slightly more on production-related service industries to support industrial development.

In the service sector, technology-related services and high-skill services also receive significant attention at all government levels, with the focus slightly higher at the city level (20% and 18%, respectively). This indicates that local governments are increasingly targeting these sectors, aligning with the national drive toward technological innovation and service-oriented economic development.

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

In the manufacturing sector, the emerging manufacturing and high-skill manufacturing sectors represent the target of a smaller proportion of policies overall (5% and 11%, respectively), but receive steady attention from both central and city governments, reflecting a targeted push toward 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 upgrading, and agriculture, reflecting regional economic specialization.

Figure 5 provides a visual overview of the distribution of industrial policies in 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. Although the proportion of industrial policies targeting agriculture has decreased, there is a notable increase in policies aimed at production services, reflecting the broader shift in the Chinese 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 manufacturing with high-skilled and emerging manufacturing industries. The proportion of industrial policies targeting high-skill manufacturing has increased steadily, reflecting China's growing emphasis on technological upgrading and innovation within its industrial policy framework. In contrast,the number of policies related to traditional manufacturing remained stable, while emerging manufacturing sectors saw gradual but consistent growth in policy support. It should be noted that, while the focus of industrial policies has gradually shifted toward the emerging and high-skill sectors, traditional manufacturing and agriculture still occupy a large share of industrial policies.

[Figure 5 about here]

Figure A5 further presents a breakdown of the targeted industry at the 3-digit level for the most frequently targeted within the manufacturing and service sector. In panel (a), we observe the time trends for six industries in the manufacturing sector, including general machinery manufacturing, motor vehicle manufacturing, electronic product manufacturing, specific machinery manufacturing, basic chemical manufacturing, and pharmaceutical manufacturing. In particular, motor vehicle manufacturing has shown a significant increase in policy focus, particularly post-2020, which aligns with China's ambitions to become a global leader in electric vehicles. Meanwhile, electronic product manufacturing and general machinery manufacturing have maintained steady policy attention, reflecting their enduring role in China's industrial base. Pharmaceutical manufacturing has experienced a more recent growth in focus, which may be linked to the increasing importance of health-related sectors. Panel (b) highlights trends in six industries in the service sector: internet services, software publishing, real estate, research and development (R&D), commercial services, and financial services. Internet services, commercial services, and software publishing have seen a substantial increase in policy attention, particularly in recent years, underscoring China's push

toward digitalization and the development of its tech industry. Meanwhile, R&D services have also experienced a significant increase, reflecting the government's prioritization of innovation and technological advancement. Real estate and financial services, while still important, have shown relatively steady trends over the period.

Figure 7 exhibits significant regional disparities in the industries targeted in their industrial policies, with a noticeable skew toward wealthier and 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 the central and western provinces, reflecting the continued importance of agriculture in these areas. In contrast, manufacturing policies are heavily concentrated in coastal regions, particularly in provinces such as Guangdong, Zhejiang, and Jiangsu, underscoring their roles as key industrial hubs. Panel (C) shows that high-skill manufacturing policies are predominantly concentrated in economically strong eastern and middle regions, aligning with China's strategic focus on technological advancement and industrial upgrading in these areas, and panel (D) suggests that emerging manufacturing industries, which often involve new technologies and sectors driven by innovation, are geared towards wealthier coastal regions, especially the south-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 the 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 more closely related to manufacturing industries, further strengthening 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, particularly in wealthier coastal areas.

[Figure 7 about here]

3.4 Implementation Tools

Industrial policy documents contain detailed information on the instruments used to support or regulate industries. Through LLM analysis, we identify and classify the specific tools used in each policy and examine their prevalence in 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 group industrial policy implementation tools into five categories: (i) Subsidy and finance, including fiscal subsidies or financial assistance. etc.; (ii) entry and regulation tools that are designed to encourage the establishment of new firms and enhance industry competition; (iii) input related tools that support firms during their production phase; (iv) demand-side tools that are intended to stimulate market demand; and (iv) supply chain tools including promotion of industrial clusters and localization policies. Of course, multiple implementation tools can be used in a single

industrial policy document. Table 5 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 by different government levels.

There are several commonly used industrial policy tools across all levels of government. The most widely used implementation tool is fiscal subsidies, and 41% of the policy documents mention its use. This is consistent with the common belief that industrial policies are usually carried out with government subsidies, but it should be noted that there are still more than half of the industrial policies do not mention fiscal subsidies, which suggests that the existing data-driven method to quantify industrial policies using ex post government subsidies is likely to result in bias. In fact, following fiscal subsidies, market access and regulation (35%), technology R&D and adoption (24%), labor policy (22%), and tax incentives (20%) are tools that are commonly used in general.

[Table 5 about here]

Although there are shared characteristics in the choice of implementation tools at various government levels, there are also significant differences. The central government predominantly employs market access and regulation as industrial policy tools (42%), followed by fiscal subsidies (25%), technology R&D and adoption (21%), tax incentives (20%) and trade protection (19%). The emphasis on market access and regulation highlights the central government's pivotal role in managing entry into crucial sectors and establishing regulatory standards. At the city level, fiscal subsidies (48%), market access and regulation (34%), labor policy (27%), and technology R&D and adoption (27%) are the most widely utilized tools. The provincial 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 different roles for the central and local government: the central government is more focused on setting industry standards and guidelines, while local governments 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. In addition, the proactive participation of local governments in supporting specific industries with specific tools is evident in their more pronounced use of labor policies (27% at the city level versus 16% at the central level), infrastructure investment (23% at the city level compared to 11% at the central level), and the encouragement of industrial clusters (18% at the city level compared to 8% at the central level).

Figure 8a shows the time trends for the usage of different categories of industrial policy tools over the past two decades. First, the use of 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 as a key element in industrial policies at different government levels. Second, tools aimed at regulating market entry have been in gradual decline, indicating a shift in policy focus away from restrictive entry and competition regulation toward more open market practices. Third, input-related tools, such as labor policies, infrastructure investment, and R&D support, have seen a slight increase over time. This reflects a growing

focus on supporting firms during the production phase, particularly through investments in skilled labor and technological development. Fourth, supply chain-focused tools, including policies that promote 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.

[Figure 8 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:

- **New tools (rapid growth):** Tools that started with low usage but grew rapidly over time, including "industrial funds," "promote industrial cluster," "environmental policy," and "promote entrepreneurship." All of these tools show a strong upward trend, indicating increasing policy focus on fostering innovation, encouraging entrepreneurial activity, nurturing local supply chain, and addressing environmental concerns.

- **New tools (moderate growth):** Tools that started with low usage but experienced relatively moderate growth, including "government procurement," "localization policy," "equity support," and "demand stimulation." While these tools have not grown as rapidly as those in the first group, they reflect the expanding role of government intervention in areas such as local sourcing and targeted demand side measures.

- **Traditional tools (strong):** Tools that have been traditionally popular and have seen steady growth over time, including "infrastructure investment," "labor policy," "technology R&D and adoption," and "fiscal subsidies."

- **Traditional tools (stable):** Tools that have retained stable usage over time, including "credit and finance," "preferential land supply," "investment policy," and "improving business environment."

- **Declining tools:** Tools that have experienced a significant decline in usage over time, including "market access and regulation," "tax incentives," and "trade protection."

Figure 8b shows the average usage pattern of these five groups of implementation tools over time in China by all levels of government in China. In Section 5 we will use these groupings of policy tools.

3.5 More Policy Details

Our LLM-analyzed industrial policy data also allow us to examine some other details of the industrial policy, including the objectives and requirements to enjoy the support provided in the policy.

Policy Objectives. Each industrial policy document contains explicit goals that guide its design and implementation. These objectives range from promoting key industries and fostering innovation to improving social welfare. Table 6 examines these objectives in detail, broken down by government level. The first panel outlines objectives related to promoting and supporting key industries. Promoting strategic industries is by far the most common objective, mentioned in 22% of all policy documents. The focus on strategic industries is consistent across government levels. City governments show a higher emphasis on promoting emerging industries (13%) compared to other levels, reflecting the focus of local governments on fostering new economic sectors, possibly to improve regional competitiveness. Policies aimed at upgrading traditional industries are also prevalent, particularly at the city level (14%), indicating local efforts to modernize established sectors.

[Table 6 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 17% policies dedicated to innovation and 8% to technology adoption. The social equity and welfare objectives are present in 26% of all documents, with the city governments putting higher weights on this objective (29%) than the central government (19%) . Meanwhile, city governments place more emphasis on stimulating employment (15%) and urbanization (7%), reflecting local concerns about job creation and regional development. These patterns demonstrate the varying focus across government levels, with the central government focusing on strategic industries and innovation, while local governments have a slightly more balanced objective in promoting emerging industries, employment, and urbanization.

Policy Requirements. In addition to outlining the policy objectives, each industrial policy document specifies the requirements that firms must meet to be eligible for support. Table 7 categorizes these eligibility conditions and provides a breakdown by government level. Almost half of all policies (44%) have a regional focus by specifying the firm location as an eligibility criterion, with a slightly higher emphasis on this condition at the city level (47%) compared to the central government (32%). 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 (33%), with city-level policies placing the most emphasis on this criterion (38%).[8] About 11% of policies include R&D and technological investment as eligibility conditions, with a slightly higher focus at the city level (12%). Central government policies focus more on designating specific set of firms (19% as compared to 15% for city-level policies), and on the type of firm ownership (17% as compared to 12% for city-level policies), likely reflecting national-level priorities for supporting certain types of enterprise (e.g., state-owned enterprises).

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

[Table 7 about here]

3.6 Central-Local Relationship

An essential feature of China's industrial policies is the intergovernmental coordination between the central and local governments. Our data capture 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. Furthermore, the data provide information on how local governments experiment with policies, both in the choice of sectors and in the choice of implementation methods, reflecting the dynamic nature of the formulation and implementation of industrial policies in China.

First, we explore the dynamics through the lens of policy citation networks. Frequently, policies refer to other policies, either to signal adherence to a hierarchical governmental strategy or for other reasons. For instance, a lower-level governmental policy might cite a higher-tier government's policy to illustrate a top-down policy transmission, enabling the adoption and execution of the higher-tier government's directives with more specific implementation tactics or to leverage them to enhance the policy's authority. Policies that refer to other government(s) of the same hierarchical level often aim at coordination, focusing on department-specific implementation details. As an example, a city-level fiscal department might refer to a municipal industrial policy to elaborate on fiscal-subsidy arrangements.

Figure 9a illustrates the policy citation rate over time for industrial policies at different levels of government. Specifically, it shows the percentage of city-level policies citing provincial government policies, the percentage of provincial policies citing central government policies, and the percentage of city-level policies citing central government policies. Three key trends emerge: First, from 2000 to 2012, both the city and the provincial governments showed a gradual decline in citing central government policies. This trend suggests that during this period, local governments were exercising more autonomy in policy formulation, relying less on central directives and perhaps focusing more on region-specific challenges. Second, during the same period, there was a steady increase in city-level policies citing provincial government policies. This growing interdependence between the city and the provincial governments reflects an increasing reliance on provincial-level frameworks to guide local policy decisions. It also suggests a stronger vertical integration within subnational levels of governance. Third, after 2013, there is a noticeable reversal in the previous trends. Both the city and the provincial governments began to cite central government policies more frequently, indicating a return to top-down coordination in the wake of national reforms or changing policy priorities. In addition, the increase in city governments that cite provincial policies accelerates during this period. However, after 2018, a slight reversal of these trends is observed, possibly reflecting a return to more localized policy experimentation or flexibility. These patterns demonstrate the evolving dynamics of intergovernmental coordination in China's industrial policy:

periods of decentralization are followed by stronger central control.

[Figure 9 about here]

Figure 9b illustrates the citation rate within the same level of government 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 and city governments show a steady increase in self-citation rates over time. This growth likely indicates improved coordination between departments within the provincial and city governments. By citing policies from the same level of government, local governments demonstrate a growing reliance on internally consistent policy frameworks, reinforcing coordination between different agencies or sectors at the local level. Second, the central government consistently exhibits the highest self-citation rate, followed by the 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 higher rate of self-citation by the central government also probably reflects its role in setting comprehensive national strategies, which are likely coordinated across multiple departments.

3.7 Political Incentives for Policy Implementation

Lastly, we dive into the details of the political incentives for policy implementation mentioned in the industrial policy documents. Table 8 highlights the role of political incentives and local adaptation in the implementation of industrial policy at different levels of government.

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

The second panel then looks at the incentives and mechanisms for policy experimentation and innovation. Provincial and city governments also often pilot new approaches to industrial policy, which, if successful, can 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. Approximately 21% of policies across all levels encourage pilot program and the demonstration effect of the pilots. 6% of the policy documents encourage local policy innovation, and only 2% explicitly mention mechanisms that allow mistakes in the policy experimentation process. On the other hand, 13% of the policies emphasize

the participation of local governments and 15% of the policies encourage the learning of existing experiences.

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

Although the central government sets broad strategic priorities, local governments customize these to fit regional economic conditions and industry strengths. This flexibility allows local governments to align with national goals while fostering regional growth. Local adaptation is particularly prominent at the city level (51%) compared to the central government (24%), indicating the greater flexibility granted to cities in tailoring policies to their specific contexts. In terms of the consideration of local advantages, 12% of the policies emphasize local industry advantage, and 8% emphasize on local supply chain advantage— both measures show significant variation across government levels.

[Table 8 about here]

Using comprehensive data on policy execution, we guide LLM to summarize the four dimensions of implementation methods above in order to assess the document content across two dimensions: policy concreteness and policy strength, both in the range of 0 to 100. Figure 10 illustrates the mean scores for the concreteness of the policy (panel a) and the strength of the policy (panel b), for different government levels. The trends in both policy metrics reveal convergence: policies at the city level consistently maintain their concreteness and strength, provincial policies experienced a dip in strength leading up to 2013, and central policies exhibited a significant increase in strength after 2013.

[Figure 10 about here]

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

4 Other Data Sets

In the rest of the paper, we will combine the industrial policy data set with rich firm-level data to investigate the effect of industrial policies in promoting entry, competition, innovation and long-term growth of the targeted industries, and we will also use a comprehensive data set of Chinese

politicians at the provincial and local levels to offer insights into political economic influence on the choice and effects of industrial policies in China.

4.1 Firm Data Sets

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

Administrative Tax Records. To enrich our measure of firm performance, we also use the administrative enterprise income tax records from the Chinese State Administration of Tax (SAT) for the years 2008-2020, covering a representative sample of more than 1 million firms from stratified sampling.[9] For tax collection and audit purposes, SAT collects firm-level records of tax payments, as well as other financial statement information used in tax-related calculations. The advantages of tax data are two-fold. First, it is representative with wide coverage. As administrative data, it is not subject to the potential measurement error problem of self-reported data. Second, it contains detailed historical information on a wide array of tax-related information about the firms, including their total production, sales, inputs, employment, etc. This allows us to examine the firms' performance in a longer time horizon and in more dimensions. Table A9 reports the summary statistics for key variables.

Value-Added Tax Data. The last firm-level data set is a unique dataset from the 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 to claim input tax credits, and failures to comply are strictly punishable by law.[10] In Section 5 we use this data set to construct city-to-city trade flows to measure the extent of local protectionism and analyze its relationship with industrial policies.

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

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

4.2 Politicians Data Set

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. Table 9 reports the summary statistics for key variables based on the politician data.

5 Four Sets of Facts of China's Industrial Policy

In this section, we document four sets of facts about China's industrial policy over the past two decades. These findings provide a comprehensive overview of the determinants, implementation, evolution, and propagation of industrial policies, as well as their effects on firm entry and performance.

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

5.1 Economic and Political Economic Determinants of Targeted Industries

As shown in Section 3.3, 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. The local government's choice of the policy target reflects an intricate balance of the top-down policy transmission and local adaptations. Both mechanisms are deeply ingrained in China's political framework. As Xu (2011) convincingly argues, China's economic success is founded on a system, referred to as *Region-*

ally Decentralized Authoritarianism, that is characterized by centralization of political authority and decentralization of administrative and economic powers. The centralized political structure incentivizes transmission of policies from the central government to provincial governments then further onto the local governments, while the decentralized economic powers, coupled with competition among local officials, encourages and fosters experimentation at the local level. Furthermore, the relative strengths of the two mechanisms is not static. It has shifted over time depending on the central government's main focus, which has oscillated between economic growth and political stability and economic growth. Understanding this interplay between central directives and local adaptation is key to analyzing the political economic determinant of China's industrial policies. We first examine the economic rationality of the choice of targeted industry/sectors by China's local governments' industrial policy (Fact 1a). We then combine the industrial policy data with the politician data set to explore the political economy underpinning these policies, where we begin by investigating the top-down policy transmission mechanism (Fact 1b), followed by an analysis of how this transmission has evolved over time (Fact 1c). Finally, we explore the regional diffusion of industrial policies and the role of politicians' career mobility in the regional diffusion (Fact 1d).

Fact 1a: *Cities' choices of the policy-targeted industries are positively correlated with both their capital-based comparative advantage and absolute advantage.*

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

To examine whether China's industrial policies at the local level, align with economic theory and the current country-level evidence, we use the 0.3 million city-level industrial policies identified by the LLM, and focus on the period between 2001 and 2020. We examine the city government's choice of policy-targeted sectors and its relationship with the cities' 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 indicator, 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]

[11] We tried different specifications for robustness. For example, whether the industry has been targeted in at

This binary variable serves as the dependent variable in our empirical analysis, allowing us to test the factors that affect the local governments' choice of the targeted industries. On average, local governments' choice of the targeted industry is selective: on average only 7% of industries in each city-year cell are targeted by industrial policies.

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

$$RCA^{p}_{cst} = \frac{Capital_{cst}}{\sum_s Capital_{cst}} \Big/ \frac{\sum_{c' \in p(c)} Capital_{c'st}}{\sum_s \sum_{c' \in p(c)} Capital_{c'st}} \quad (1)$$

$$RCA^{n}_{cst} = \frac{Capital_{cst}}{\sum_s Capital_{cst}} \Big/ \frac{\sum_{c'} Capital_{c'st}}{\sum_s \sum_{c'} Capital_{c'st}} \quad (2)$$

$$AA_{cst} = \frac{Capital_{cst}}{\sum_s Capital_{cst}} \quad (3)$$

The two RCA measures, RCA^{p}_{cst} and RCA^{n}_{cst} are defined by the relative importance of industry s within city c, as proxied by the registered capital, compared to its overall importance of the industry in the province p and in the nation overall, respectively; it captures whether a city is more specialized in a particular industry than other cities in the province or in the nation overall. The AA measure AA_{cst}, on the other hand, reflects the absolute importance of industry s in city c, and proxied by the cumulative registered capital of firms registered in the city-industry-year cell.

Table 9 reports the summary statistics for key measures based on firm registration data for the period 2001-2020.

[Table 9 about here]

We estimate the following Poisson pseudo-maximum likelihood (PPML) estimator, which accounts for the large share of zeros in the dependent variable:

$$Policy_{cst} = \exp\left[\lambda_1 L.RCA^{n}_{cst} + \lambda_2 L.RCA^{p}_{cst} + \lambda_3 L.AA_{cst} + \delta_c + \eta_s + \gamma_t\right] \times \epsilon_{cst}, \quad (4)$$

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

least three city-level government documents; or whether the industry has been targeted at least once in a narrowly-targeted policy document (a policy document mentioning no more than 5 4-digit industries); or the number of documents targeting the industry. Our results remain robust with different measures of policies.

[Table 10 about here]

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

Remark 2 *One potential concern is that the policies are serially correlated, and previous policies enhance the subsequent local RCA. In such a scenario, the observed link between policy focus and RCA could be attributed to this endogenously developed advantage rather than the deliberate strategies of the local government. To differentiate between these factors, we analyze the initial year in which each industry was targeted in each city, examining the relationship between policy targeting and the local comparative advantage measures constructed from the year prior to the initial target year. Table A11 reports the regression results. It shows that the correlations between the industry target and local RCA and AA remain robust.*

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

Remark 3 *The capital-based AA measure we constructed can also proxy for the political influence*

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

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

We now delve into the political economic factors that also affect local governments' industrial policy choices; in particular we examine the "pass-through" effects that capture how city-level governments align their industrial policy sectoral choices with those of both the provincial government and the central government. This interaction between different levels of governments is essential to the understanding of how centrally coordinated policy directives are executed at the local level.

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

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

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

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

Figure 11 plots the estimated coefficients from the regression equations (5)-(6), showing the local response to the upper-level government policies with different leads and lags. The x-axis represents the event time which ranges from six years before to six years after the issuance of upper-level policies, and the y-axis shows the magnitude of the response. The red and blue dots respectively represent the policy pass-through from provincial governments and the from central government to city governments, estimated from Eq. (5), while the green triangles plots the policy pass-through from central government to provincial governments estimated from Eq. (6). They show that the same-year correlation between the target sectors for city and provincial industrial policies is the strongest, but there is also some weak serial correlations for proximate leads and lags. The alignment between provincial policies and central policies shows similar patterns with

the strongest same-year correlation and weaker serial correlation over time. On the other hand, the response of city policies to central policies is generally weaker than their response to provincial policies, and is also weaker compared to the response of provincial policies to central policies. This is consistent with China's one-level-up political system, which implies that provincial governments are more directly accountable to central authorities than the city governments.

[Figure 11 about here]

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

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

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

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

[Table 11 about here]

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

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

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

The two panels in Figure 12 plot the estimated coefficients, $\hat{\beta}_{1t}$ and $\hat{\beta}_{2t}$, over time, representing the degree of pass-through from provincial and national governments to city level, respectively. It shows that the pass-through of the targeted sectors from the central and provincial governments to the city governments exhibit notable changes over time, and the results underscore 2013 as a pivotal year. Panel (a) shows the time-varying response of city-level industrial policies to the provincial policies, where the downward trend from year 2005 illustrates a decline in the province-to-city pass-through, but there has been a resurgence after 2013. Panel (b) depicts the policy pass-through from the central to city-level governments. The correlation between city and central policy choices of targeted sectors was largely insignificant before 2013, suggesting a period of relative local autonomy in policy formulation. This is consistent with the common belief of China's one-level-up political system and the corresponding incentive scheme of the local bureaucracies. Post-2013, however, the correlation became significantly positive, marking a clear shift towards stronger alignment with central government directives. This shift after 2013 can be attributed to various factors, including a political reorientation towards centralization, stronger monitoring mechanisms, and perhaps the changing national priorities that required a more coordinated policy framework across all levels of governments.

[Figure 12 about here]

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

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

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

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

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

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

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

[Table 12 about here]

Having shown that new local politicians tend to reverse the support for some sectors favored by the predecessors, we now further examine what sectors the new local politicians will support. To do so, we identify a subsample of politicians who experienced lateral moves across cities, namely the newly appointed party secretary or mayor have served as either the party secretary or the mayor of another city in the previous year. We examine the policy choice of the city and decompose 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 by politician.

Table 12 columns (3)-(4) report the regression results. Column (3) shows that, when there is a turnover of local politicians, the correlation with previous year's policy drops to 0.28. Interestingly, there is a positive correlation between the targeted sectors of the new city and those targeted in the politicians' previous jurisdiction, as the coefficient estimate of the term *L.Policy (same politician)*

is 0.09 and statistically significant at 1% level. To address the concern that the positive correction with *L.Policy (Same Politician)* follows from the fact that the politician's previous and the current cities are in the same province, we construct a measure of the average lagged policy indicator for all the other cities in the province, which we denote by *L.Policy (Neighobor Cities)*, and include it in the regression. Column (4) shows that the coefficient estimate of *L.Policy (Same Politician)* remains positive and statistically significant, with a somehwat larger magnitude, while the coefficient estimate for the placebo control – the neighbor's average policy – is small (0.04) and not statistically significant.

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

5.2 Policy Tools: Regional and Sectoral Variations and Dynamic Evolution

We now turn the focus to the choice of policy tools. In Section 3.4, we observe a notable increase in the variety of policy tools over time and a more balanced use of the traditional tools and the new tools. The ultimate success of industrial policy depends on the fiscal and administrative capacity of the local government (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 aspects: How does the choice of policy tools vary across different levels of government (Fact 2a), across regions (Fact 2b), and across industries (Fact 2c)? Our goal is to understand the driving factors behind the selection and use of policy tools by examining their adoption and evolution over time. These details shed light on the processes by which industrial policies are carried out in China.

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

We first explore how local, provincial, and central governments differ in their use of 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:

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

where $\mathbb{1}(Tool_{ikgst})$ is a binary variable that takes value 1 if a specific tool type k is used by industrial policy i for industry s in government level g during year t; $\mathbb{1}\{g=n\}$ is an indicator for central-level policy, and $\mathbb{1}\{g=p\}$ is an indicator for provincial-level policy; $Year_t$ are year indicators, and δ_s and γ_t are industry and year fixed effects. Note that city-level policy is used as the default group whose tendency to use the type k policy is absorbed in the year fixed effect γ_t. Because the focus of the analysis is the dynamics in the choice of policy tool over time, to sharpen the contrast, we categorize them into five distinct groups based on their initial usage and growth patterns as in Section 3.4.

Specifically, k can represent one of these categories: rapidly growing new tool, moderately growing new tool, stable traditional tool, increasing traditional tool, or a declining traditional tool.

Figure 13 illustrates the trend in tool usage across government levels over time. Panels (a) and (b) plot $\hat{\beta}^n_{k,t}$— the coefficient estimated for the central government, and Panels (c) and (d) plot $\hat{\beta}^p_{k,t}$— the coefficient estimated for the provincial governments— relative to the city-level government in tool usage.

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. In general, city-level governments are more entrepreneurial in experimenting with new tools, reflecting their flexibility in adjusting policies to local needs and innovation, while the central government remains more consistent in its use of traditional tools, 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 are more entrepreneurial in implementation, and they are the main agent in policy tool experimentation.

[Figure 13 about here]

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

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

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

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

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

Figure 14 plots the estimated coefficients $\hat{\beta}_{k,t}$ to illustrate how the use of different policy tools interacts with the level of the city's economic development. As seen in Panel (a), more developed

cities are earlier adopters of new policy tools like industrial fund, industrial promotion, and demand stimulation, etc. However, there is a significant converging trend over time. Panel (b) shows that the more developed regions also rely much more heavily on traditional tools like tax deduction and trade protection— 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 14 about here]

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

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

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

where $Industry_s$ are indicators for industry type— we first compare manufacturing industry versus other industries (i.e. $Industry_s = 1$ for manufacturing industry and 0 for others), and we also focus on the subsample of policies targeting the manufacturing sector and 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, and ϵ_{ikcst} is the error term.

Panels (a) and (b) of Figure 15 plot the estimated coefficients, $\hat{\beta}_{k,t}$, when we compare the policy tool choices for industrial policies targeting manufacturing industry with those targeting other industries. Panel (a) suggests that the fast growing new tools such as industrial fund, promoting industrial cluster, and encouraging entrepreneurship are more prevalently used in supporting the manufacturing sector. Panel (b) indicates that manufacturing sectors more frequently use traditional market protection tools while rely less on other traditional tools, such as fiscal subsidy or financial support.

[Figure 15 about here]

Panels (c) and (d) compare the policy tool choices supporting skill-intensive and other manufacturing industries. Panel (c) suggests that governments more frequently use the new tools such as demand stimulation, promoting industrial cluster, and encouraging entrepreneurship, etc. to support skill-intensive manufacturing industries ; Panel (d) suggests that monetary incentives (fiscal and finance) are used more prevalently to support the skill-intensive manufacturing industries, while traditional market protection methods are used less frequently.

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

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

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

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

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

Figure 16 Panel (a) 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 boosting firm entry and government-led demand stimulation. The commonly used tools are those targeting the firms' entry stage and attempting to lower firms' fixed cost and entry barrier, for example, fiscal subsidies, favorable land allocation, industrial funds, market access and regulation, and entrepreneurship encouragement. On the demand side, government procurement is used more often in the initial development stage. Over time, the focus gradually shifts to industrial upgrading, market-based selection mechanism, and consumer-based demand stimulation. The policy tools that are used more often are technology R&D, labor and talent development, environmental protection, promoting industrial cluster, etc. Compared to entry promotion, these tools focus more on facilitating firms' production and industrial upgrading. On the demand side, policy tools increasingly rely on industrial promotion and consumer-based demand stimulation. While government procurement relies on the government's ability to pick the winners, consumer subsidies and trade fairs foster market transactions and allow the market to pick the winners. Overall, the results suggest that local governments are not only choosing different tools for different industries, but also dynamically changing the tools according to the industry's development stage.

[Figure 16 about here]

Fact 2e: *For a given industry over its development phase, the choice of implementation method evolves over time, and the implementation strength increases.*

With the same empirical setting, we then examine the local governments' dynamic choice of implementation methods over an industry's development phase. Figure 16 Panel (b) plots the estimated coefficients β^ks for various implementation methods, where a positive coefficient indicates an increased likelihood of utilization as the industry matures. The results depict the dynamic evolution of the implementation methods— specifically, the political incentive scheme for policy implementation (blue triangles), the promotion of policy experimentation and innovation (purple triangles), the government's organizational support (red triangles), and the considerations of local conditions in policy implementation (orange triangles)— over time.

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

5.3 Spatial Diffusion and Potential Inefficiency of Industrial Policies

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

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

We examine the spatial correlation of policy sector choices across cities to assess the degree of policy similarity. For each city in each year, we construct an industrial policy vector consisting of the 0/1 indicators for whether each industry is supported or not by an industrial policy. We then calculate the *cosine similarity* of the policy vectors between each city pairs in the same province, from which we calculate the city-year level policy similarity index as the average of the cosine similarity measure for the city with all the other cities in the *same province*. Figure 17 plots the over-time and geographical distribution of policy similarity, revealing significant increase in policy similarity over time, as well as great regional variations.[12]

[Figure 17 about here]

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

Figure 18 presents the bin-scatter plot for the city's within-province policy similarity index and the two intra-city trade shares we created. Panel (a) uses the share of intra-city trade in the city's total trade volume on the x-axis, and Panel (b) uses the share of intra-city trade in the city's 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, and the effect is stronger for city pairs within the same province. Thus, more similar industrial policy choices may lead to similar economic structures across regions and thus reduce the incentive for inter-regional trade, potentially contributing to elevated local protectionism harming overall economic efficiency.

[Figure 18 about here]

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 can lead to overly homogeneous industrial structures.[13]

[12] 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 lower similarity in policy choices.

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

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 and maximize local tax revenue. Local protectionism, which often involves policies aimed at protecting local industries from competition within the same country, has been a prevalent issue in China, driven by both fiscal incentives and political motives (Fang, Li, and Wu, 2022; Young, 2000).

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

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

Local protectionism is therefore reinforced by both fiscal and political imperatives. From a fiscal point of view, local governments are incentivized to protect and nurture local industries to secure tax revenues and create jobs. Politically, local officials are evaluated based on their city's economic performance relative to their peer cities in the same province, which motivates them to adopt policies that favor local industry retention and growth. This protectionism can manifest 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 similarity is earning, where cities imitate successful industrial policies from other cities. This effect is especially pronounced in high-growth sectors such as high-tech and renewable energy, where regional officials may see the success of other cities as a blueprint to follow. However, this imitation can dilute regional specialization, as cities pursue the same industries rather than capitalizing on their relative comparative advantages (see Fact 3b below).

Fact 3b: *As policies diffuse across regions, it leads to diminishing policy effectiveness.*

We now explore the efficiency implications of industrial policy diffusion across regions. 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 tend to promote the same industries over time. However, this diffusion can lead to inefficiencies, particularly in terms of overcapacity when too many cities target the same industries.

We analyze how the sequence of cities targeting a particular industry affects the policy effectiveness on the new firm entry, firm's capital investment, and performance. Specifically, we examine whether earlier adopters (pioneers) benefit more than later adopters (followers). For each industry,

we define the order in which cities start to support it, allowing us to differentiate between early and late adopters. We estimate the following regression at the city-industry-year level:

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

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

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

[Table 13 about here]

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

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

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

Table 14 shows the firm-level effects. Firms in policy pioneer cities benefit from higher firm revenues and profits, but as more cities start to target the same industry, these gains diminish, and the firms in policy follower cities experience lower or even negative revenue and profit gain. This suggests that later entrants face more intense competition and overcapacity, which erodes the effectiveness of the policy. In summary, the policy pioneers may enjoy significant benefit from more firm entry and higher firm profit, as the number of cities targeting the same industries increases, it may lead to diminishing and even negative returns.

[Table 14 about here]

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

We advance two possible reasons for the diminishing returns for industrial policy in follower cities, as documented in Fact 3b. The first is overcapacity, as a result of excessive entry under government support. As more cities adopt similar industrial policies, it leads to excessive entry of firms into the same industries, ultimately creating overcapacity. With too many firms competing in the same market, resources such as labor, capital, and upper-level government support become stretched, reducing efficiency and productivity for all firms. In Fact 3b, we documented the negative correlation between the policy adoption order and the effectiveness of policy to induce firm entry and capital formation in the targeted industries.

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

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

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

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

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

[Table 15 about here]

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

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

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

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

[Figure 19 about here]

Third, with the same empirical specification, we also examine the differences between pioneer and follower cities in their choices of policy implementation methods. In Panel (b) of Figure 19 we plot the coefficients estimated for each implementation method. It shows that, in general, policy follower cities show less local dynamism in their choice of policy implementation methods: they are less likely to set specific targets, and use more negative incentive and less positive incentive scheme; they are less likely to encourage policy innovation, and accordingly, are less tolerant for mistakes in policy implementation; they emphasize more on top-down strict policy enforcement, while providing less funding; and they significantly emphasize less on local advantages, which is consistent with the previous fact that they are less likely to target industries with local comparative advantage.

Now we take a different perspective and examine to what extent the local governments, especially those of the policy follower cities, adopt the policy tool bundles as specified in the upper-level government policies. Specifically, within each city-industry-year cell, we construct a tool vector representing each government's choice of policy tools— the k-th element of the vector takes the value 1 if the government uses type k tool for this industry in this year. We then calculate the cosine similarity between the tool vector of each city government and the provincial government (or central government) in each industry each year. Figure 20 presents the bin-scatter plot of the tool similarity index with the order of policy adoption on the horizontal axis. The figure shows a strong correlation between the order and the similarity index, indicating that follower cities fol-

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

low the upper-level government in the choice of policy tools with less local experimentation and adaptation.

[Figure 20 about here]

5.4 Effects of Industrial Policies on Firm Performance

The success of industrial policies hinges not only on the choice of the targeted industry but, more importantly, on how these policies are implemented using various industrial policy tools. We now combine LLM-analyzed industrial policy data with microlevel firm data to investigate the policy impact on firm performance. In this subsection, we attempt to shed some light on the effectiveness of different tools in achieving key policy objectives. 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 4a). Second, we examine whether industrial policies lead to an increase in firm entry, and whether different policy tools have heterogeneous impacts on new firm formation (Fact 4b). Third, we assess whether industrial policies enhance firm productivity and analyze the differential effects of various tools (Fact 4c).

Fact 4a: *Industrial policies are effective in reducing tax rates, providing subsidies, and increasing firm leverage, and the effect depends on the characteristics of the firm and the tools used.*

First, we employ the administrative tax records of firms to determine whether those in sectors targeted by industrial policies indeed receive government support, such as tax breaks, subsidies, or better financing options. This analysis ensures that the allocation of policy supports aligns with their intended goals, particularly with regard to providing meaningful support to firms in target industries.

We first regress various measures of firm outcomes on the policy dummy; in order to capture the differential effects of policies with different tones, we make the full use of our LLM policy output and separately include indicators for whether the city has supportive policies, denoted by $Policy^{+}_{sct}$, or regulatory/suppressive policies, denoted by $Policy^{-}_{sct}$, for industry s in year t. The regression equation is as follows:

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

where the dependent variables, Y_{fsct}, measure various aspects of firm-level financial conditions, including: (1) tax deduction rate defined as the ratio of total tax exemption to before-tax revenue; (2) log of the total amount of subsidies received by a firm; (3) 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. We include either the industry by city fixed effect or the firm fixed effect δ_f, and year fixed effect γ_t.[15]

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

Table 16 presents the regression results. We begin by controlling for industry-by-city and year fixed effects to examine the average correlation between policies and firms in the targeted industries. We then replace the industry by city fixed effect by the firm fixed effect, which enable us to track the same firms over time. These specifications allow us to estimate the effect of industry policy on the average firms in the target industry, and on the existing individual firms in the target industry, respectively. Columns (1) and (2) find that supportive industry policy is associated with a 6% industry-wide average increase in firm subsidy, and the effect drops to 1.8% on the intensive margin among existing firms after controlling firm fixed effect. Columns (3) and (4) suggest that firms in targeted industries with supportive industrial policy, on average, enjoy a 5 percentage point lower effective tax rate, and the effect turns null after controlling for firm fixed effect. Columns (5) and(6) present the results of firms' long-term debt, and they show a significant industry-wide effect of policy support on firms' financing condition: the probability of acquiring long-term debt increases by 2.3 percentage points under policy support. The magnitude of the effect decreases to 1.1 percentage points on the existing firms when we control for firm fixed effect.

[Table 16 about here]

Comparing the coefficients for supportive policies and regulatory policies reveals an interesting pattern worth further investigation— both types of policies show positive correlations with firm benefits like subsidies and enhanced financing conditions. Two potential explanations may explain the observed contemporaneous correlations between firm performance and policy indicators. First, the positive coefficients for regulatory policies might stem from endogenous targeting: these policies frequently focus on industries that already surged due to earlier industrial support. As a result, the regulatory policy indicator becomes positively correlated with benefits that firms accrued pre-regulation. Second, the policies themselves might directly contribute to increased firm benefits.

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

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

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

The results are reported in Figure 21. It unveils the different mechanisms that drive the positive contemporaneous correlation between policy indicators and firm outcomes for supportive policies and regulatory policies. Forward terms of regulatory policies, indicating future policy targeting, are positively correlated with firm subsidies and financing conditions, while lagged terms are either negatively correlated or statistically insignificant. This temporal pattern supports the endogenous

targeting channel, where regulatory policies aim to regulate previously heavily subsidized industries. In contrast, supportive policies exhibit an opposite dynamic: their lagged terms are positively correlated with firm benefits, suggesting that these policies directly contribute to increased subsidies, tax deductions, and financing opportunities for firms over time. The results show similar patterns when controlling for city-by-industry FE and for firm FE, although the magnitudes are less pronounced in the case of firm FE.

[Figure 21 about here]

We further decompose the effect of the policy 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 3.4, and run the following regression:

$$Y_{fsct} = \sum_{k} \beta_k \times Policy_{ksct} + \delta_{sc} + (\delta_f) + \gamma_t + \epsilon_{fsct} \tag{20}$$

The results are reported in Table 17, and they show the heterogeneous effect of different tools on different dimensions of firm benefits. First, fiscal and financial tools have consistent and robust positive effects in providing firms with subsidies, tax deductions, and access to finance. This is the only category that directly target monetary benefits, and once controlled for tools in this category, the impact of other tools on firm outcomes is mixed.[16] Examining the effect of the other tool categories, the results show that: First, tools to foster industrial clusters (mostly with special economic zones) are positively correlated with subsidy and financing options, while negatively correlated with tax deduction rate; Second, demand stimulation is negatively correlated with subsidies and financing options, while positively correlated with tax deduction opportunities, suggesting that tax deduction is mostly frequently employed to stimulate demand; Third, tools in the entry and regulation category is only positively correlated with industry-wide subsidy, and the effect turns negative for the incumbent firm, probably due to that greater new entry dilutes the benefits for the incumbent firm; Lastly, tools in the input and R&D category is only positively correlated with better financing opportunities. 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 17 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

[16] 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 the other tools. For example, the coefficients for industrial clusters should be interpreted as the net effect of the policies that mention industrial cluster-related policy tools but do not directly mention the tools in the other categories.

policy dummies with the firm's log of registered capital. Table 18 reports the regression results. It suggests that, on average, larger firms benefit more from industrial policies.

[Table 18 about here]

Fact 4b: *Industrial policies are effective in increasing 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.

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

$$Y_{sct} = \sum_{l=-6}^{6} \beta_t^+ \times Policy^+_{sc(t-l)} + \sum_{l=-6}^{6} \beta_t^- \times Policy^-_{sc(t-l)} + \delta_{sc} + \gamma_t + \epsilon_{sct}, \tag{21}$$

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

Figure 22 plots the estimated coefficients for β_t^+s and β_t^-s. It indicates that supportive policy is associated with positive firm entry rate, and regulatory policy is associated with negative firm entry rate. Further examining the intertemporal correlation indicates that the positive firm entry rate leads supportive policies by one period, suggesting a potential anticipation effect. On the other hand, the negative response to regulatory policies takes 2 years to prevail.

[Figure 22 about here]

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

$$Y_{sct} = \sum_{k} \beta_k \times Policy_{ksct} + \delta_{sc} + \gamma_t + \epsilon_{sct} \tag{22}$$

Figure 23 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 subsidies, labor policies, preferential land supply, industrial promotion are the most effective tools to increase the entry of new firms, followed by tools to promote entrepreneurship, market access and regulation methods, and infrastructure investment. These tools provide direct benefits, and thus lower entry barriers for new firms. Access to credit and finance, tax deduction, demand stimulation, promoting industrial clusters, and industrial fund

have relatively mild effects on attracting new firms. Tax incentive, technology R&D and adoption, investment policy, equity support, and improving the business environment show a null effect on the entry of new firms. It may be because these tools mainly benefit the incumbent firms. In sharp contrast, environmental policies, trade protection, and government procurement policies have significantly negative effects on new firm entry. Environmental policy deters new firm entry because of the elevated environmental standards and compliance costs. Trade protection, while on the one hand, may protect domestic or local firms, maybe at the cost of deterring foreign firms and firms from other cities. Government procurements are usually biased toward larger or state-owned enterprises and thus may lead to more concentrated market power and deter the entry of smaller new firms.

[Figure 23 about here]

Fact 4c: *Industrial policies have a mixed effect on firm productivity.*

Lastly, we examine whether and how industrial policies affect firm's production and productivity. Unlike the largely positive effects on preferential treatment and new firm entry, the impact of industrial policy on firm productivity may be undetermined ex ante. Several mechanisms can operate simultaneously under industrial policies, particularly when different policy tools are employed. For example, entry subsidies and low-cost land allocations promote new firm entry, fostering market competition; Labor subsidies, particularly for high-skilled labor, reduce labor costs and may enhance productivity by enabling firms to attract better talent; Demand stimulation policies not only increase firm revenues, but also potentially enhance productivity through market selection, where more productive firms capture a larger share of the increased demand; Tools to foster industrial cluster can generate economies of scale, leading to productivity gains from shared resources, improved infrastructure, and a more skilled labor pool. However, there can also be downsides. Policies that encourage the entry of new firms can lower the threshold for market participation, allowing less productive firms to enter, which can dilute overall productivity. In addition, excessive entry could lead to overcapacity and resource crowding, 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 and crowd out market resources for the good ones.

While it is 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 Equation (19) to examine the policy impact on the firm's productivity, revenue, employment, intermediate input, and capital formation.

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 policy effect into different policy tools. Figure 24 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 measures 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 positive 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. Panels (a) (c) and (e) further inform us on the selection pattern of supportive policies versus regulatory policies— the forward terms of regulatory policies are positively correlated with firm TFP and that of supportive policies are negative, suggesting that regulatory policies more often target high-TFP industries and supportive policies target low-TFP industries. In addition, it is worth noting that the impact of supportive policy on revenue-based TFP and output-based TFP shows larger magnitudes when controlling for firm FE as compared to controlling for city-by-year FE. Considering that This result suggests that the newly entered firms would be excluded when we control for firm fixed effect, the result suggests that policy-induced new entrants, on average, have lower productivity as compared to incumbents— consistent with the policies' lower-screening threshold mechanism.

[Figure 24 about here]

Figure 25 presents the results of the impact of industrial policy on firms' 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 impact of supportive policies and a negative impact of regulatory policies. The positive impact of supportive policy on value-added-based TFP measure only lasts for 2 periods and turns negative afterwards.

[Figure 25 about here]

Figure 26 presents the effects of policy on firms' input, 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 increase 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 is 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 26 about here]

Tables 19-21 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 the firm benefits as reported in Table 17, from which a clearer quantity-quality trade-off in the impact of the policy can be seen.

[Tables 19-21 about here]

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 firm's 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, has 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. This is probably due to the fact that demand-based tools do not directly target firms, but rather aim to foster long-term industrial growth with a market-driven selection process.

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.

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, implementation methods, 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 microlevel 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, direct fiscal subsidies and input-based tools mostly have positive effects, whereas entry promotion may create excessive entry and competition, and market 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 target the same industry, the effectiveness diminishes, often due to overcapacity and less strategic choices of the target industry and implementation tools by follower cities. This suggests that policy design must be more carefully tailored to regional advantages and economic contexts, rather than simply replicating successful policies from other regions.

Our new approach paves the way for future research, demonstrating the potential of 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 the central and local levels will be crucial to assess the long-term impact of these policies on economic growth and innovation. 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 design and implement policies more effectively to promote 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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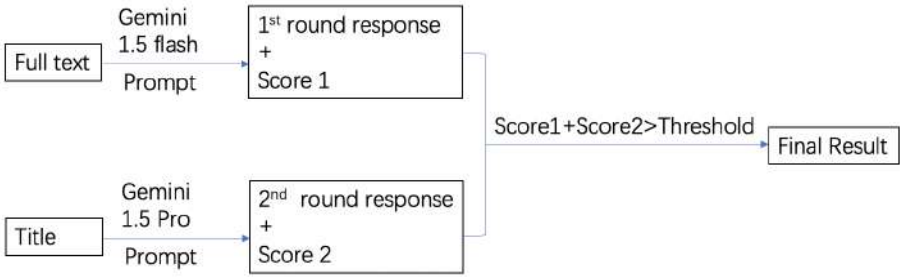
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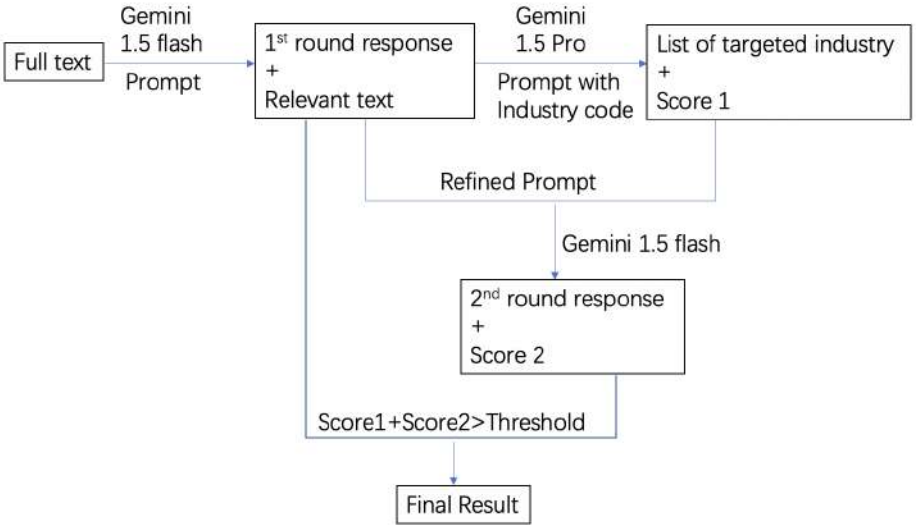
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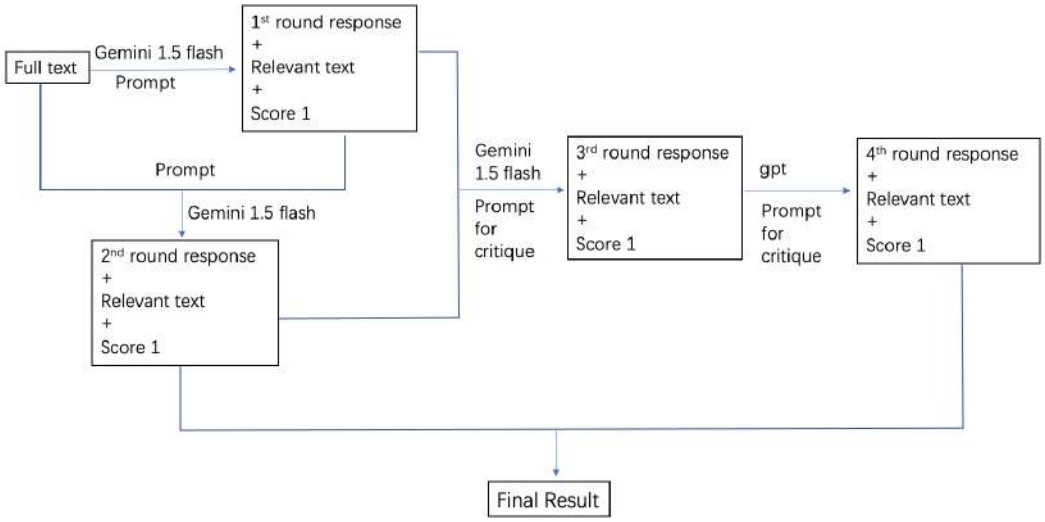
Figure 1: LLM Implementation Roadmap



(a) Determine Industrial Policy

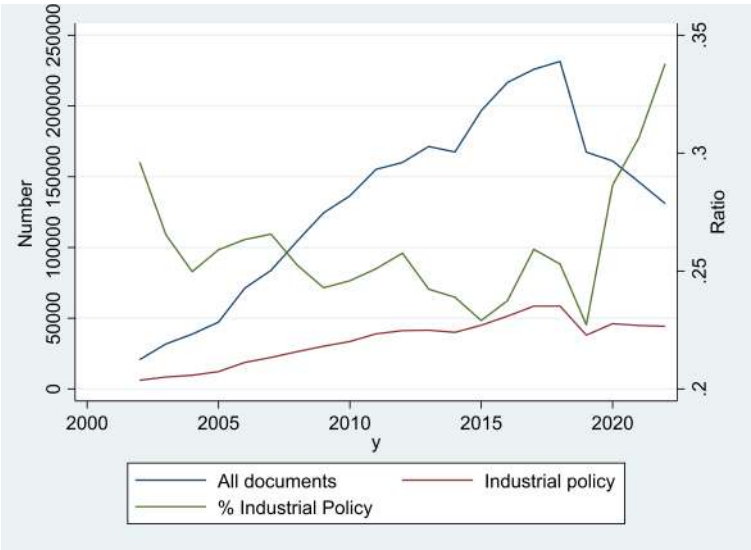


(b) Policy-targeted Industry



(c) Policy Tool and Implementation

Figure 2: Evolution of the Industrial Policies



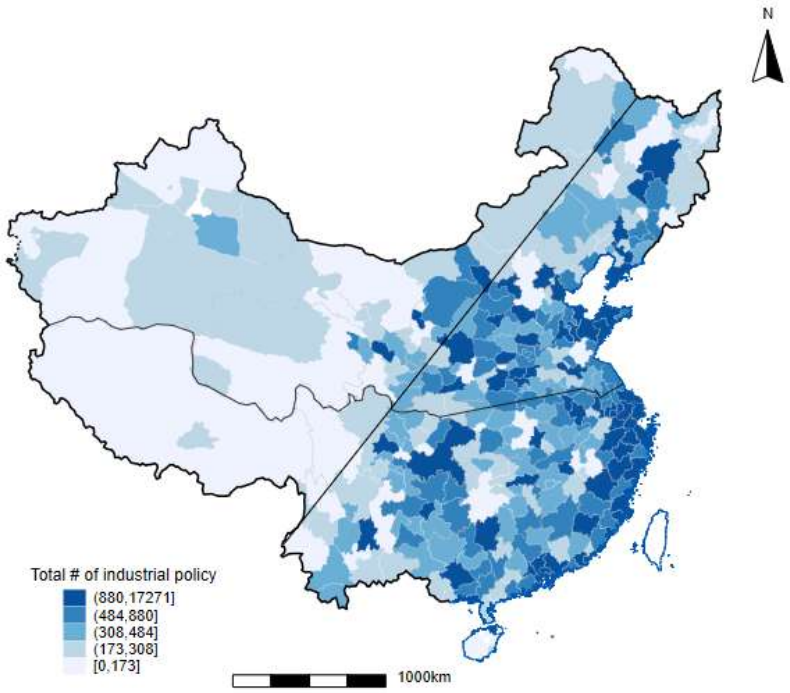
(a) Overall Volume



(b) By Government Level Ratio

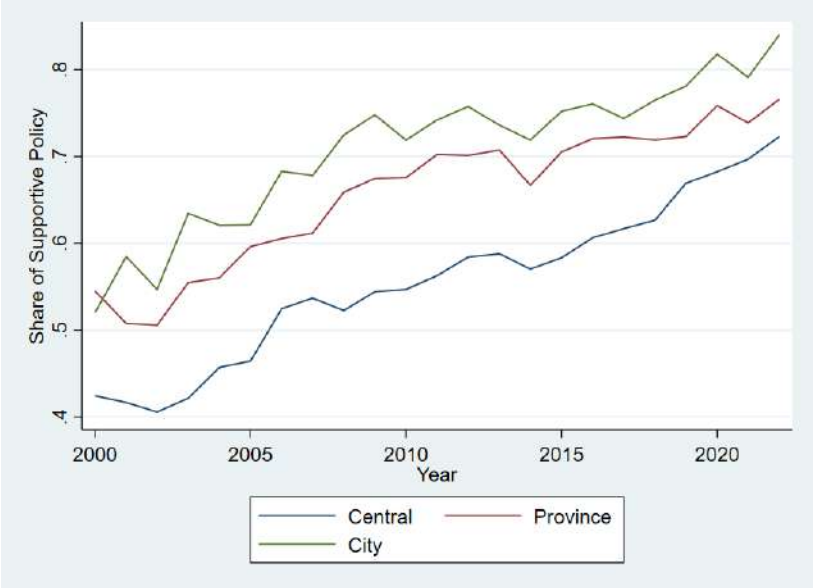
Notes: This figure presents the evolution of the share of industrial policies over time by the level of the issuing government entity. Each level of government includes all affiliated government departments and entities at the same level.

Figure 3: Geographic Distribution of the Industrial Policies



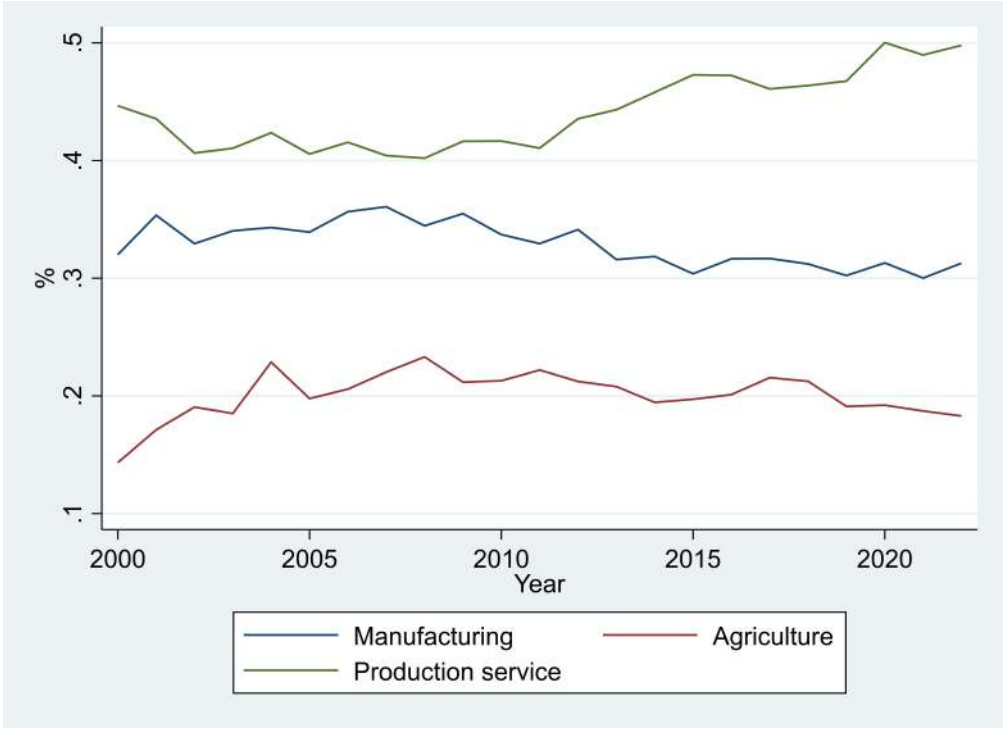
Notes: This figure presents the geographic overview of the distribution of the city-level industrial policies across China.

Figure 4: Evolution of the Tone of Industrial Policies

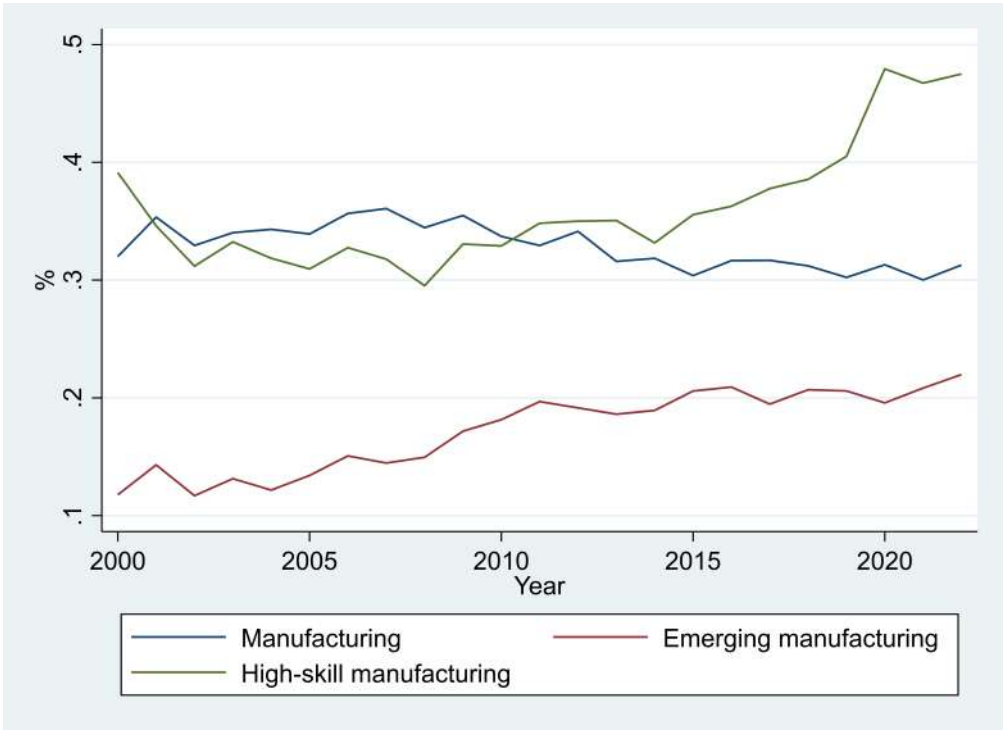


Notes: This figure presents the evolution of the tone of industrial policies over time by the level of the issuing government entity.

Figure 5: Time Trend of Policy-Targeted Industrial Sector



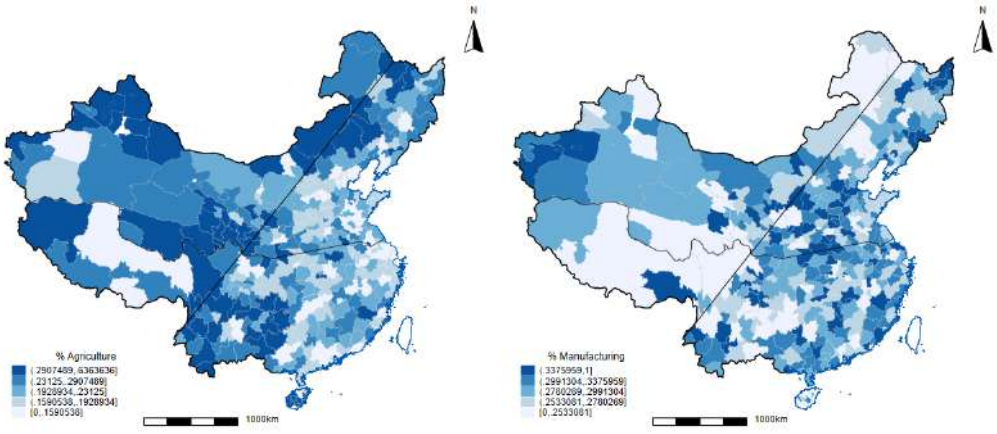
(a) Overall



(b) Manufacturing

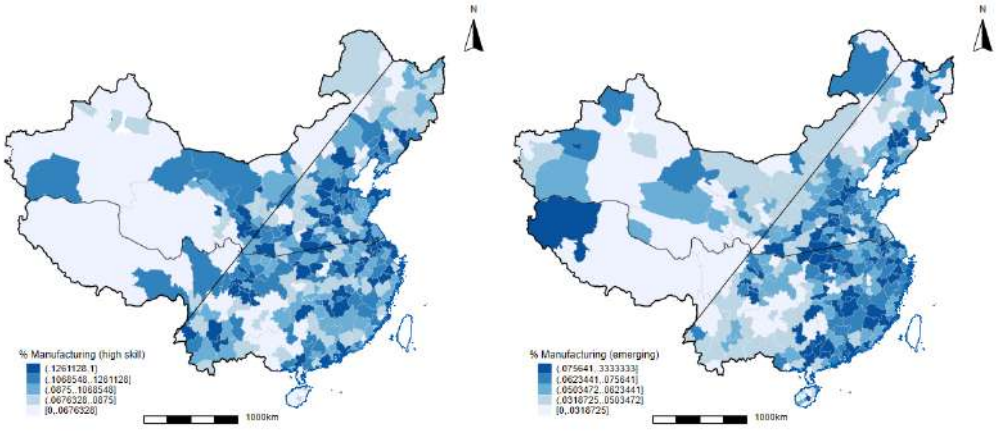
Notes: This figure presents the trends of the policy-targeted sector at the 2-digit level. The vertical axis represents the proportion of policies that target each sector within each government level.

Figure 7: Geographical Distribution of Policy-Targeted Industrial Sector



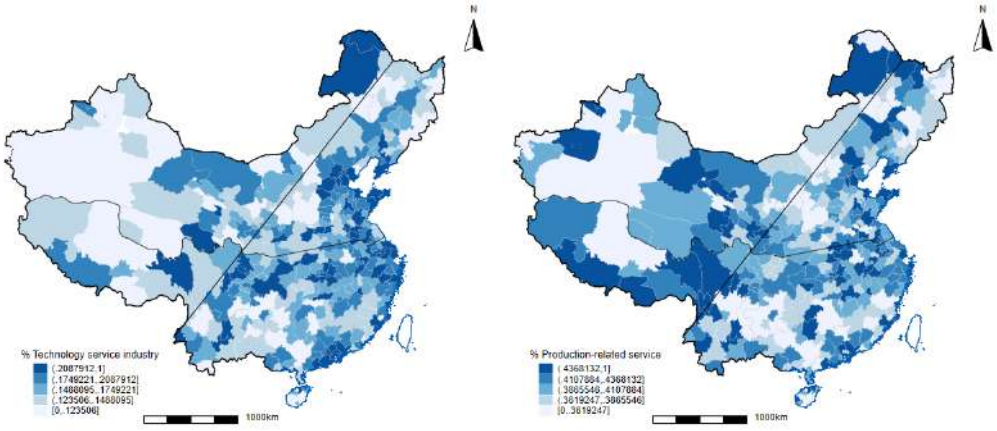
(a) % Agriculture

(b) % Manufacturing



(c) % High-skill Manufacturing

(d) % Emerging New Manufacturing

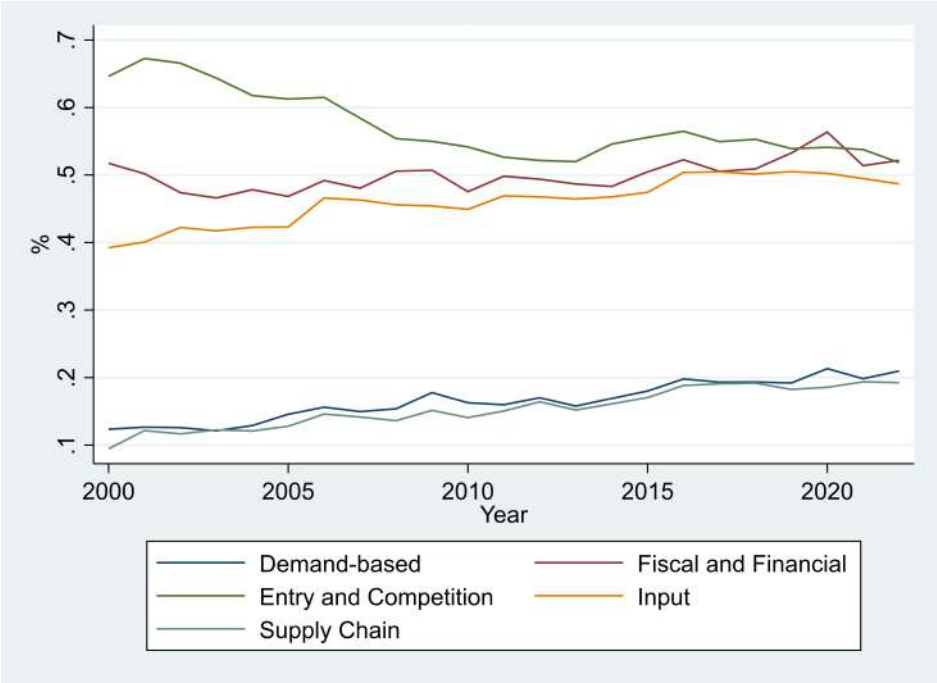


(e) % Technology-related Service

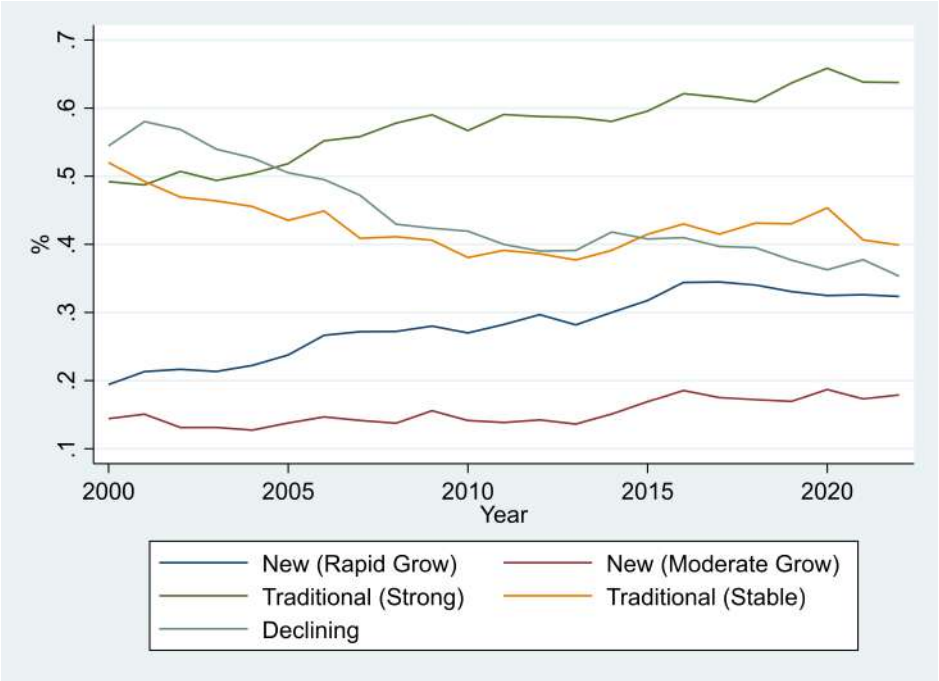
(f) % Production-related Service

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 8: Time Trend of Industrial Policy Tool Usage



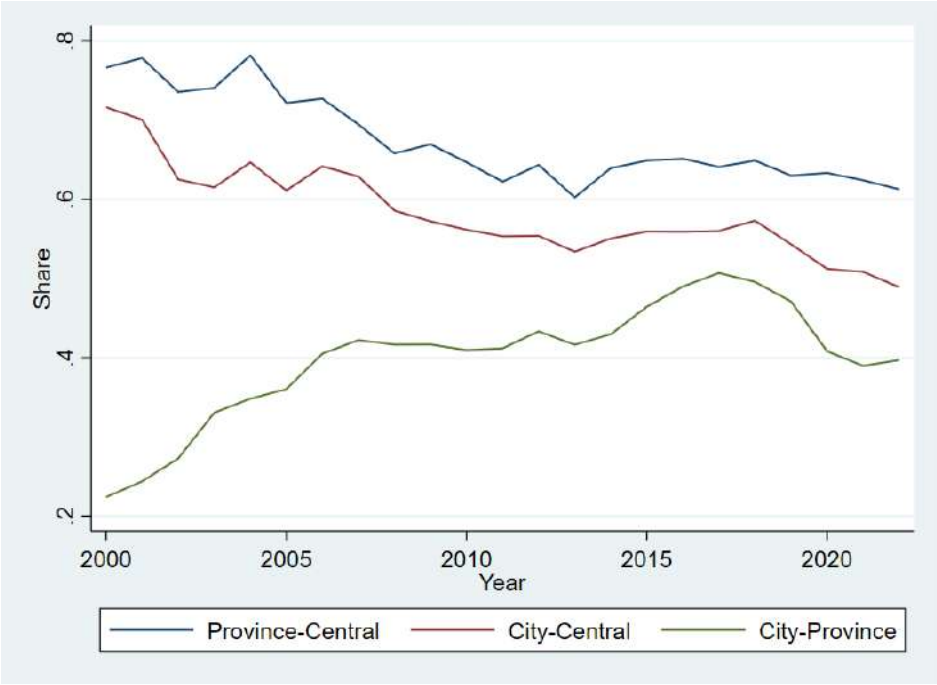
(a) By Tool Category



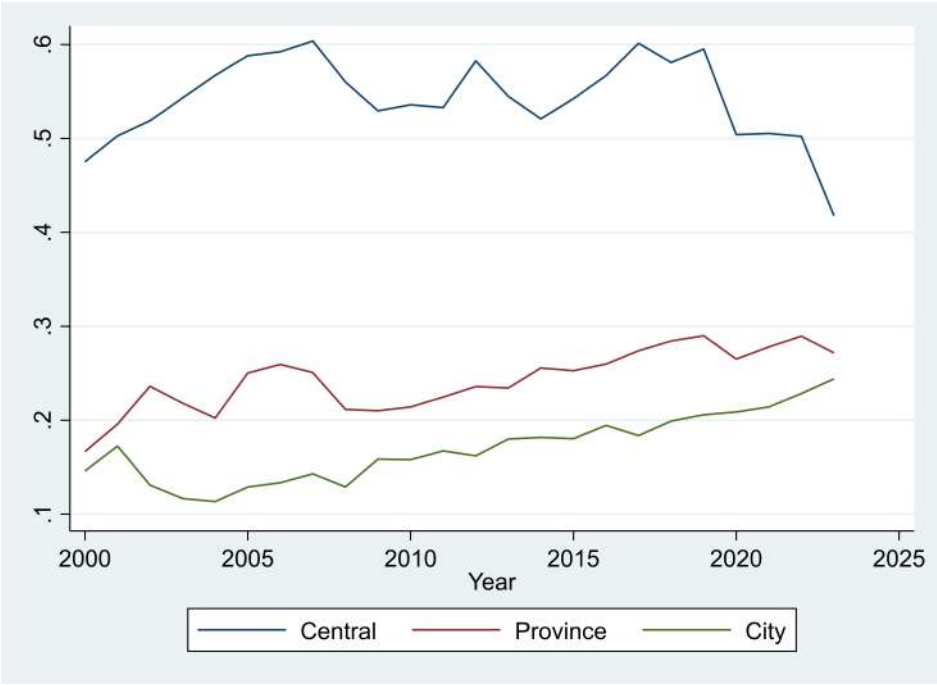
(b) By Usage Growth Pattern

Notes: This 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) groups the tools by their initial usage intensity and growth patterns.

Figure 9: Time Trend of Policy Citation



(a) Upper-level Government



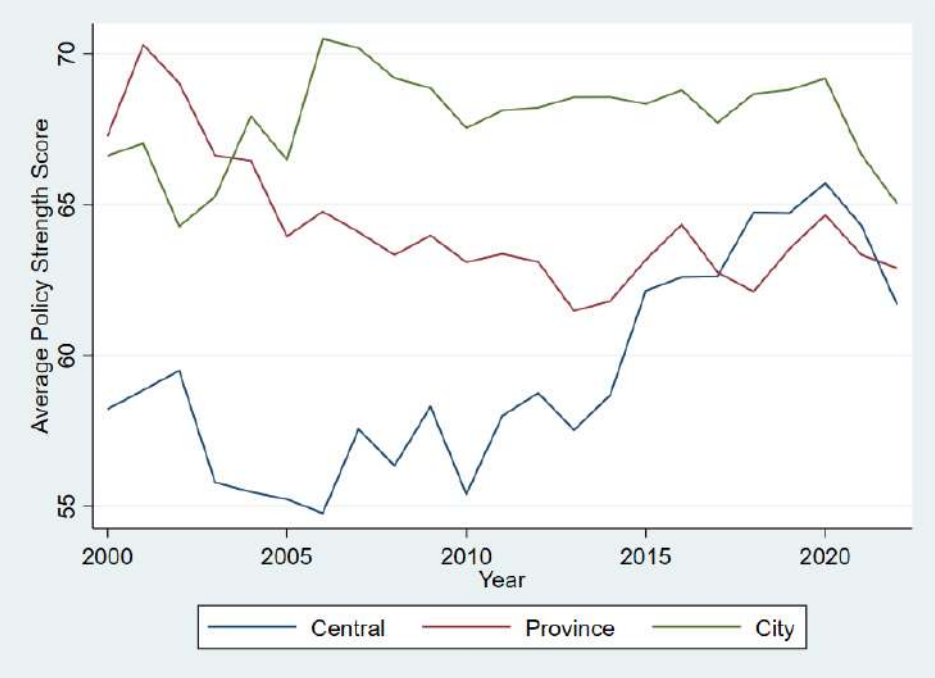
(b) Same-level-government

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 10: Policy Strength Score



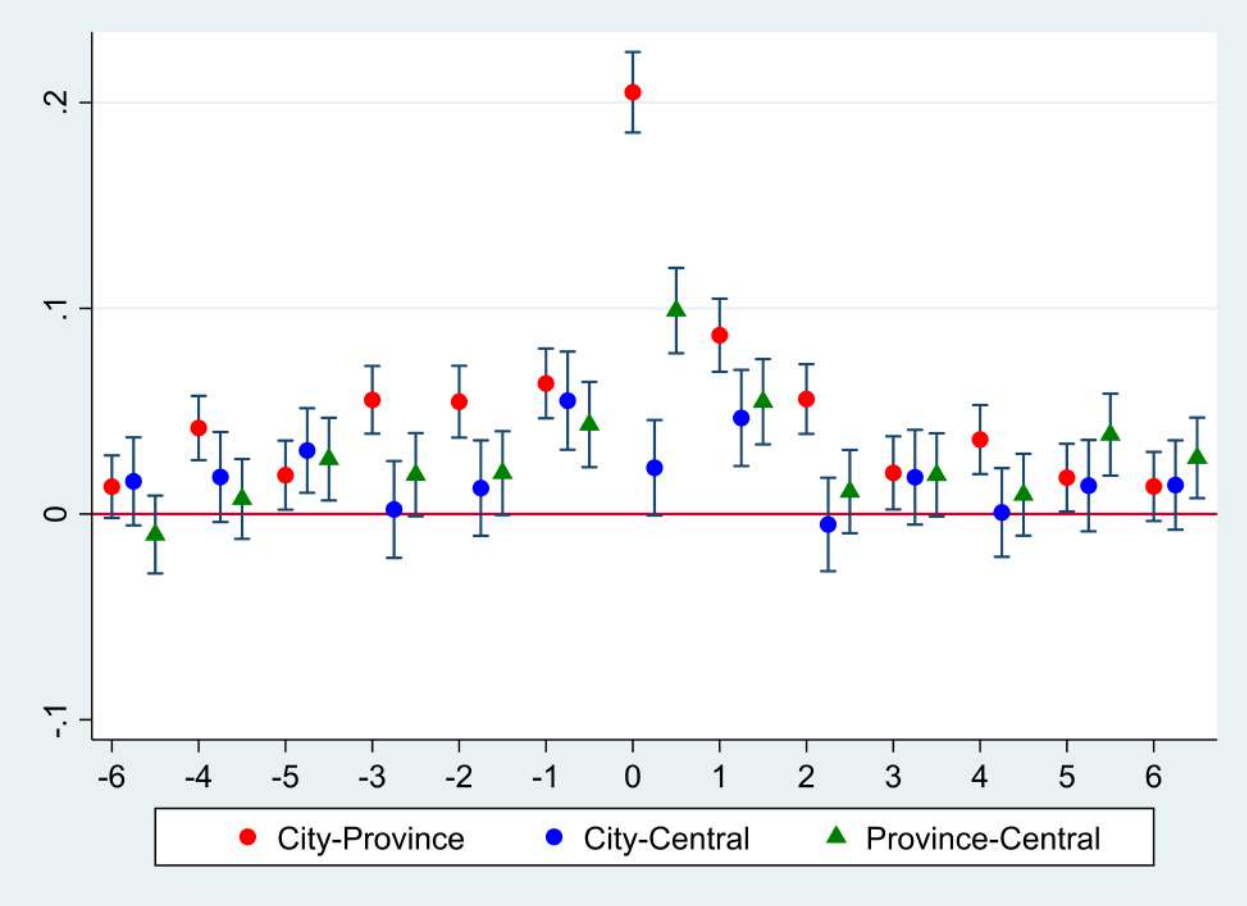
(a) Policy Concreteness



(b) Policy Strength

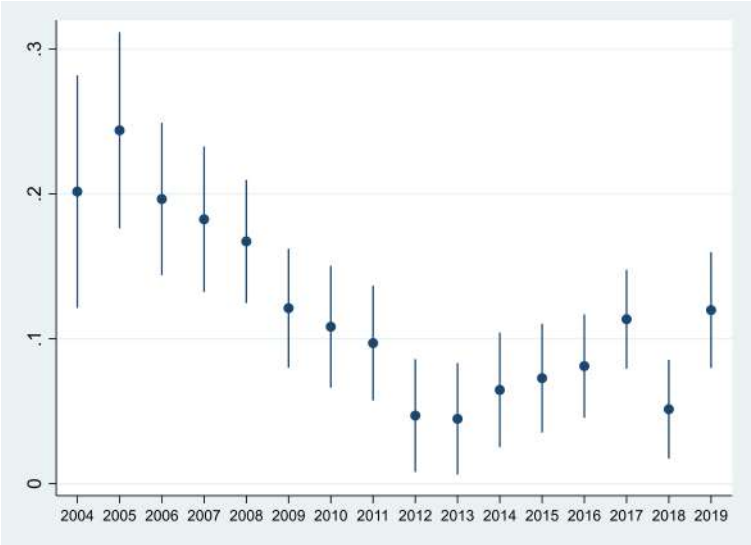
Notes: This figure plots the average score of policy strength at each government level over time. Panel (a) represents the score for policy concreteness, and Panel (b) represents the score of policy implementation strengths.

Figure 11: Policy Top-down Pass-through

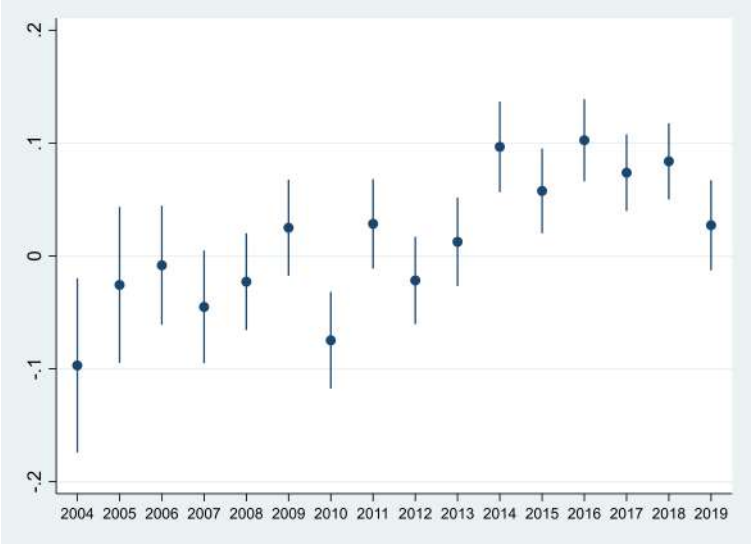


Notes: This figure plots the coefficients and the corresponding 95% confidence intervals of estimating Equations (5) and (6). The red dots represent the coefficients estimated for β_t^p in Equation (5), blue dots for β_t^n in Equation (5), and green triangles for β_t^n in Equation (6). The unit of observation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

Figure 12: The Dynamics of Policy Pass-through



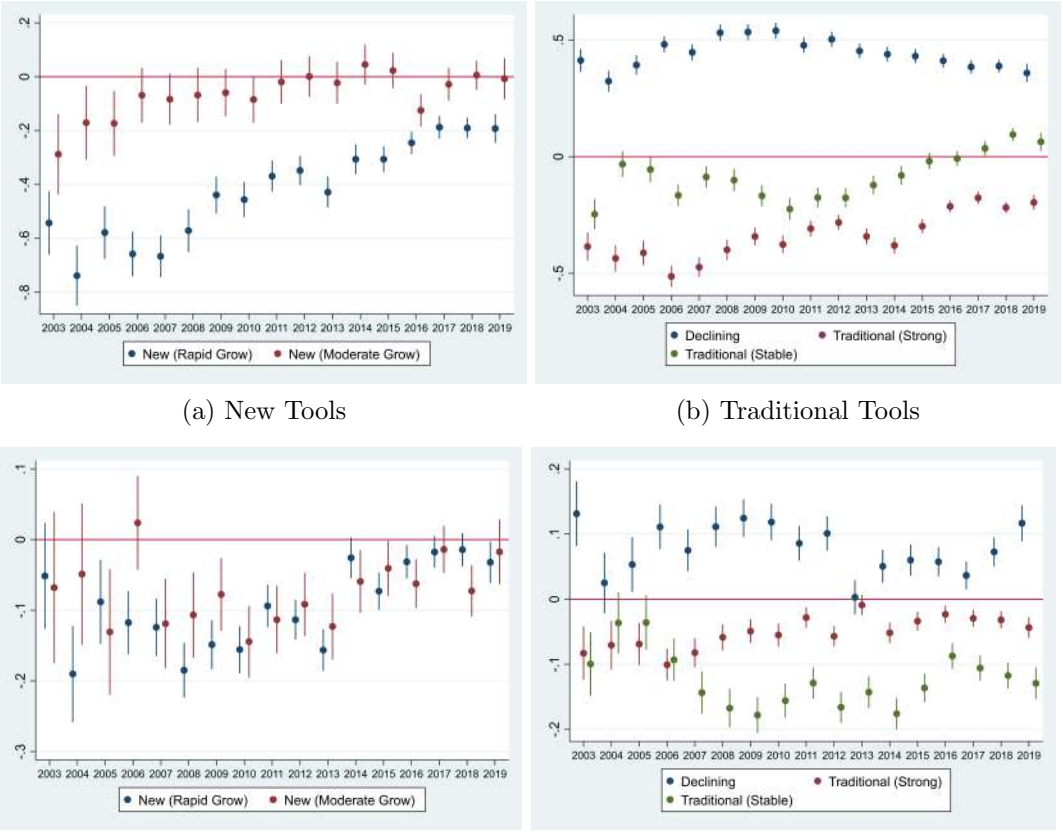
(a) Policy Pass-through (Province)



(b) Policy Pass-through (Nation)

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

Figure 13: Time Trend of Tool Adoption by Government Level



(a) New Tools

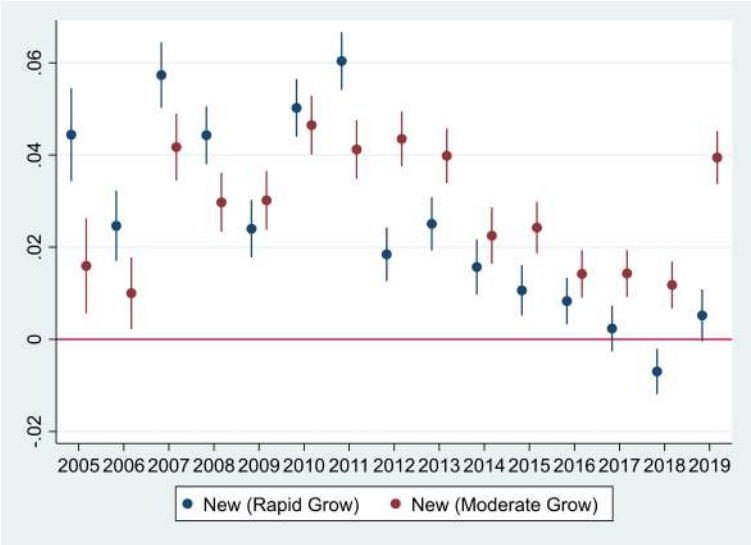
(b) Traditional Tools

(c) New Tools

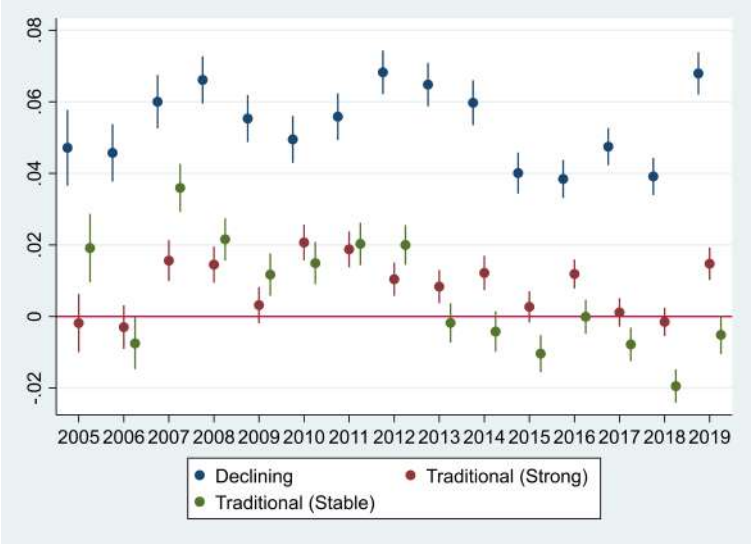
(d) Traditional Tools

Notes: This figure plots the time trend in tool usage across government levels by estimating Equation (10) 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 14: Time Trend of Tool Adoption By City GDP



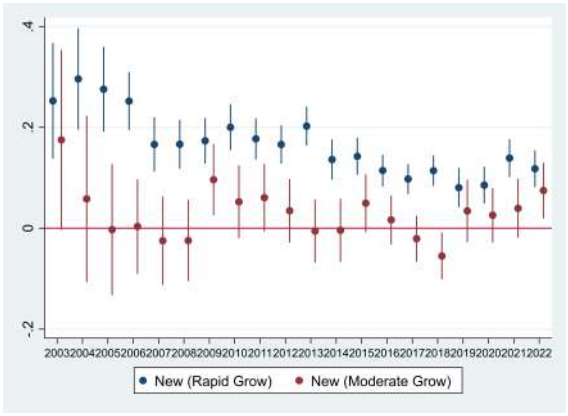
(a) New Tools



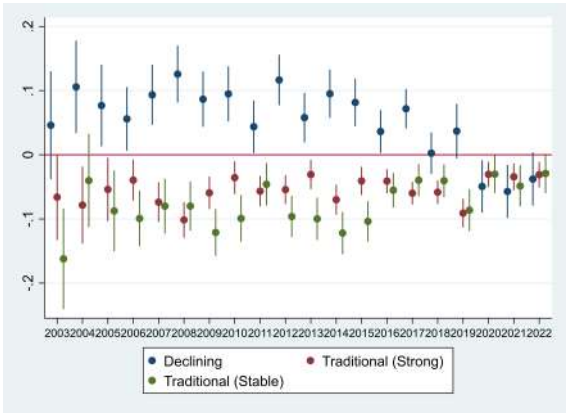
(b) Traditional Tools

Notes: This figure plots the estimated coefficients for β_t by estimating Equation (11) to illustrate the time trend of tool adoption by city development level.

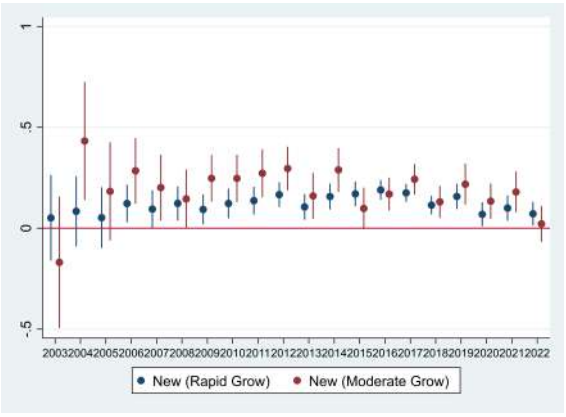
Figure 15: Time Trend of Tool Adoption (Manufacturing)



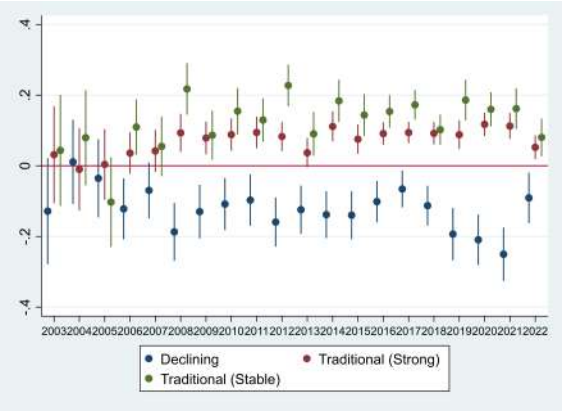
(a) Manu. vs. Others (New Tools)



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



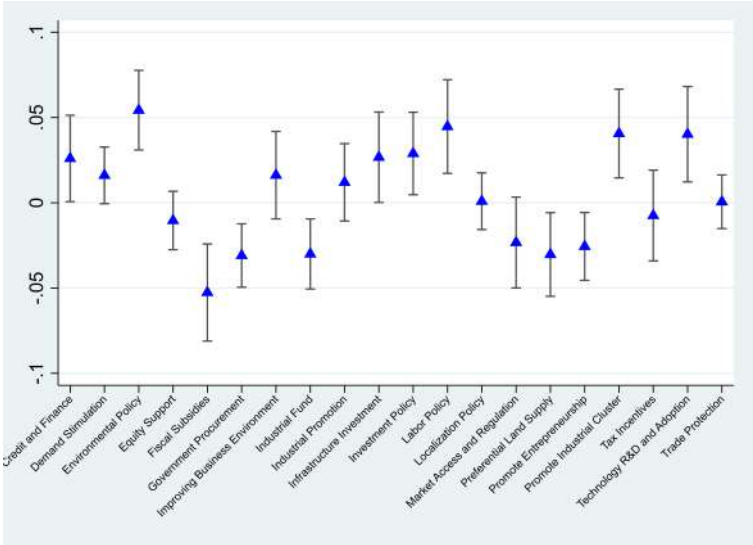
(c) Skill-intensive vs. Others Manu. (New Tools)



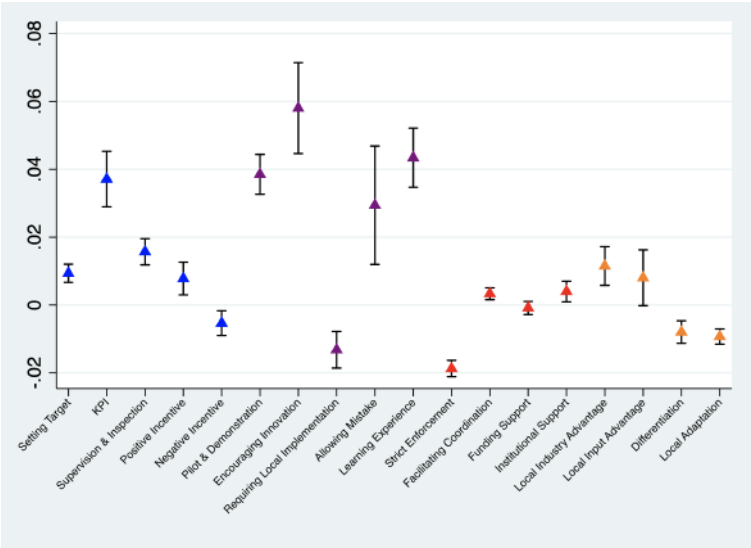
(d) Skill-intensive vs. Others Manu. (Traditional Tools)

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

Figure 16: Within-industry Change in Policy Tool and Implementation Method



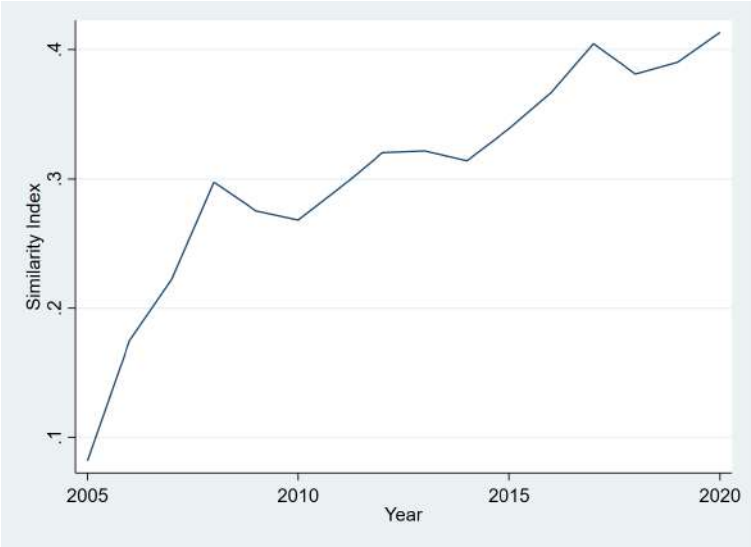
(a) Policy Tool



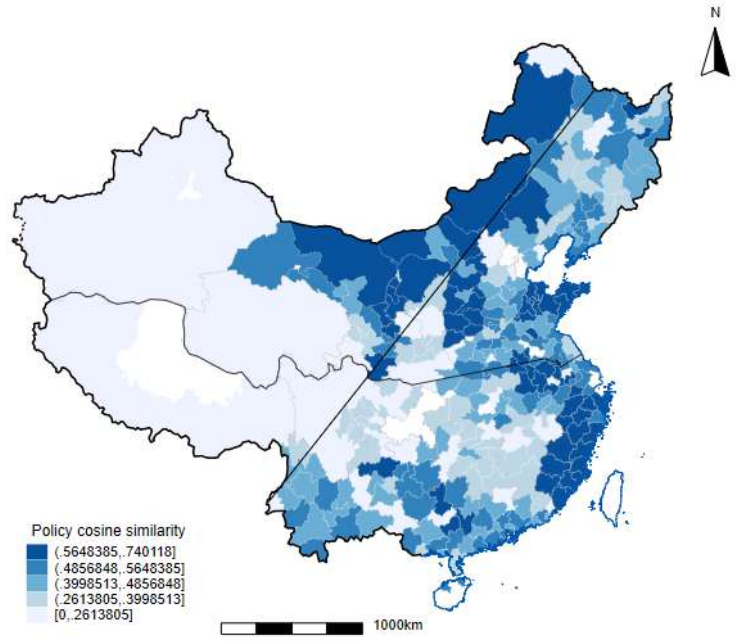
(b) Policy Implementation Method

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

Figure 17: Policy Sector Similarity



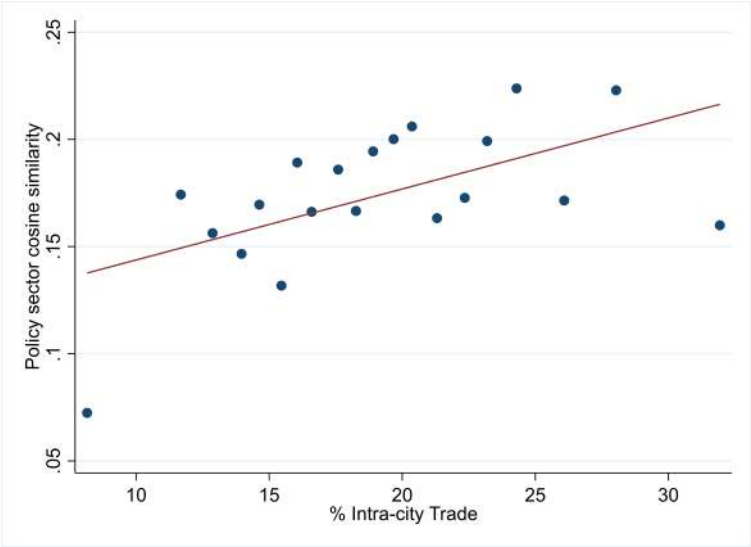
(a) Evolution of Policy Sector Similarity



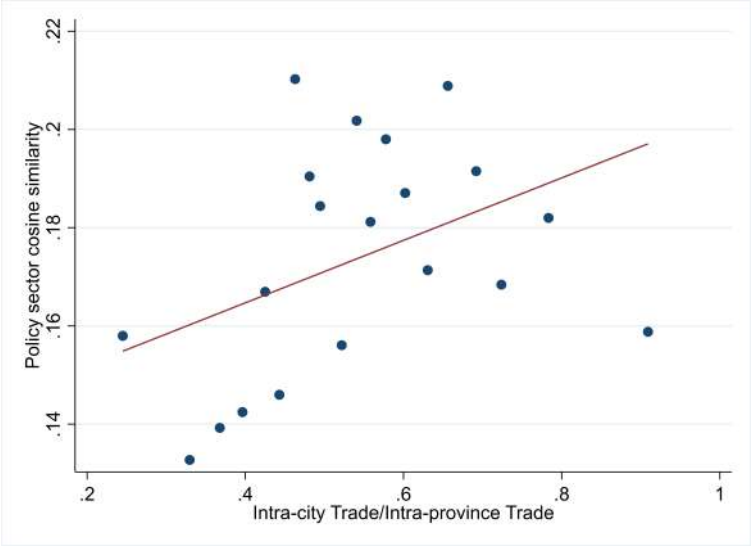
(b) Geographical Distribution of Policy Sector Similarity

Notes: This figure plots the overtime evolution and geographical distribution of policy similarity. Policy similarity is calculated as the cosine similarity of industry-level policy vector between city pairs, focusing on intra-province similarities. 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 18: Policy Sector Similarity and Local Protectionism



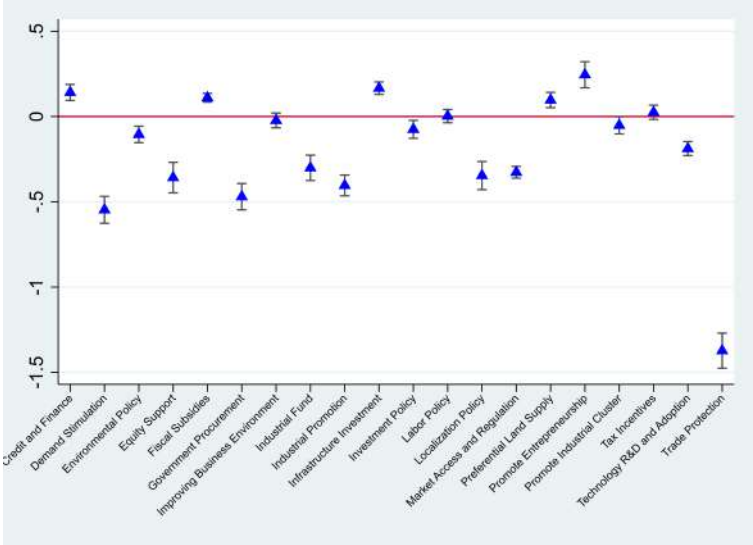
(a) %Intra-city Trade (Intra-city Trade/Total City Trade)



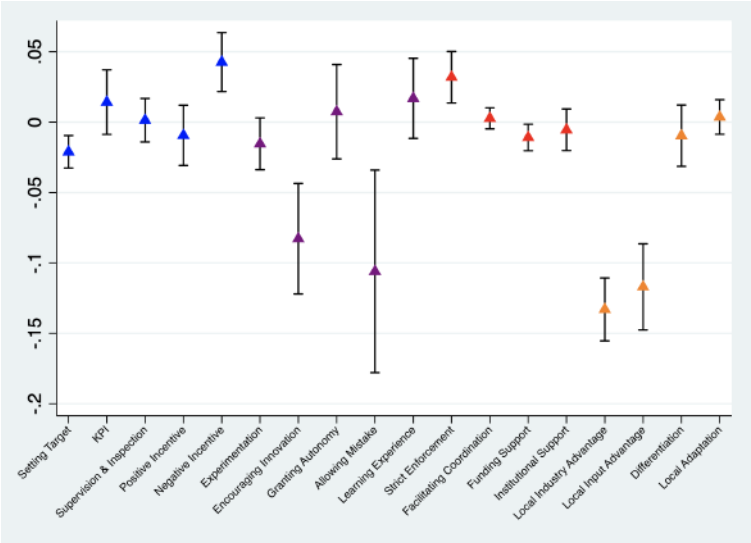
(b) %Intra-city Trade (Intra-city/Intra-province Trade)

Notes: This figure presents the binscatter plot for the citie's similarity index and their intra-city trade share. Panel (a) uses the share of intra-city trade in total trade volume on the x-axis, and Panel (b) uses the share of intra-city trade in total intra-province trade on the x-axis. Policy similarity is calculated as the cosine similarity of industry-level policy vector between city pairs, focusing on intra-province similarities. 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 19: Policy Diffusion and Policy Tool and Implementation



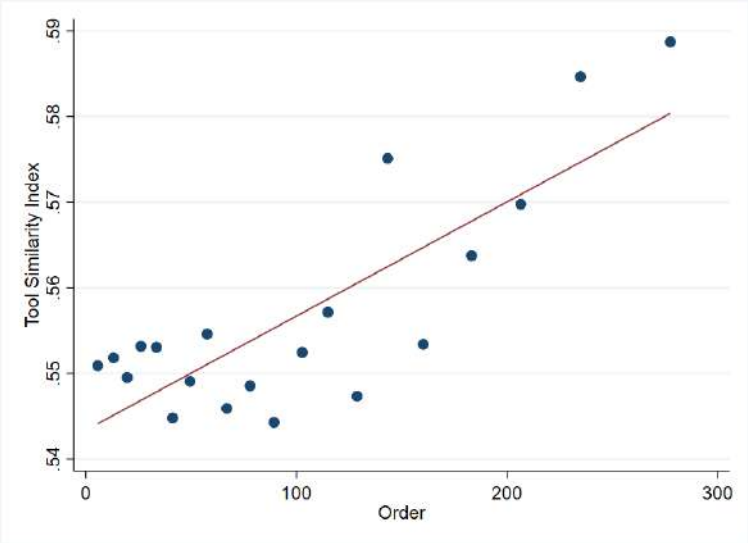
(a) Policy Tool



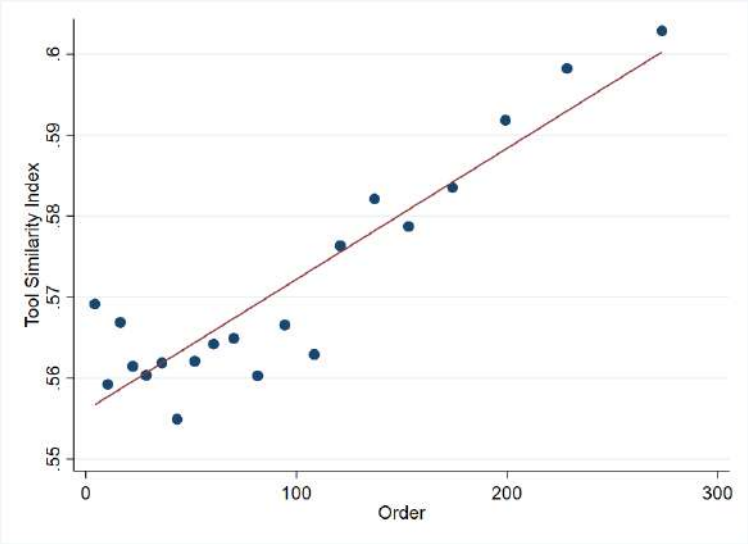
(b) Policy Implementation Method

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

Figure 20: Policy Diffusion and Policy Tool



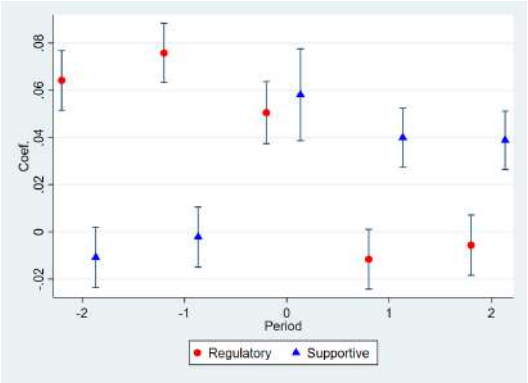
(a) Tool similarity with provincial gov.



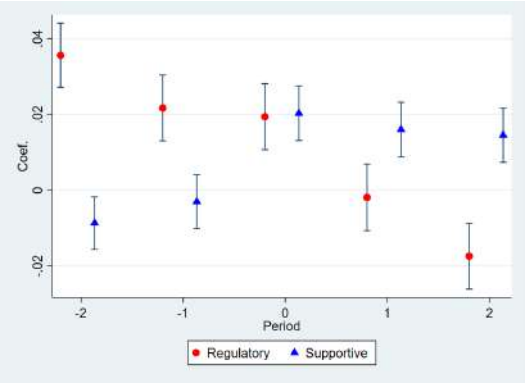
(b) Tool similarity with central gov.

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

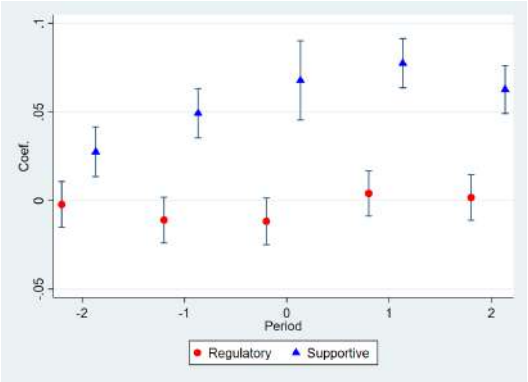
Figure 21: Effect of Industrial Policy: Subsidy, Tax Deduction, and Long Term Debt



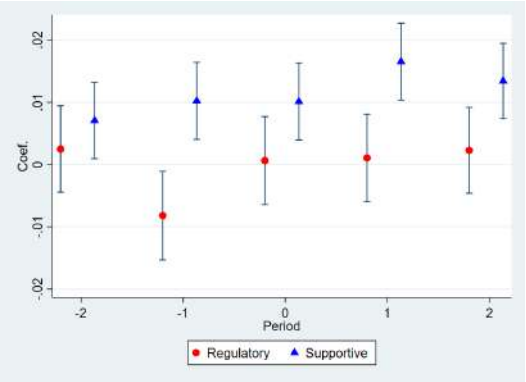
(a) Subsidy (City-by-industry FE)



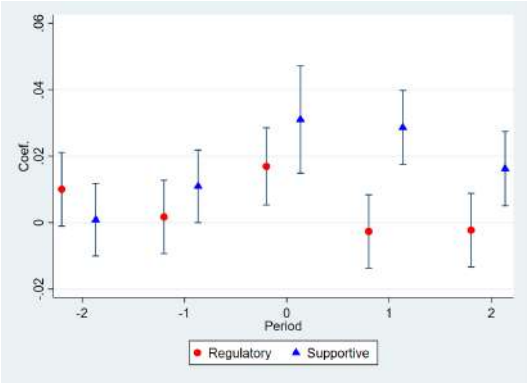
(b) Subsidy (Firm FE)



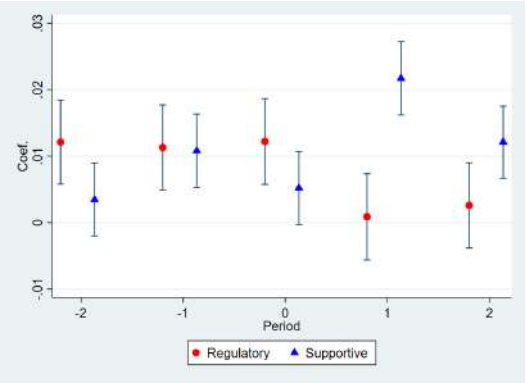
(c) Tax Deduction (City-by-industry FE)



(d) Tax Deduction (Firm FE)



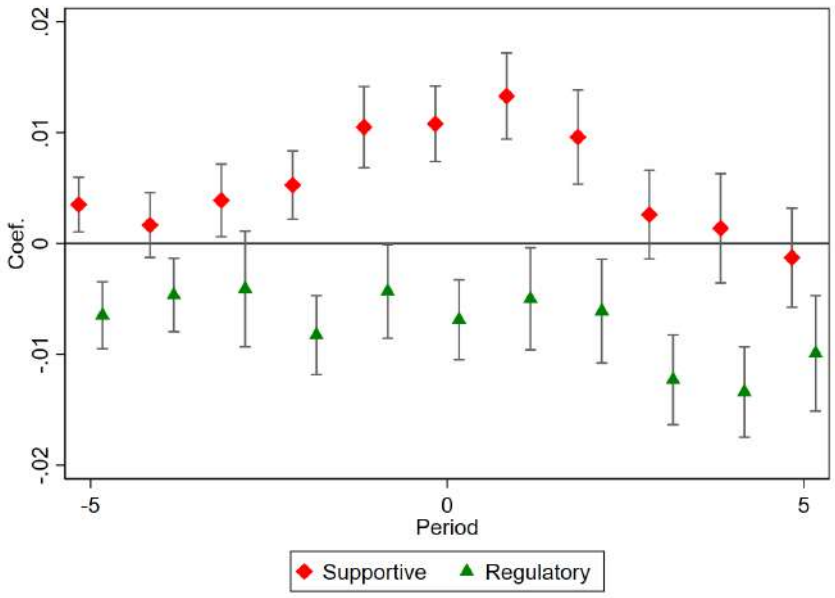
(e) Long Term Debt (City-by-industry FE)



(f) Long Term Debt (Firm FE)

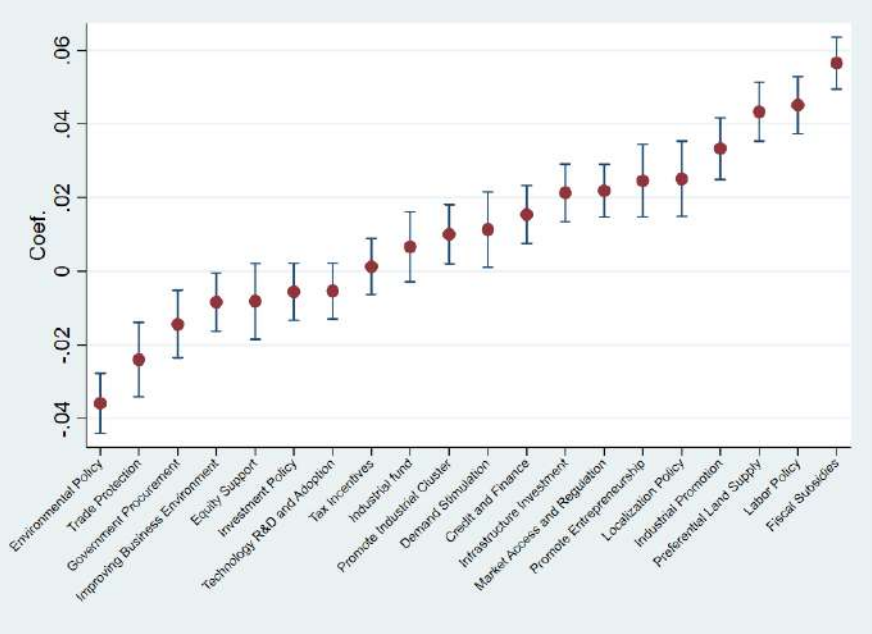
Notes: This figure plots the coefficients and the corresponding 95% confidence intervals of estimating Equation 19. The unit of observation is firm-year level, and the sample coverage is 2008-2020. Panel A, C, and E control for city-by-industry and year fixed effects. Panel B, D, and F control for firm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

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



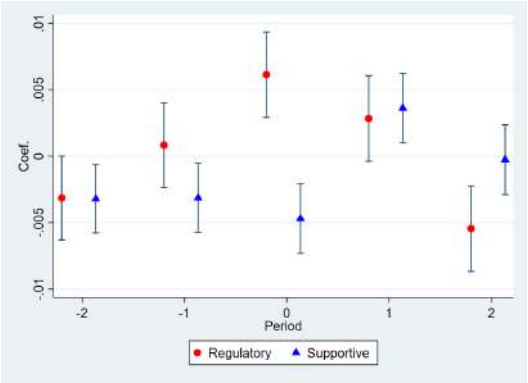
Notes: This figure plots the coefficients and the corresponding 95% confidence intervals of estimating Equation 21. The unit of observation is 4-digit industry-city-year level, and the sample coverage is 2001-2020. Standard errors are clustered at the city-by-industry level.

Figure 23: Effect of Industrial Policy Tools: New Firm Entry

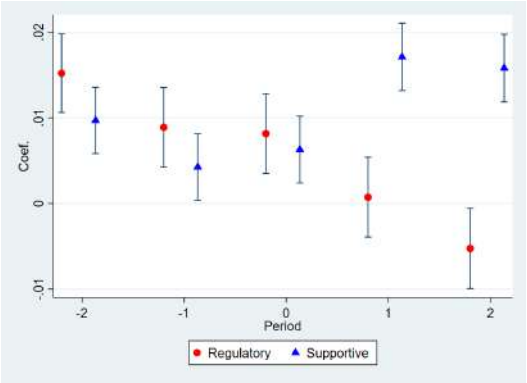


Notes: This figure plots the coefficients and the corresponding 95% confidence intervals of estimating Equation 22 for each industrial policy tool. The unit of observation is 4-digit industry-city-year level, and the sample coverage is 2001-2020. Standard errors are clustered at the city-by-industry level.

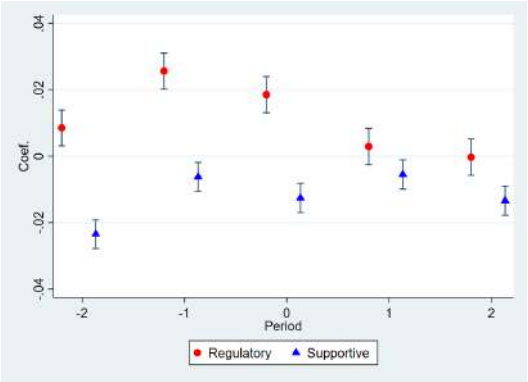
Figure 24: Effect of Industrial Policy: TFP



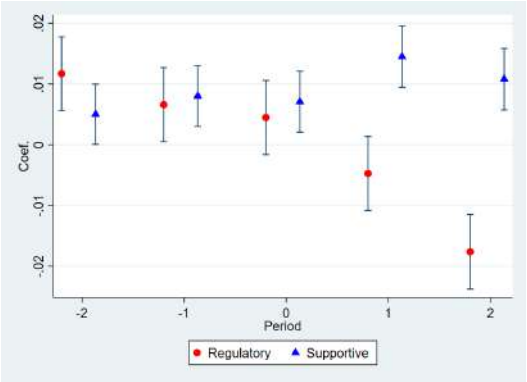
(a) TFP Revenue (City-by-industry FE)



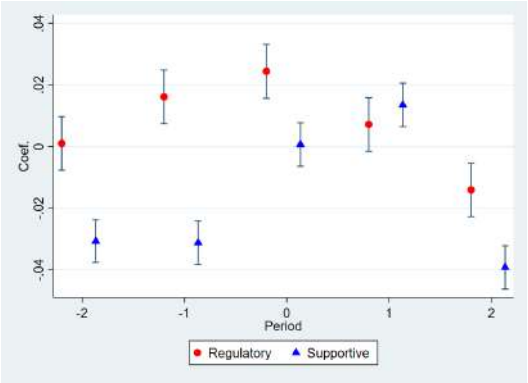
(b) TFP Revenue (Firm FE)



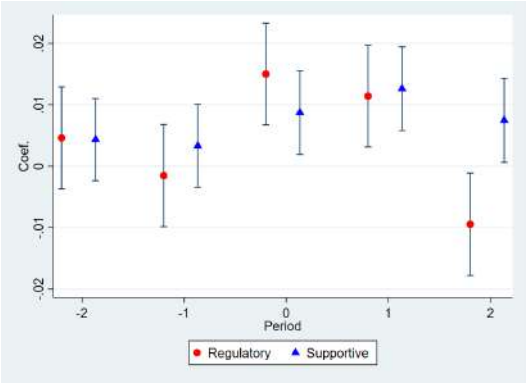
(c) TFP Output (City-by-industry FE)



(d) TFP Output (Firm FE)



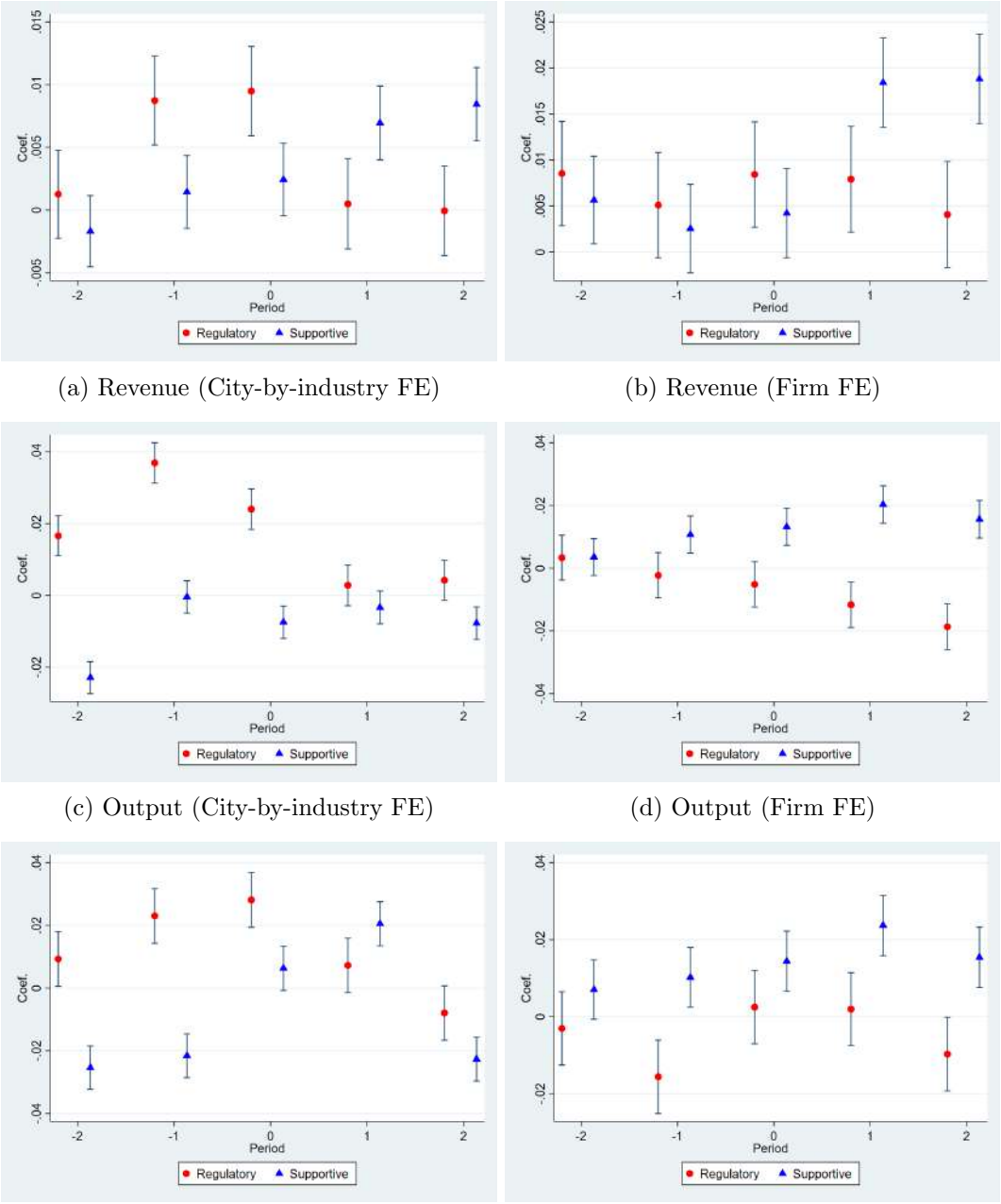
(e) TFP Value-added (City-by-industry FE)



(f) TFP Value-added (Firm FE)

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

Figure 25: 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)

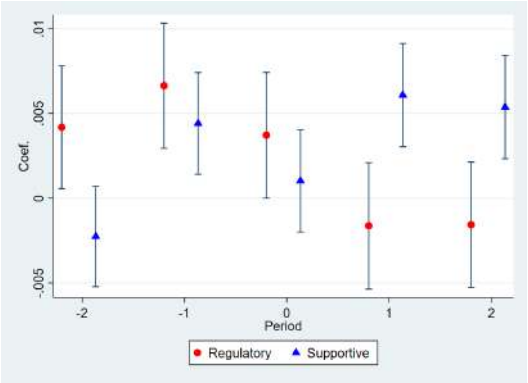
(d) Output (Firm FE)

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

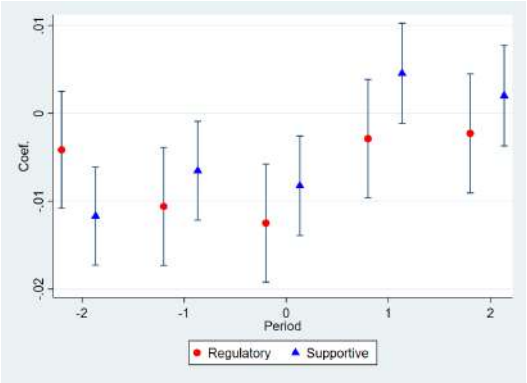
(f) Value-added (Firm FE)

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

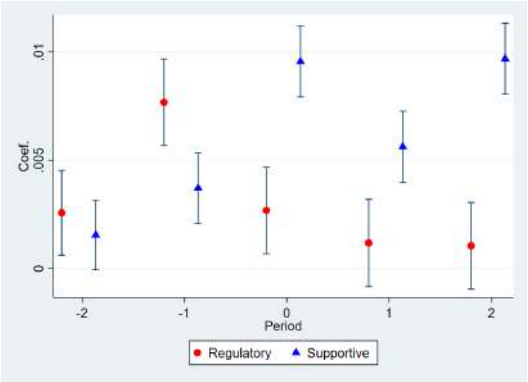
Figure 26: Effect of Industrial Policy: Input



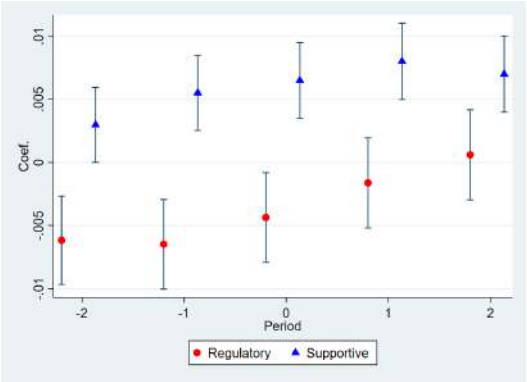
(a) Capital (City-by-industry FE)



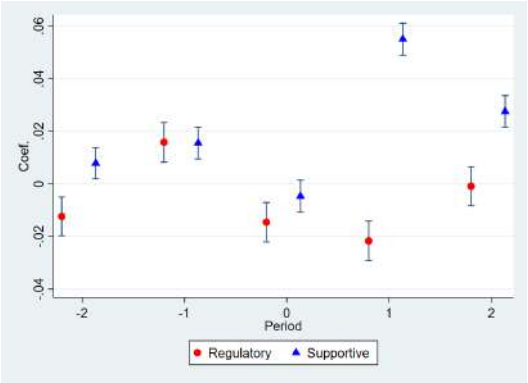
(b) Capital (Firm FE)



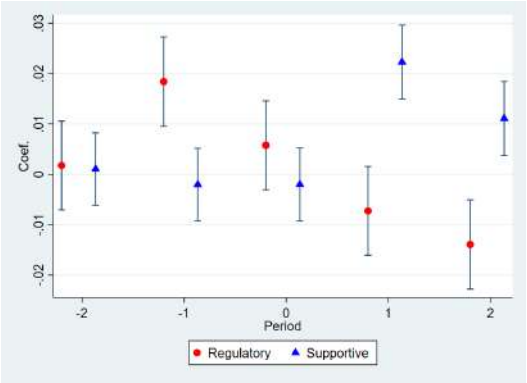
(c) Labor (City-by-industry FE)



(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 19. The unit of observation is firm-year level, and the sample coverage is 2008-2020. Panel A, C, and E control for city-by-industry and year fixed effects. Panel B, D, and F control for firm and year fixed effects and city-by-industry trend. 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 Tones by Government Level

	Supportive		Suppressive		Regulatory	
	#	Share	#	Share	#	Share
Central	57,200	0.56	3,168	0.03	40,879	0.40
Province	238,621	0.69	3,923	0.01	101,762	0.30
City	219,986	0.74	4,148	0.01	71,552	0.24
All	515,807	0.70	11,239	0.02	214,193	0.29

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

Table 4: Industrial Policy Target Sector by Government Level

	All	Central	Province	City
Agriculture	0.17	0.14	0.19	0.17
Manufacturing	0.29	0.35	0.28	0.28
Manufacturing (emerging)	0.05	0.05	0.05	0.06
Manufacturing (high skill)	0.11	0.12	0.11	0.11
Service	0.49	0.47	0.48	0.50
Service (high skill)	0.18	0.15	0.18	0.18
Production related service	0.40	0.41	0.40	0.41
Technology related service	0.20	0.21	0.20	0.20
Life service	0.29	0.28	0.27	0.32
Observations	741269	101250	344321	295698

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 5: Industrial Policy Tool Classification

	All	Central	Province	City
Fiscal and Financial				
Credit and Finance	0.14	0.11	0.12	0.18
Tax Incentives	0.20	0.20	0.16	0.23
Equity Support	0.05	0.04	0.04	0.06
Fiscal Subsidies	0.41	0.25	0.39	0.48
Entry and Regulation				
Industrial Fund	0.07	0.04	0.06	0.09
Promote Entrepreneurship	0.06	0.04	0.05	0.08
Investment Policy	0.13	0.11	0.12	0.16
Improving Business Environment	0.18	0.13	0.15	0.22
Market Access and Regulation	0.35	0.42	0.34	0.34
Trade Protection	0.09	0.19	0.08	0.07
Input				
Labor Policy	0.22	0.16	0.21	0.27
Preferential Land Supply	0.13	0.06	0.10	0.17
Infrastructure Investment	0.18	0.11	0.16	0.23
Technology R&D and Adoption	0.24	0.21	0.23	0.27
Environmental Policy	0.13	0.09	0.12	0.16
Demand-side				
Consumer subsidy	0.05	0.04	0.05	0.07
Government Procurement	0.07	0.05	0.07	0.08
Industrial Promotion	0.10	0.07	0.10	0.12
Supply Chain				
Promote Industrial Cluster	0.14	0.08	0.12	0.18
Localization Policy	0.05	0.03	0.04	0.06
Observations	741269	101250	344321	295698

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 6: Industrial Policy Objective by Government Level

	All	Central	Province	City
Key industry				
Promote strategic industry	0.22	0.20	0.21	0.24
Promote pillar industry	0.05	0.03	0.04	0.06
Promote emerging industry	0.10	0.07	0.09	0.13
Support traditional advantageous industr	0.11	0.09	0.12	0.11
Upgrade traditional industry	0.12	0.09	0.12	0.14
Support green industry	0.13	0.09	0.13	0.14
Promote other key industry	0.09	0.08	0.09	0.10
Innovation				
Promote innovation	0.17	0.14	0.16	0.18
Promote new technology adoption	0.08	0.06	0.07	0.10
Social welfare				
Urbanization	0.04	0.02	0.03	0.07
Stimulate employment	0.13	0.10	0.12	0.15
Promote social equity and welfare	0.26	0.19	0.25	0.29
Observations	741269	101250	344321	295698

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 7: Industrial Policy Requirement by Government Level

	All	Central	Province	City
Firm Location	0.44	0.32	0.45	0.47
Specific Firms	0.16	0.19	0.17	0.15
R&D Technology/Investment	0.11	0.08	0.10	0.12
Firm Age	0.09	0.06	0.08	0.10
Firm Ownership Type	0.13	0.17	0.11	0.12
Firm Scale	0.33	0.24	0.30	0.38
Observations	741269	101250	344321	295698

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 8: Industrial Policy Implementation by Government Level

	All	Central	Province	City
Incentive Scheme				
Setting Target	0.48	0.36	0.49	0.52
KPI	0.13	0.05	0.11	0.18
Supervision & Inspection	0.45	0.37	0.47	0.46
Positive Incentive	0.13	0.06	0.12	0.18
Negative Incentive	0.30	0.25	0.28	0.33
Experimentation and learning				
Pilot & Demonstration	0.21	0.18	0.21	0.23
Encouraging Innovation	0.06	0.05	0.06	0.07
Requiring Local Implementation	0.13	0.14	0.13	0.14
Allowing Mistake	0.02	0.01	0.01	0.02
Learning Experience	0.15	0.14	0.15	0.15
Organizational Support				
Strict Enforcement	0.45	0.48	0.44	0.44
Facilitating Coordination	0.65	0.50	0.64	0.71
Funding Support	0.43	0.28	0.42	0.50
Institutional Support	0.36	0.30	0.34	0.39
Local Condition				
Local Industry Advantage	0.12	0.05	0.11	0.15
Local Input Advantage	0.08	0.04	0.07	0.09
Differentiation	0.18	0.17	0.16	0.20
Local Adaptation	0.42	0.24	0.39	0.51
Observations	741269	101250	344321	295698

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 9: Summary Statistics for Firm Registration

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

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

Table 10: Sector Choice and Regional Advantage

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

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

Table 11: Policy Pass-through from Central to Local

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

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

Table 12: Policy Persistence and the Change of Local Politician

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

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

Table 13: Policy Diffusion and Overcapacity: Entry and Capital

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

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

Table 14: Policy Diffusion and Overcapacity: Firm Performance

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

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

Table 15: Policy Diffusion and Sector Choice

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

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

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

	log(Subsidy)		Tax deduction rate		1(Long-term debt)	
	(1)	(2)	(3)	(4)	(5)	(6)
Policy^{+}	0.0599***	0.0184***	0.0533***	-0.00269	0.0229***	0.0110***
	(0.00405)	(0.00349)	(0.00282)	(0.00199)	(0.00321)	(0.00254)
Policy^{-}	0.0327***	0.0159***	-0.00822	-0.00935	0.0183**	0.0107***
	(0.00491)	(0.00429)	(0.000349)	(0.00948)	(0.00992)	(0.00315)
log(Register capital)	0.289***		-0.0560***		0.0228***	
	(0.000725)		(0.000529)		(0.000605)	
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	3,075,274	3,174,825	5,144,683	5,624,432	5,970,610	6,633,852
R-squared	0.265	0.671	0.211	0.705	0.160	0.566

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

Table 17: Effect of Industrial Policy: Subsidy, Tax, and Debt

	log(Subsidy)		Tax deduction rate		1(Long-term debt)	
	(1)	(2)	(3)	(4)	(5)	(6)
Industrial cluster	0.0108*	0.0131**	-0.0307***	-0.00718**	0.0294***	0.0211***
	(0.00611)	(0.00534)	(0.00430)	(0.00306)	(0.00484)	(0.00389)
Demand stimulation	-0.0414***	-0.0243***	0.0222***	-0.00863	-0.0107**	-0.0057
	(0.00577)	(0.00503)	(0.00408)	(0.00291)	(0.00460)	(0.00371)
Entry and regulation	0.0124*	-0.00275	-0.00219	0.00116	-0.00690	-0.00811*
	(0.00667)	(0.00583)	(0.00470)	(0.00336)	(0.00558)	(0.00452)
Input and R\&D	-0.00178	-0.0171***	-0.0110**	-0.00963***	0.0130**	0.0225***
	(0.00707)	(0.00620)	(0.00496)	(0.00356)	(0.00530)	(0.00428)
Fiscal and finance	0.0624***	0.0430***	0.0591***	0.0111***	0.0190***	-0.00265***
	(0.00652)	(0.00570)	(0.00452)	(0.00324)	(0.00513)	(0.000413)
log(Register capital)	0.289***		-0.0560***		0.0228***	
	(0.000725)		(0.000529)		(0.000605)	
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	3,075,274	3,174,825	5,144,683	5,624,432	5,970,610	6,633,852
R-squared	0.265	0.671	0.211	0.705	0.160	0.566

Note: This table reports the results of estimating 20. 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 18: Effect of Industrial Policy: Heterogeneity by Size

	log(Subsidy)		Tax deduction rate		1(Long-term debt)	
	(1)	(2)	(3)	(4)	(5)	(6)
$Policy^{+}$	-0.366***	-0.0280**	-0.00125	-0.0114	-0.0182***	-0.00790***
	(0.00997)	(0.0130)	(0.00704)	(0.00699)	(0.000806)	(0.000927)
$Policy^{+}$*log(Register capital)	0.0627***	0.00732***	0.00230**	0.00127	0.00429***	0.00106***
	(0.00144)	(0.00189)	(0.00105)	(0.00106)	(0.000118)	(0.000138)
log(Register capital)	0.270***		-0.0567***		0.0214***	
	(0.000851)		(0.000625)		(7.14e-05)	
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	3,075,274	2,663,526	5,144,683	4,835,261	5,970,610	5,580,712
R-squared	0.266	0.667	0.211	0.690	0.160	0.571

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

Table 19: 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 20. 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: 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 20. 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: 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 20. 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.

Online Appendix (Not For Publication)

Appendix A Verification of LLM Outputs

In this appendix, we describe the results of several verification checks that we use to evaluate the quality of the LLM outputs.

A.1 Word Cloud and Manual Checks

We first present two important verifications of key variables in our LLM-analyzed data set. First, we present evidence for manual checks and 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 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. In addition, 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 holistically evaluate sentences, paragraphs, and entire documents 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 helps confirm that 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 768,387 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 D 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.

A.2 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 policies that affect 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 main 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.

Figure A11a 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.

Appendix B Major Components of LLM Prompts

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. M**arket 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. E**ntrepreneurship 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 Condition: 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 Relationships

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 Policy Citations

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.

Appendix C 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 A11 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[17]. 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.

[Figure A11 about here]

Geographical distribution Figure A12 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 A12 about here]

Implementation tools We then examine the industrial policy tools utilized in each one of the three sectors. Table A7 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 A7 about here]

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

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[18]. 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 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 A8 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 (31%) compared to chips (21%) and EVs (24%), while positive incentives (e.g., rewards or support) are used most in the chip industry (15%), which are consistent with the heavier central directive in the solar industry and active local enthusiasm in the chip and EV industry.

[Table A8 about here]

All three industries rely heavily on setting explicit targets, significantly higher than the all-industry average level. Encouraging pilot and the corresponding demonstration effect is slightly more common in the EV (31%) and chip (28%) industries compared to solar energy (26%). 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

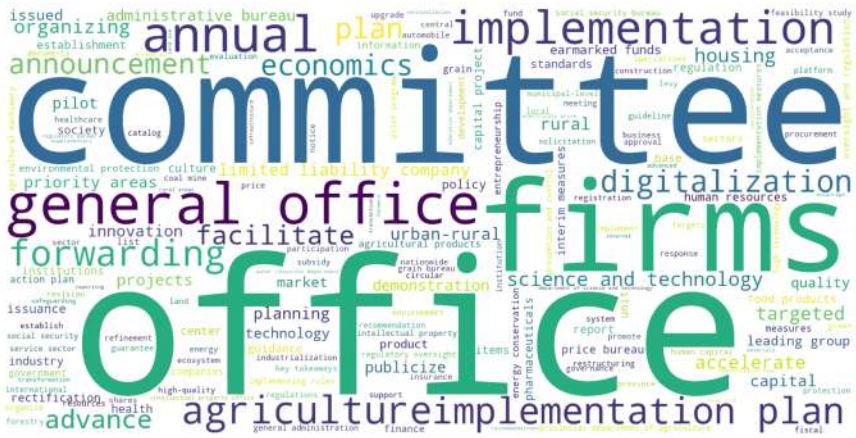
[18] https://36kr.com/p/2796503120703107

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 (68%). This highlights the complex nature of the semiconductor industry, where strong inter-agency coordination is necessary for successful policy execution.

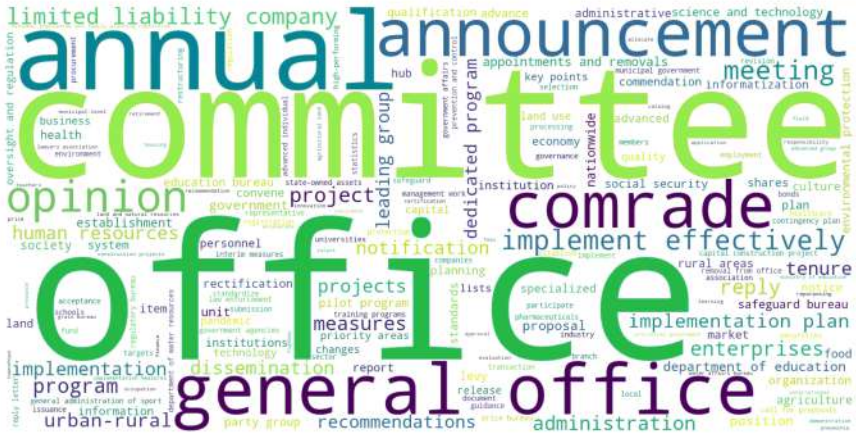
Overall, the table illustrates that chip and EV industries are more localized, with significant local adaptation and experimentation, while the solar energy industry appears to be more centrally driven, with stronger negative incentives and target-setting mechanisms.

Appendix D Appendix Figures and Tables

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



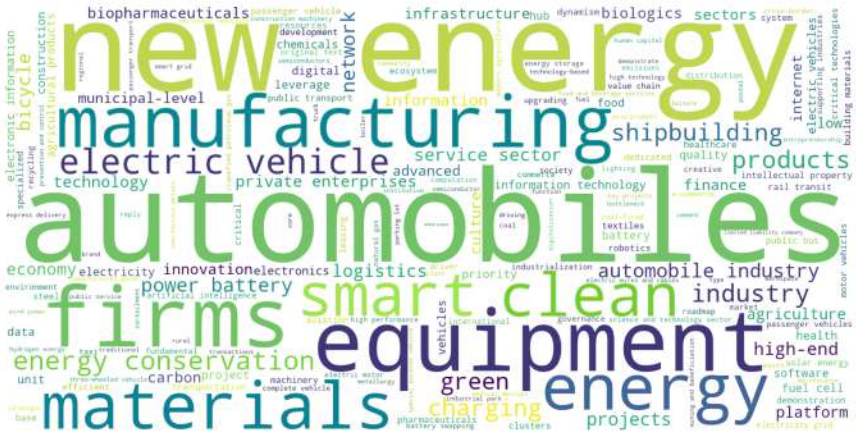
(a) Industrial Policy



(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



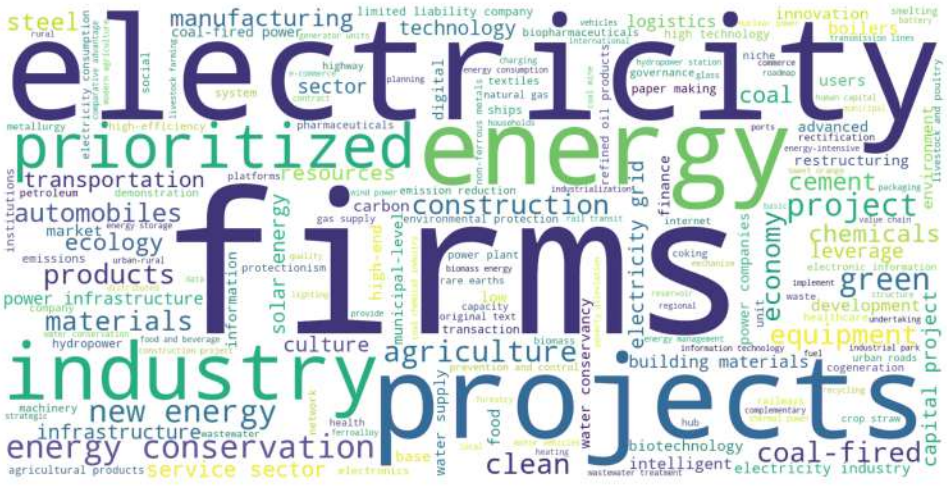
(a) Title



(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

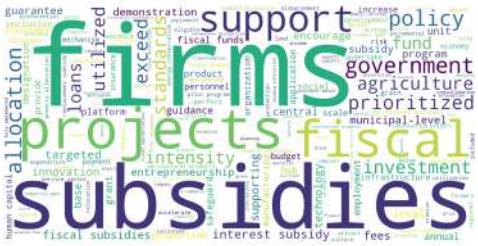
(b) Full Text

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)

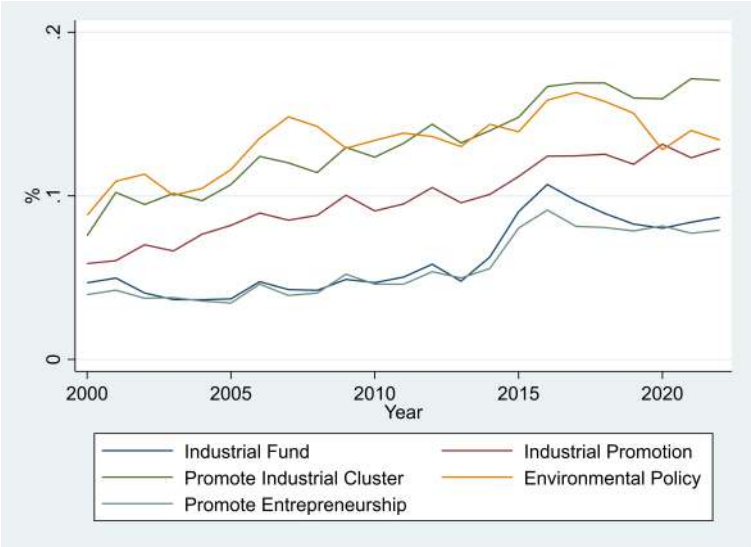


Figure A7: Time Trend of Industrial Policy Tool (New)

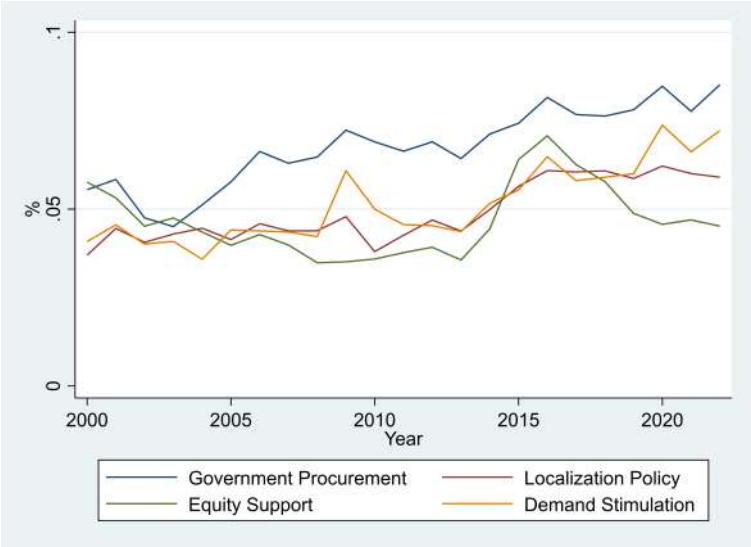
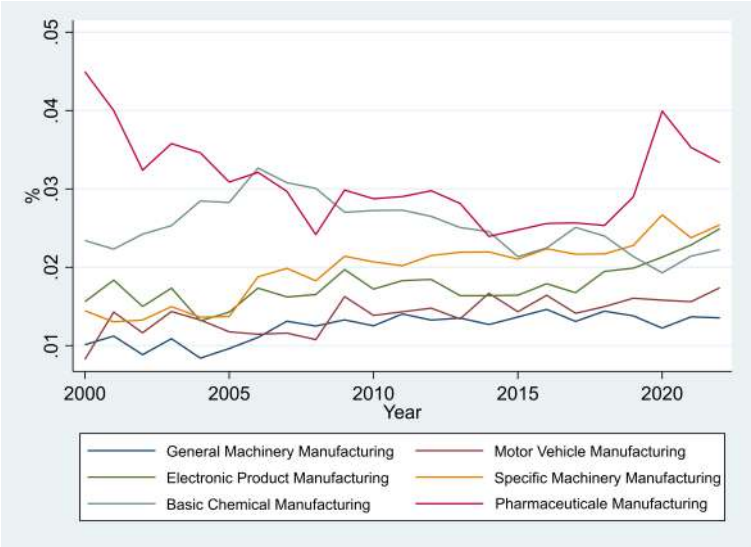
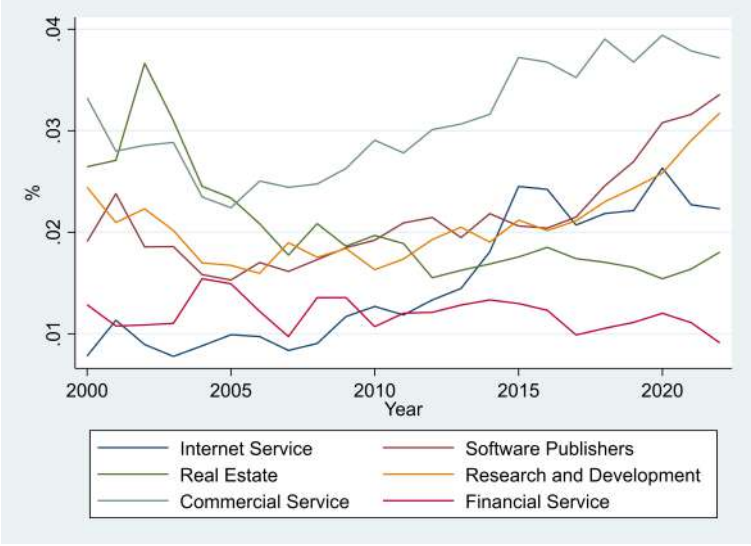


Figure A5: Time Trend of Policy-Targeted Industries in Manufacturing and Service Sectors (Breakdown)



(a) Manufacturing Sector



(b) Service Sector

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)

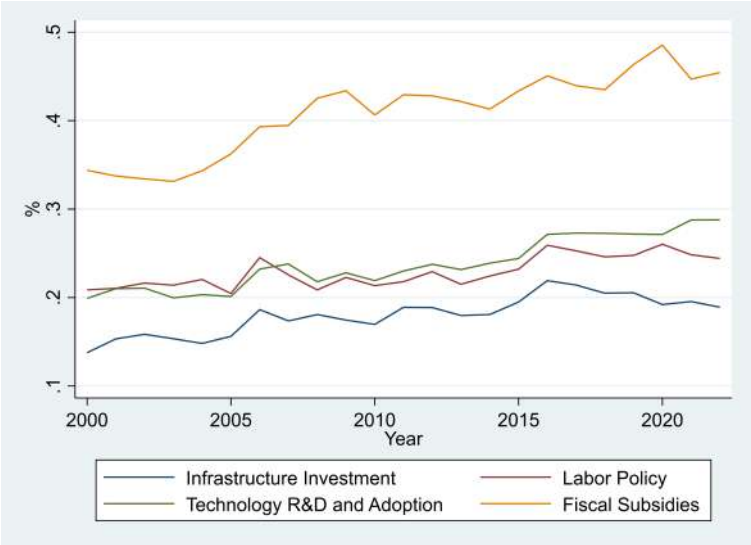


Figure A9: Time Trend of Industrial Policy Tool (Traditional)

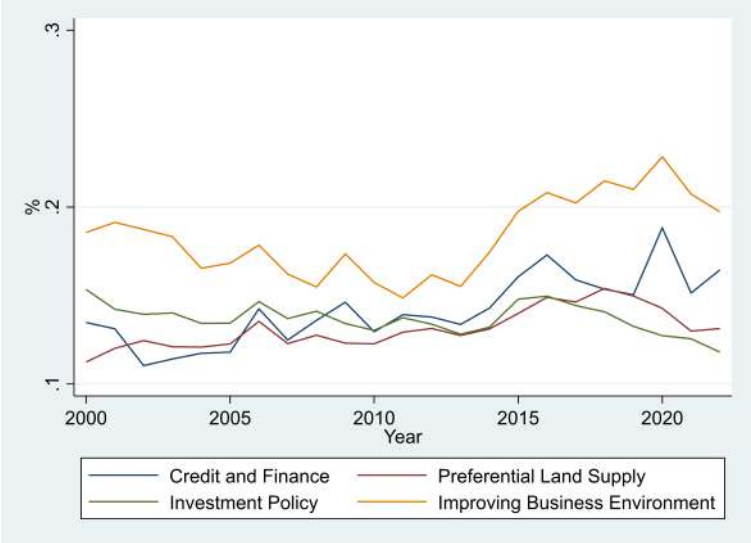


Figure A10: Time Trend of Industrial Policy Tool (Declining)

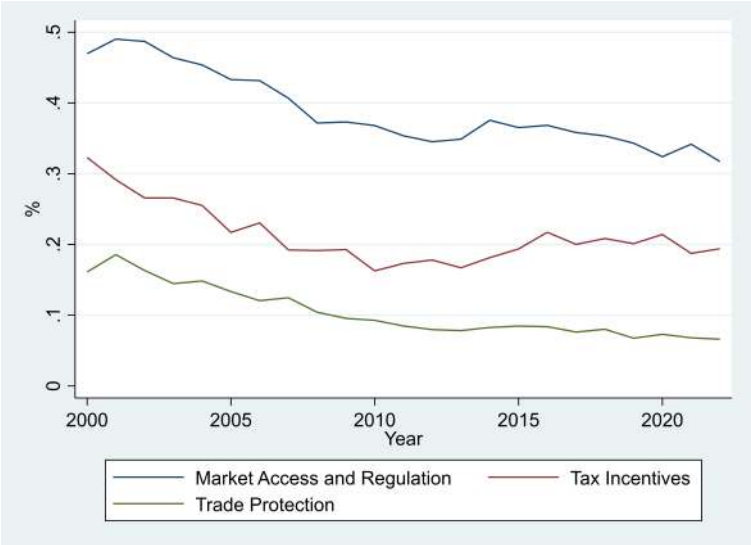
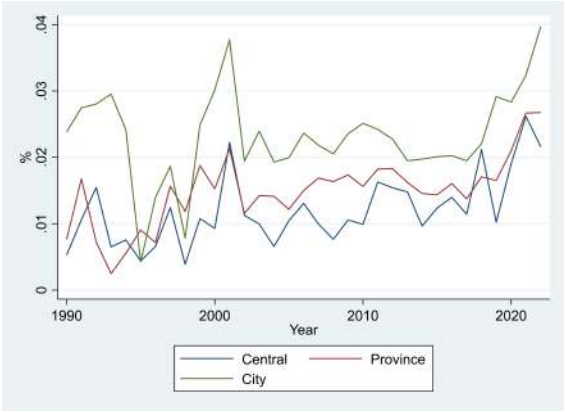
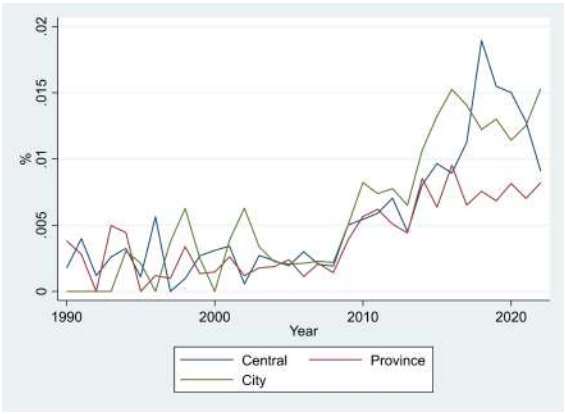


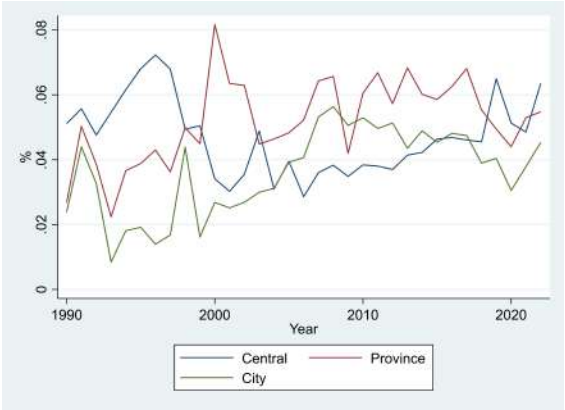
Figure A11: Time Trend of Chip, EV, and Solar Industrial Policy



(a) Chip



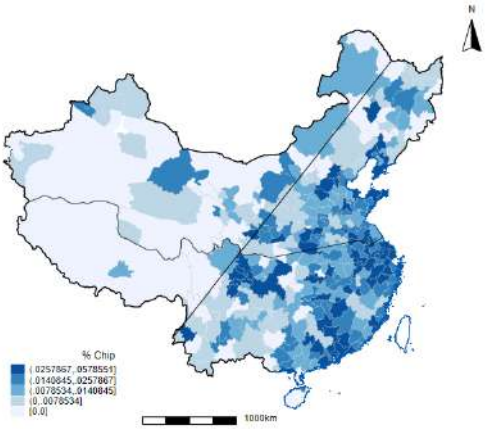
(b) EV



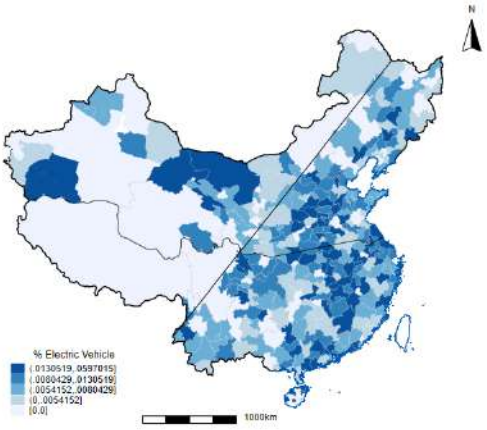
(c) Solar

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.

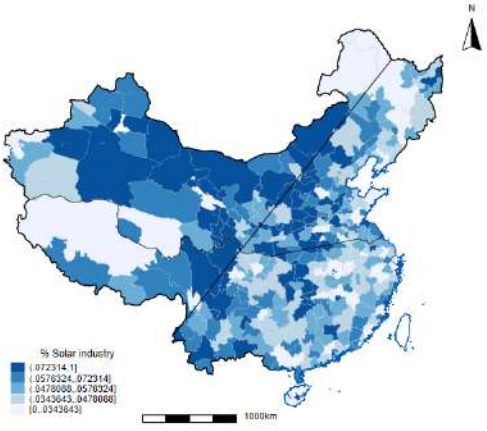
Figure A12: Geographic Distribution of Chip, EV, and Solar Industrial Policy



(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.

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

Panel A: 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
Panel B: 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 Live Pigs 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 Electricity Price 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 Subsidies
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 Biopharmaceuticals ETF	Biopharmaceuticals
Notice from the Audit Division of Jiangsu Provincial Department of Education on Holding a Symposium on Auditing the Construction Project of Advantageous Disciplines in Provincial Universities	Advantageous
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	Cultivating

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.

Table A7: 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 A8: Industrial Policy Implementation: Chip, EV, and Solar Energy

	Chip	EV	Energy
Incentive Scheme			
Setting Target	0.50	0.53	0.54
KPI	0.13	0.15	0.17
Supervision & Inspection	0.34	0.38	0.47
Positive Incentive	0.15	0.14	0.14
Negative Incentive	0.21	0.24	0.31
Experimentation and learning			
Pilot & Demonstration	0.28	0.31	0.26
Encouraging Innovation	0.08	0.09	0.07
Requiring Local Implementation	0.12	0.14	0.13
Allowing Mistake	0.03	0.03	0.02
Learning Experience	0.13	0.14	0.13
Organizational Support			
Strict Enforcement	0.32	0.40	0.50
Facilitating Coordination	0.68	0.69	0.66
Funding Support	0.55	0.57	0.51
Institutional Support	0.39	0.41	0.35
Local Condition			
Local Industry Advantage	0.23	0.21	0.13
Local Input Advantage	0.11	0.11	0.12
Differentiation	0.20	0.23	0.21
Local Adaptation	0.37	0.44	0.44

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 A9: Summary Statistics for Administrative Tax Data

	Obs.	Mean	SD	Min	Max
Subsidy (thousand RMB)	3,760,219	349.61	1,936.95	0	20,727
Tax deduction rate	6,080,762	0.07	0.23	0	1
Leverage (equity/asset)	7,027,631	0.66	0.64	-0.07	6.27
1(Long term debt)	7,239,822	0.07	0.26	0	1
Revenue (thousand RMB)	7,012,096	121,218.30	447,571	1	4,508,752
Output value (thousand RMB)	5,361,358	84,565.97	323,932.10	0	3,262,687
Value-added (thousand RMB)	4,499,134	15,736.92	67,731.90	-11257	688,829
Asset (thousand RMB)	7,198,993	258,310.20	1,227,122	0	13,100,000
Input value (thousand RMB)	4,391,739	70,188.01	273,349.80	0	2,766,013
Employment	7,170,999	111.66	302.69	1	2797
TFP (revenue-based)	5,957,269	6.07	1.73	-19.92	18.02
TFP (output-based)	3,705,065	5.90	1.78	-21.83	28.10
TFP (value-added-based)	2,523,638	3.21	1.98	-28.81	16.10

Note: The table reports the summary statistics for key variables based on the administrative tax data. The unit of observation is firm-year level, and the sample coverage is 2008-2020.

Table A10: Summary Statistics for City Politicians

	Secretary	Mayor
	Mean	Mean
Age	52.62	50.63
Gender (Male=1, Female=0)	0.96	0.94
Tenure	2.72	2.58
Change (Yes=1, No=0)	0.28	0.29
Connection with provincial governor (Yes=1, No=0)	0.11	0.11
Connection with provincial secretary (Yes=1, No=0)	0.09	0.06

Note: The table reports the summary statistics for key variables based on the city-level policitian data. The unit of observation is city-year level, and the sample coverage is 2001-2020.

Table A11: Sector Choice and Regional Advantage

	(1)	(2)	(3)	(4)
l.RCA^n	0.00198***			0.000946***
	(0.000181)			(0.000153)
l.RCA^p		0.0147***		0.0127***
		(0.000708)		(0.000698)
l.AA			3.439***	2.520***
			(0.193)	(0.206)
Constant	-2.133***	-2.150***	-2.142***	-2.157***
	(0.00408)	(0.00419)	(0.00412)	(0.00422)
Industry-by-year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Observations	1,234,115	1,234,115	1,234,115	1,234,115

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