Market-Based Innovation Policy:
Evidence from High-Tech Incubators in China*

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Abstract

Using proprietary data of all high-tech incubators in China, we study a new approach by government to implement industrial policy through market intermediaries instead of directly allocating resources. Exploiting a highly localized industrial policy that targets different "strategic emerging industries" across provinces, we find that the incubators in policy-targeted industries receive higher government subsidy after the policy relative to their peers in other industries. Moreover, we find evidence that government subsidy to high-tech incubators increases the incubated startups' innovation activity. Privately owned incubators in targeted industries, relative to their state-owned peers, receive less government subsidy, although they utilize government subsidy much more efficiently than do their state-owned peers.

Keywords: Entrepreneurship, Incubators, High-tech startups, Industrial policy, Innovation

JEL Classification: D22, G24, G32, L52, L53, O31, O34, O38

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1. Introduction

After four decades of rapid growth, the Chinese economy has reached a crossroads and faces an innovation imperative as two primary sources of its growth—labor force expansion and heavy capital investment—fade away (Woetzel et al., 2015; Wei et al., 2017). As early as 2010, Chinese policymakers publicly declared the country's intent to upgrade from traditional manufacturing industries to an advanced technology-driven economy. By common measures of innovation, China has already become a global innovation leader. For example, its research and development (R&D) intensity has quickly caught up with the major developed economies, and patents filed by Chinese firms have quadrupled in the past decade and surpassed those granted in the United States (Panels A and B of Figure 1). The rise of China in the world economy has become one of the most contested topics by scholars and policymakers (e.g., Han et al., 2020; Hoberg et al., 2021). While a large strand of the literature studies China's rapid growth in traditional industries (e.g., Brandt and Zhu, 2000; Li and Zhou, 2005; Song et al., 2011; Hsieh and Song, 2015; Xiong, 2018), little has been done to explore China's progress in high-tech areas. In this paper, we examine a unique mechanism in which the Chinese government uses high-tech incubators as a market intermediary to achieve policy goals in high-tech industries.

High-tech incubators specialize in screening and nurturing startup firms in their infancy, and they have grown rapidly in China during the last decade, with their number reaching over 5,000 in 2019 with over 200,000 incubated startups. While incubators can be either privately owned (70%) or state owned (30%), their incubated startups are almost entirely privately owned. High-tech incubators provide startups with services such as office space, tutoring, professional agencies, technical support, and capital financing to help them "graduate" after a period of successful growth. Incubators profit from service charges and, more importantly, from their equity investments in startups, so their success hinges on their ability to screen and nurture incubatees.[1]

[1] We discuss more details about the institutional background of Chinese high-tech incubators in Section 2.2.

As China attempts to boost the innovative "strategic emerging industries" (SEIs)[2] to become a global technology powerhouse, the traditional approach that directly allocates resources to companies, especially state-owned enterprises (SOEs), in preferred industries has been rendered inefficient because SOEs are inefficient in converting R&D investments into innovation output (e.g., Wei et al., 2017). In contrast, high-tech incubators, equipped with expertise and tools in screening and supporting startups, can help government carry out industrial policy by efficiently allocating resources to high-tech startups. Under this hybrid model, the government provides support, including direct subsidy, tax breaks, and equity investments, to high-tech incubators as market intermediaries that are responsible for boosting their startups' innovation activity.

In this paper, we study the effect of this market-based approach using unique data of all high-tech incubators in China from 2015 to 2019. This database, obtained from China's Ministry of Science and Technology (MOST), includes 20,243 incubator-years and 1,032,383 startup-years from 2015 to 2019, accounting for a considerable fraction of high-tech industries in the country. For example, the startups of our sample incubators employ 11% to 16% of new STEM graduates and file 10% to 14% of new patent applications in China during our sample period. The data contain information on firm characteristics, including year of establishment, year of incubation, location, industry, characteristics of the entrepreneurs, investments received from different sources, employment, operating performance, and intellectual property (IP, e.g., patents filed and granted) for both incubators and firms.

Our empirical design exploits the variation in industrial policies that target different SEIs across provinces. We focus on a highly localized industrial policy implemented under the 13^{th} Five-Year Plan (FYP, 2016–2020), which targets different SEIs with cash subsidies, equity investments, and tax benefits provided by the local governments. The 13^{th} FYP documents are released by province governments in either 2016 or early 2017, and implemented from 2017. We read the policy document for each province and identify the top three SEIs for a province

[2] SEIs include seven innovative industries: energy-efficient and environmental technology, next-generation information technology, biotechnology, high-end equipment manufacturing, new energy, new materials, and new-energy vehicles.

as its *targeted industries*.[3] The targeted industries display significant variations across regions. For example, electronic information is a policy-targeted industry in the Anhui province but not in the Yunnan province. Accordingly, incubators in this industry are defined to be treated if they are located in Anhui, but not treated if they are located in Yunnan. We estimate the effect of the industrial policy on incubators' government support and their startups' innovation using a difference-in-differences (DID) framework by comparing the differential outcomes between the targeted and control industries and between the periods before and after the policy.[4]

Our analyses yield several important findings. First, we find that high-tech incubators in the targeted industries, relative to those in the control industries, receive 3.3 times more government support than their pre-policy levels following the policy.[5] This result is true for all three forms of government support: cash subsidy, equity investment, and tax reduction. This finding holds after we control for incubator, province-by-year, industry-by-year, and province-by-industry fixed effects and time-varying incubator characteristics. In contrast, incubators in targeted industries experience little change in funding after the policy from non-government sources (e.g., corporations, nonprofit organizations, or individuals) relative to control incubators, suggesting that the increased government support is driven by the industrial policy rather than economic or market-wide factors.

Second, we find that government support for incubators has a significant and positive effect on the innovation activity of incubated startups. We use six measures of startups' innovation activity—R&D investment, number of employees, number of patent applications filed, sales, amount of VC funding received, and likelihood of startups' "graduation"—as the dependent variables. We estimate incubator-level OLS regressions of the innovation measures on the government support received by incubators. For all six measures, we observe a significantly positive relation between innovation activity and government support, which is consistent with

[3]The SEIs in the policy documents are listed in order of importance, and their number ranges from three to ten across provinces. We therefore choose the top three SEIs of each province for consistency.

[4]Since the policy is implemented from 2017, we use 2017 as the start of post-event period.

[5]This result is based on DID regressions. In univariate analysis, the average annual government support received by untreated incubators declines from RMB 6.09 million in the pre-policy years to RMB 3.64 million in the post-policy years, while that for treated incubators rises from RMB 3.31 million to RMB 6.04 million in the same period.

a positive effect of government support on incubated startups' innovation activity. Government support also has a significantly positive effect on the services rendered by incubators, including educating startup employees, hiring professional agencies for startups, providing tutoring sessions, and investing in shared platforms.

We acknowledge that the observed positive relation between government support and innovation activity may be endogenously driven by omitted variables. For example, a well-managed incubator may be good at both securing government subsidy and boosting its startups' innovation activity. We address the endogeneity concerns by conducting two-stage least squares (2SLS) regressions with two instrumental variables (IVs) for government support. The first IV is the predicted tenure of local politicians, proposed by Ru (2018) who finds that local officials tend to increase public investments in the early years of their tenure. We therefore expect that government subsidy to incubators will be higher in the earlier years of local politicians' tenure. The second IV is local exposure to China's anti-corruption campaign, for which we expect the government support to decrease with local exposure, as Fang et al. (2022) find that the anti-corruption campaign can deter government officials from dealing with private firms. The 2SLS results continue to indicate a significantly positive effect of incubators' government subsidy on the incubated startups' innovation activity.

Third, we assess the relative importance of the incubator approach with respect to the total impact of the industrial policy on startups' innovation. Combining our first two findings, we estimate that the incubator approach generates post-policy increases of R&D investment by 6.6%, employment by 9.3%, patent applications by 8.3%, total sales by 3.0%, VC funding by 97.0%, and graduation rate by 2.3% for the incubated startups in targeted industries relative to their peers in other industries.

We then assess the overall policy effect on incubators' innovation activity, and estimate that the incubator approach accounts for 4.3% of the total policy effect on startups' R&D, 20.1% for employment, 12.5% for patent applications, 11.1% for total revenue, 28.2% for outside-VC funding, and 5.4% for the probability of startup graduation. Overall, 13.6% or over one-seventh of the policy effects on the high-tech startups come through incubators.

Fourth, we use the granular data at the startup level to examine the heterogeneous policy effect across different types of startups. We first conduct startup-level analysis and find that, consistent with our incubator-level findings, startups in the targeted industries experience significant growth in their innovation activity after the policy implementation. The placebo tests show that our finding is not driven by the pre-policy differences among incubators due to their industries or locations. More importantly, we find that, unlike traditional policy that directly targets large firms or state-owned enterprises (SOEs), the industrial policy on high-tech industries leads to significantly more growth in less resourceful startups such as "non-HTE" enterprises and younger startups.[6]

Lastly, we compare the efficiency of private incubators in carrying out the innovation policy with that of SOE incubators. In the absence of counterfactual policy, SOE incubators could behave similarly to the government, because executives in these firms share similar career concerns as government officials (Li and Zhou, 2005; Ru, 2018), while private incubators have incentives to act as efficient market intermediaries to maximize profits by promoting their startups' innovation activity. We find that treated state-owned incubators receive disproportionately more support from local governments than do the treated private peers after the industrial policy. However, startups in the treated state-owned incubators experience significantly lower growth in innovation activity following the policy than do those in the treated private incubators. In addition, we find evidence that treated state-owned incubators recruit fewer startups as well as startups with lower quality relative to their treated private peers after the policy. The fact that the less efficient state-owned incubators receive more government subsidy post-policy than do private incubators indicates potential resource misallocation despite the market-based approach.

Our paper contributes to the literature on industrial policy, especially regarding how government policy affects innovation. Previous studies find mixed evidence on the effect of govern-

[6] "Non-HTE startups" are those that are not officially recognized by the Chinese government as "high-tech" firms. As a result, they generally receive much less government support than officially recognized HTE startups do.

ment spending on promoting innovation.[7] Wei et al. (2017) suggest that government subsidies tend to favor state-owned firms even though private sector firms and foreign-invested firms are more effective in converting R&D investment into innovation outcomes than are state-owned firms. Tian and Xu (2021) examine the effect of place-based high-tech zones in China on corporate innovation. Guo et al. (2016) study the Innofund that provides R&D financing, and Chen et al. (2021b) study the InnoCom program that provides tax incentives in the tax reform of 2008. We extend this literature by documenting the unique incubator-based toolkit to promote innovation that is vastly different from the traditional approach to implementing industrial policies.

Our paper also contributes to the literature on high-tech incubators. We are the first to examine the market-based approach to implement innovation policy through high-tech incubators. While previous studies on high-tech incubators focus on their business models and operations (Gonzalez-Uribe and Leatherbee, 2018; Madaleno et al., 2018; Yu, 2020; Hallen et al., 2020; González-Uribe and Reyes, 2021), we find that high-tech incubators can play an important role in passing through the government policy promoting innovation.

2. Institutional Background and Related Literature

2.1. Industrial Policies in the 13^{th} Five-Year Plan

Despite the marketization reform, China has largely maintained its tradition of a Soviet-style five-year plan to align the economy with top policy goals and communicate this directive throughout the government bureaucracy. Targets outlined in the FYPs highlight the top national priorities and set red lines for evaluating the performance of the numerous ministries and local governments. Earlier plans all dictated economic and social behavior, and it was not until the 11^{th} FYP (2006–2010) that China started to implement an industrial policy aimed at

[7]See, for example, Hall and Van Reenen (2000); Bloom et al. (2002); Wu (2005); Gurley-Calvez and Bruce (2008); Acs et al. (2009); Howell (2017); Acemoglu et al. (2018); Babina and Howell (2018); Agrawal et al. (2020); Stantcheva (2021).

revitalizing targeted traditional manufacturing industries. These mega projects were financed by billions of RMBs of the government's annual budget.

Beginning with the 12^{th} FYP (2011–2015), Chinese policymakers publicly declared their intent to upgrade the economy from traditional industries and develop a more advanced and technology-driven economy by creating the concept of the *strategic emerging industry*.[8] The government, in its 2010 policy document, established a quantitative target for SEIs to account for 8% of GDP by 2015 and 15% by 2020. The *Made in China 2025* Action Plan, an industrial master plan announced in 2015, lays out 12 targets with 2020 and 2025 deadlines that focus on enhancing China's innovation, productivity, quality, digitalization, and efficiency.[9] The 13^{th} FYP (2016–2020) reiterates support for the SEIs and targets increasing the technological contribution to economic growth from 55% to 60%, R&D spending as a share of GDP from 2.1% to 2.5%, and the number of patents filed per 10,000 people from 6.3 to 12 by 2020 (Koleski, 2017).

The Chinese government has channeled significant state funding to support the targeted industries. For example, in November 2016, the China Development Bank announced it would provide at least $44.8 billion (RMB 300 billion) in total financing to support the implementation of the *Made in China 2025* initiative. Other state funding includes a newly created $20 billion (RMB 139 billion) National Integrated Circuit Fund, a $3 billion (RMB 20 billion) Advanced Manufacturing Fund, and a $6 billion (RMB 40 billion) Emerging Industries Investment Fund. Unlike previous innovation policies, local governments that are ultimately responsible for direct implementation also provided strong financial support by pledging unprecedented subsidies for targeted industries during the 13^{th} FYP.[10] The heterogeneity among provinces allows us to exploit the variation in targeted industries across provinces to study the effect of the industrial policy on firm-level innovation outcomes.

[8]SEIs include seven innovative industries: energy-efficient and environmental technology, next-generation information technology, biotechnology, high-end equipment manufacturing, new energy, new materials, and new-energy vehicles.

[9]See Wübbeke et al. (2016) for more details.

[10]Other innovation policies include place-based high-tech zones (Tian and Xu, 2021), Innofund that provides R&D financing (Guo et al., 2016), and InnoCom that provides tax incentives in the tax reform of 2008 (Chen et al., 2021b).

2.2. High-Tech Incubators

Although the first Chinese high-tech incubator was established by the state in 1987, it was not until 2014 that the Chinese government introduced a "Mass Entrepreneurship and Innovation" initiative that provides a substantial amount of financial support, tax incentives, and policy support to incubators and startups. In a short period of time, the number of high-tech incubators in the country grew to more than 5,000 in 2019, with over 200,000 incubated startups.

While Chinese incubators provide similar services to incubated startups as their counterparts in other countries, including management training, office space, technology platforms, professional agencies, and capital financing, they play a much more prominent role as a catalyst tool in the country's innovation ecosystem. All high-tech incubators are registered, credentialed, assessed, and classified (e.g., national, provincial, and municipal) by the MOST agencies on a regular basis, based on which central and local governments award various policy support, including free land or space, reduced taxes, equity investment, and direct monetary subsidies. Incubators can be rewarded by MOST agencies at different levels (e.g., municipal, provincial, and central governments). For example, the MOST agency in a Shenzhen district provides each local incubator with a one-time subsidy of up to $300,000 (RMB 2,000,000) and an annual bonus based on performance. Incubators profit from service charges and, more importantly, from their equity investments in the incubated startups, so their success hinges on their ability to screen and nurture incubatees, which "graduate" after a period of successful growth.

High-tech incubators in China can be either privately or state owned, although their incubated startups are almost always privately owned. There are various categories of incubators with diverse business models, including big tech incubators (e.g., Tencent, Ali, Baidu, Microsoft), angel incubators (e.g., Innovation Works, Virtue Inno Valley, TusStar), shared space (e.g., Innospace), media platforms (e.g., Cyzone, 36Kr), and new real estate leasing centers (e.g., SOHO, UrWork). Big tech incubators focus more on technological breakthroughs and innovative products by providing technological support, training, and venture capital, and less on return on equity investment, which is a primary objective for other incubators.

2.3. Literature on Incubators and Entrepreneurship

Entrepreneurship is often considered to be the major driver of sustainable, long-run growth and development for an economy. Early works describe that entrepreneurs not only play a transformational role in shaping markets, but also in accelerating the dissemination and adoption of new technologies (e.g., Kortum and Lerner, 2000). Recent works focus on how institutional differences, cultural considerations, and even personal characteristics contribute to the success of entrepreneurs.

Incubators and accelerators offer startups a combination of equity, shared office space, and entrepreneurship schooling, which is essential to new venture performance given the fragility of these young firms. Gonzalez-Uribe and Leatherbee (2018) provide novel quasi-experimental evidence that business accelerator programs increase new venture performance. Accelerators are also found to promote entrepreneurial firm performance and resource allocation through other channels, such as colocation (Madaleno et al., 2018), timely detection of poorly performing firms (Yu, 2020), providing learning mechanisms within accelerators (Hallen et al., 2020), and providing customized advice and visibility (González-Uribe and Reyes, 2021).

We differ from previous studies by examining whether high-tech incubators play an important role in passing through the government policy promoting innovation in China, a country known for the predominant role of government policy and subsidy in economic development. In this massive policy experiment, the Chinese government makes available tens of billions of dollars to over 5,000 high-tech incubators which in turn increase the innovation activity of hundreds of thousands of incubated high-tech startups. This mechanism is vastly different from the ordinary toolkit of policies to promote innovation, such as providing direct allocation to entrepreneurs, R&D subsidies, and government research grants; increasing the supply of human capital; protecting intellectual property rights; and promoting competition (Bloom et al., 2019).

2.4. Government Policies Promoting Innovation

Our paper is also related to the broad literature on if and how government policy affects innovation. This literature points out that government intervention in innovation is necessary because of the failure in private investment and innovation decisions caused by reasons such as knowledge spillovers, information asymmetry, or financial constraints.[11] Among a number of the main innovation policy levers adopted by governments, especially by the U.S. government, the effects vary. For example, Howell (2017) studies the Small Business Innovation Research program and finds that while the Phase I awards have very positive effects on new technology ventures such as doubling the probability of receiving venture capital and boosting patenting and revenue, the much larger Phase II awards have no positive impacts on the ventures. Other studies also provide mixed evidence on the effect of government spending on promoting innovation (Hall and Van Reenen, 2000; Bloom et al., 2002; Wu, 2005; Gurley-Calvez and Bruce, 2008; Acs et al., 2009; Acemoglu et al., 2018; Babina and Howell, 2018; Agrawal et al., 2020; Stantcheva, 2021).

To this date, there has been limited work on the effect of government policies on innovation in China, a country with unprecedented growth in innovation activity, and the predominant role played by the government in promoting innovation.[12] Wei et al. (2017) suggest that Chinese firms have demonstrated a capacity to become more innovative in response to the challenges due to rising wages and global competition. However, government subsidies tend to favor state-owned firms even though private sector firms and foreign-invested firms are more effective in converting R&D investment into innovation outcomes than state-owned firms are. König et al. (2020) estimate that the aggregate productivity growth in China's manufacturing

[11] For example, financial constraints may limit the amount of innovation carried out by innovative firms at an early stage, as investors face information asymmetry before innovations are patented or demonstrated in the market.

[12] There is an extensive literature that explores the effect of government policies on economic growth, for example, Zheng et al. (2017); Lu et al. (2019).

sector could have been higher by one-third to one-half without R&D misallocation.[13]

This paper is the first, to our knowledge, to study the effect of the government's industrial policy on firm-level innovation activity in China. Unlike traditional industrial policies, the recent stimulus package includes a combination of fiscal subsidy, equity investment, and tax breaks. More importantly, all these subsidies are implemented via a market intermediary. The hybrid model delegates the screening and allocation decisions into the hands of thousands of high-tech incubators with the explicit goal to alleviate resource misallocation.

The rich data also allows us to explore the effectiveness of different incubators, in particular SOE and private incubators, in passing through the government policy. We find that while the overall policy effect on innovation outcomes is large and significant, the SOE incubators are significantly less effective in passing through policy effects than are private ones, highlighting the lower efficiency of direct government intervention in high-tech innovation. We also find that the policy implemented through incubators has a greater effect on more vulnerable firms—young firms and non-HTE firms that have traditionally been given less favorable treatment in prior policies.

3. Data and Sample Construction

3.1. Incubator and Startup Data

We obtained data on all Chinese high-tech incubators from 2015 to 2019 from the MOST of China. This database is constructed under China's "Torch Program" to promote the development of high-tech industries. All high-tech incubators are required by the MOST to report detailed information about themselves as well as the incubated startups to the program annually. In total, the database contains 20,243 incubator-years and 1,032,383 startup-years from 2015 to 2019, or an average of 4,050 incubators and 206,500 startups per year. Panel A of Figure 2 plots the numbers of high-tech incubators and their underlying startups over our

[13] Besides the efficiency issue, China's ability to innovate is also affected by its intellectual property rights protection, to which private firms are very sensitive in their innovation activity (Fang et al., 2017).

sample period, which shows rapid growth in both incubators and startups during that period. For example, the number of high-tech incubators has grown from 2,900 in 2015 to 5,200 in 2019, and their incubated startups from 144,600 to 275,900.

To assess the relative importance of incubators and their incubated startups in China's high-tech industry, we plot in Panel B of Figure 2 the share of the sample startups' activity in the overall economy. Over the sample period, the incubated startups employ 10% to 14% of all new STEM graduates in the country and file 11% to 16% of all new patent applications. These results demonstrate that high-tech incubators and incubated startups represent a considerable portion of China's high-tech industry and innovation activity.

[Insert Figure 2 Here.]

The characteristics of incubators and startups in our data set include year of establishment, incubator level (national, provincial, or municipal incubators), ownership (SOE vs. private), amount of registered capital, location, industry, year of incubation (for startups), and HTE status (for startups). Our data set also contains annual financial information of the startups, including shareholder information, employment, R&D expenditure, amount of export, taxes, intellectual property (e.g., patent applications, patents granted, technology transactions), sales, operating costs, profit, and VC funding received. For incubators, the data set also captures incubator services provided to their incubated startups such as number of tutorial sessions, number of agencies hired for the startups, and equity investment in the startups.

3.2. Classifications of Policy-Targeted Industries

To identify the industries targeted by government policy at the province level, we obtained the information from individual provinces' 13^{th} FYP documents that are released by province governments in either 2016 or early 2017. Consistent with the SEIs in *Made in China 2025*, each provincial plan states at least two "key development industries" to be prioritized in the next five years, listed in the order of importance. The industries selected by individual provinces include electronic information, advanced manufacturing, aerospace, modern transportation, medical devices and biomedicine, new materials, new energy and energy conservation, environmental protection, geospatial and marine, nuclear application technology, modern agriculture, and cultural and creative industries. We identify the first three industries in a province's 13^{th} FYP as the province's policy-targeted industries.

Figure 3 plots policy-targeted industries for the provinces, showing a very diversified set of targeted industries. The five most common targeted industries are electronic information, new materials, advanced manufacture, medical devices and biomedicine, and new energy, which is consistent with the notion that China seeks to move its manufacturing up the global value-added chain and reestablish itself as a global center of innovation and technology in areas such as green energy. While all 12 industries are high-tech and SEIs, there is a large variation in policy-targeted industries across provinces.

[Insert Figure 3 Here.]

We classify high-tech incubators as $Treated$ (= 1 or 0) based on whether their industries are policy-targeted in their provinces. There are two types of incubators in the data: general and specialized. A specialized incubator focuses on nurturing startups in only one of the twelve industries listed in *Made in China 2025*, and thus we use their reported industries. General incubators can admit and service firms in more than one industry, so we define their industry as the one with the highest number of incubated startups. It is worth noting that incubators in an industry can be classified as either treated or control in different provinces. For example, electronic information is a policy-targeted industry in the Anhui province but not in the Yunnan province. Accordingly, incubators in this industry are defined to be treated if they are located in Anhui, but not treated if they are located in Yunnan.

3.3. Sample Construction and Summary Statistics

Although our data starts from 2015, our test period starts from 2016 because the regression analysis requires lagged incubator and startup attributes. We set 2016 as the pre-policy year ($Post = 0$) and years from 2017 on as the post-policy period ($Post = 1$), since the 13^{th} FYPs take effect in 2017. We further restrict the sample incubators to those that exist in 2016 in order to evaluate the effect of the industrial policy on existing incubators. For the analysis of startups, we also require startups to exist in 2016. Our final sample of incubators contains 8,322 incubator-year observations from 2016 to 2019, and the sample of startups contains 169,377 startup-year observations from 2016 to 2019.

We examine six outcomes based on available data to evaluate the innovation activity of incubated startups: R&D investment, number of employees, number of patent applications, sales, VC funding received, and a dummy variable that equals 1 if the startup graduates in year t and 0 otherwise (Graduate). Out of these six measures, R&D investment and patent applications directly measure startups' innovation activity. We also examine number of employees, sales, and VC funding received which reflect the growth of these high-tech startups. Finally, we examine the dummy of graduation, which indicates that a startup proceeds from the incubation stage after a period of successful growth.[14] These outcome variables are available at the incubator and startup levels.

Governments channel three forms of support to high-tech incubators, including cash subsidy (Govt Subsidy), equity investment (Govt Invest), and tax reduction (Govt Tax). We sum up the three sources of support to construct a measure of total government support (Govt All), which measures the total government subsidies received by the incubators. For incubators, we observe four outcomes that evaluate the amount or quality of incubating services rendered to startups each year: the percentage of incubator staff with college degrees or above (Staff_Edu), number of professional agencies hired for startups (Agents), number of tutoring

[14] A startup graduates from its incubator after a period of successful growth and meeting other requirements. A graduate can end up filing an IPO, being funded by VC, being acquired by other firms or investors, or remaining an independent firm.

sessions to startups (Tutorships), and the incubator's investment funds (Invest_Funds).[15]

[Insert Table 1 Here.]

Panels A and B of Table 1 present the summary statistics for the incubator sample and the startup sample, respectively. Both panels report the means and standard deviations of the variables used in our analysis for the four subsamples based on $Treated$ (=0 or 1) and $Post$ (=0 or 1). Panel A shows that the untreated incubators generally experience decreases or smaller increases in innovation activity, government support, and services rendered from pre- to post-policy years, probably due to the declining growth of the Chinese economy in recent years. In contrast, the treated incubators generally experience increases in innovation activity, government support, and services rendered from pre- to post-policy years. For example, the average annual government support (Govt All) received by untreated incubators declines from RMB 6.09 million in the pre-policy years to RMB 3.64 million in the post-policy years, while that for treated incubators rises from RMB 3.31 million to RMB 6.04 million in the same period. We observe similar patterns for startups in Panel B. For example, the logarithm of R&D of startups in untreated incubators decreases from 14.201 to 12.340, while that in treated incubators increases from 14.781 to 15.424 in the same period. These univariate results provide preliminary evidence of a shift of government resources to the policy-targeted industries from other industries.

Panel C of Table 1 presents summary statistics for the new startup sample containing newly incubated startups during the 2015–2018 period. As discussed later in the paper, we use this sample to analyze the policy effect on the quality of newly incubated startups.

4. Incubator-Level Analysis

We take three steps to examine the role of high-tech incubators as a market-based mechanism for carrying out industrial policies. First, we examine whether the industrial policy

[15] An incubator's investment funds are the total funds available to the incubator for investing in startups.

increases government support for high-tech incubators in the policy-targeted industries. Second, we examine whether the increase in government support for high-tech incubators leads to an increase in the innovation activity of incubated startups. Third, we assess the relative importance of the incubator channel in the overall policy effect on high-tech startups.

4.1. Industrial Policy and Government Support to Incubators

In this subsection, we conduct a difference-in-differences (DID) analysis to examine the effect of the industrial policy on government support for high-tech incubators in the policy-targeted industries relative to other industries. We estimate the following DID regressions at the incubator level:

$$s_{i,t} = \beta \cdot Treated_i \cdot Post_t + X_{i,t-1} + \gamma_i + \gamma_{l,s} + \gamma_{l,t} + \gamma_{s,t} + \varepsilon_{i,t} \tag{1}$$

where $s_{i,t}$ is a measure of government support to incubator i in time t; $Treated_i$ is a dummy variable that equals 1 for the incubators belonging to the policy-targeted industries in their provinces, and 0 otherwise; $Post_t$ is a dummy variable that equals 1 for the years following the implementation of the industrial policy (2017–2019); and $X_{i,t-1}$ includes a set of incubator-level attributes in $t-1$ which might also affect government support, including incubator size, number of incubated startups, a dummy variable for old incubators (aged five years and above), a dummy variable for SOE incubators, and a dummy variable for incubators located in the high-tech zones.[16] These incubator-level variables can potentially influence government support received by the incubators. γ represents fixed effects of incubator i, province l by industry s, province l by time t, and industry i by time t, which absorb the time-invariant characteristics of these dimensions that affect government support received by incubators. β is our main coefficient of interest, which captures the changes in government support to incubators in targeted industries, relative to other industries, after the policy implementation.

[16] We measure incubator size using registered capital, as the value of total assets is not available. The registered capital is more closely related to asset size in the earlier period of an incubator than in the later years.

We take the natural logarithm of the continuous variables to control for outliers. We report t-statistics using robust standard errors clustered at the industry-province level.

We present the regression results in Panel A of Table 2, in which Columns (1) to (3) present the regressions of the three forms of government support measures: cash subsidy, equity investment, and tax reduction. Column (4) presents the regression of the sum of those three forms of support. We find that β is positive and significant at the 1% level in all four regressions. These results show that in the post-policy period, the government increases its support to incubators in the policy-targeted industries relative to peer incubators. The increase in government support is also economically large. For example, the β of 3.310 in Column (4) indicates that the total government support to a policy-targeted incubator increases by 3.31 times (331%) from the pre-policy level relative to a non-policy-targeted peer.

[Insert Table 2 Here.]

It is possible that the increase in government support to policy-targeted incubators is due to an overall increase in resources flowing into the cutting-edge policy-targeted industries rather than to the policy effect. To address this concern, we examine three measures of funding received by incubators from non-government sources, including investment from corporations, investment from nonprofit organizations, and investment from other sources (mainly individuals). We estimate regressions similar to Panel A but replace the dependent variable with the three measures of non-government funding, and report the results in Panel B of Table 2. Interestingly, Panel B shows that the DID coefficient β is small and insignificant in all three regressions. Therefore, in a sharp contrast to the large increase in government support for treated incubators, there is little increase in funding from non-government sources to treated incubators. Therefore, the results in Table 2 suggest that the increased government support to incubators in policy-targeted industries is driven by the industrial policy rather than an economy-wide resource reallocation.

4.2. Government Support and Innovation of Incubated Startups

Given the observed large increases in government support to incubators in the policy-targeted industries, it is important to examine whether and by how much the government support to incubators influences the innovation activity of incubated startups. We first conduct an OLS analysis and then address the endogeneity concerns using two instrumental variables for government support.

4.2.1. OLS Analysis

We estimate the following OLS regression of the innovation activity of incubated startups on government support received by incubators:

$$y_{i,t} = \beta \cdot Govt\_All_{i,t-1} + X_{i,t} + \gamma_i + \gamma_{l,s} + \gamma_{l,t} + \gamma_{s,t} + \varepsilon_{i,t} \tag{2}$$

where $y_{i,t}$ is one of the six measures that reflect the amount of innovation activity of startups in incubator i and year t: R&D expenditure, number of employees, number of patent applications filed in the year, total sales, the amount of VC funding received, and the number of incubated startups that graduate in the year. We take the natural logarithm of these innovation measures. The main independent variable is $Govt\_All_{i,t-1}$, defined as the logarithm of total government support received by incubator i in year $t-1$. All controls are the same as in Equation (1). β captures the effect of government support to incubators on the innovation activity of incubated startups. We report t-statistics using robust standard errors with clustering at the industry-province level.

Panel A of Table 3 presents the regression results, in which β is positive and significant at the 1% level in all six regressions, suggesting a significantly positive effect of government support on incubated startups' innovation activity. The values of β indicate that doubling government support is associated with an increase of R&D investment by 2.0%, employment by 2.8%, patent applications by 2.5%, total sales by 0.9%, VC funding by 29.3%, and graduation rate by 0.7%.[17] The previous results in Table 2 indicate an increase of government support by 3.31 times for the treated incubators after the policy implementation. Taking the results in Tables 2 and 3 together, we estimate that the policy effect through the incubator channel generates an increase of R&D investment by 6.6%, employment by 9.3%, patent applications by 8.3%, total sales by 3.0%, VC funding by 97.0%, and graduation rate by 2.3% for startups in the treated incubators after the policy implementation.

[Insert Table 3 Here.]

We also examine whether government support to incubators has a positive effect on incubator services provided to incubated startups. This practice can provide further evidence of how incubators utilize government support to increase the innovation activity of incubated startups. We repeat the regression analysis in Equation (2) but replace the dependent variable with one of the four measures that reflect the amount or quality of incubator services: percentage of incubator staff with college degrees or above (Staff_Edu), number of professional agencies hired for startups (Agents), number of tutoring sessions to startups (Tutorships), and the amount of incubator investment funds available for making an equity investment in incubated startups (Invest_Funds). Panel B of Table 3 presents the regression results, in which the coefficient of government support is positive and statistically significant at the 1% level in all four regressions. These results corroborate the analysis in Panel A and provide further evidence of the positive effect of the industrial policy on high-tech startups through the incubator channel.

4.2.2. Two-Stage Least Squares (2SLS) Regression Analysis

While the results of our OLS analysis are consistent with a positive effect of government support on incubated startups' innovation activity, these results are subject to endogeneity

[17] We also conduct this analysis using the three government support measures separately (i.e., cash subsidy, equity investment, and tax reduction) and find similar positive relations, with the effect of cash subsidy and equity investment being stronger than that of tax reduction.

concerns because omitted variables may drive both government support and startups' innovation activity. For example, a well-managed incubator may be good at chasing government support as well as boosting its startups' innovation activity. To address the endogeneity concerns, we conduct a 2SLS analysis using two instrumental variables for government support.

Our first instrument for government support is motivated by Ru (2018) who finds that local politicians tend to increase public investment in the early years of tenure because public investment takes time to produce economic growth. Following Ru (2018), we construct a dummy variable that equals one for the predicted first and second years of the tenure of a city's party secretary, and zero otherwise. We expect this dummy variable to be positively related to government support. Specifically, we obtained tenure information for each city's party secretary from the Chinese Research Data Services Platform (CNRDS). Since the tenure of a city's party secretary is typically five years, we take the first and the second years of the previous party secretary's tenure and add five years to calculate the predicted first and second years of a party secretary's tenure.[18] Because the predetermined municipal turnover cycles are not affected by current economic factors (Shue and Townsend, 2013), using the predicted tenure instead of the actual tenure addresses the concern that political turnovers may be driven by economic factors.

Our second instrument for government support exploits local exposure to China's anti-corruption campaign. The massive anti-corruption campaign, which started in 2012, has been the largest anti-corruption campaign in the history of China, with millions of people prosecuted or punished (Griffin et al., 2022). Recent work by Fang et al. (2022) documents that the anti-corruption campaign can deter government officials from dealing with private firms because of these officials' reduced career incentive or their effort to play safe by adopting a passive policy. As a result, higher local exposure to the anti-corruption campaign may lead to less government support to incubators. We obtain the city-years with investigations of government officials using the investigation data from the websites of the Central Commission for Discipline

[18] If a party secretary starts in the first half of the year, then we count the first and the second calendar years. If a secretary starts in the second half of the year, then we count next two calendar years.

Inspection and National Supervisory Commission, and construct a dummy variable for the first and second years after a city's party secretary or mayor is investigated for corruption. We expect this dummy variable to be negatively related to government support to incubators.

Panel A of Table 4 presents the 2SLS regressions using political tenure as the instrumental variable. Column (1) shows that the coefficient on predicted political tenure is significantly positive in the first-stage regression, which is consistent with Ru (2018)'s finding of increased public investment in the early years of local politicians' tenure. Columns (2) to (7) present the second-stage regressions of innovation measures, and the coefficient on government support is significantly positive in all six regressions. It is worth noting that the majority of the coefficients are similar in magnitude to the OLS analysis (Table 3), except the coefficient in the regression of patent applications, which is larger than the baseline coefficient. We also conduct the Kleibergen-Paap weak instrument test and find that the F-statistic is 45.313, which shows that political tenure is unlikely to be a weak instrument. The results in Panel A corroborate the OLS analysis and alleviate the endogeneity concerns.

[Insert Table 4 Here.]

Panel B of Table 4 presents the 2SLS analysis results using local corruption investigation as the instrumental variable. Consistent with our prediction that local corruption investigations reduce government support to incubators, we find in Column (1) that the coefficient of local corruption investigation is significantly negative in the first-stage regression. This finding is consistent with Fang et al. (2022)'s result that the anti-corruption campaign may cause government officials to adopt more conservative government policies. In the second-stage regressions, the coefficient on the fitted value of government support is positive and significant for all six innovation measures. Overall, the 2SLS regression results using the two instrumental variables, which generate exogenous shocks to government support, consistently show that government support to incubators has a positive causal effect on incubated startups' innovation activity.

4.3. Relative Importance of the Incubator Channel in Overall Policy Effect

Our results so far provide strong evidence that the industrial policy increases government support to incubators in policy-targeted industries and that government support to incubators increases their incubated startups' innovation activity. These two pieces of evidence together show that incubators serve as an effective market-based mechanism for the Chinese government to carry out industrial policy and direct resources to the targeted high-tech industries. In the meantime, the industrial policy can affect high-tech startups' innovation activity through channels other than incubators, such as increasing direct government support to startups, creating a more favorable business environment, and increasing non-government funding to startups (e.g., bank loans, PE funds, VC funds). In this subsection, we analyze the relative importance of the incubator channel in the overall effect of the industrial policy on startups' innovation activity.

As we estimate in Section 4.2.1, industrial policy through the incubator channel generates an increase in R&D investment by 6.6%, employment by 9.3%, patent applications by 8.3%, total sales by 3.0%, VC funding by 97.0%, and graduation rate by 2.3% for the incubators in the targeted industries after policy implementation. To assess the relative importance of the incubator channel, we first assess the overall effect of the industrial policy on startups' innovation activity. Specifically, we run the DID regression in Equation (1) but at the startup level rather than the incubator level, with the dependent variables being the measures of startup-level innovation activity.

Table 5 presents the regression results, in which β is significantly positive in all regressions, suggesting a positive overall effect of the industrial policy on the innovation activity of startups in targeted industries. Turning to the economic magnitude, the values of β suggest that the industrial policy leads to an increase in R&D investment by 154.2%, employment by 46.2%, patent applications by 66.2%, total sales by 26.9%, VC funding by 343.7%, and graduation rate by 43.2%.

Comparing the effects of the incubator channel with the overall policy effects, we estimate that the incubator channel accounts for 4.3% of the policy effect on R&D, 20.1% of the policy effect on startup employment, 12.5% of the policy effect on patent applications, 11.2% of the policy effect on total revenue, 28.2% of the policy effect on outside-VC funding, and 5.3% of the policy effect on startup graduation rate. On average, the incubator channel accounts for 13.6%, or around one-seventh, of the total policy effect on the sample high-tech startups.

[Insert Table 5 Here.]

We acknowledge two caveats for the above relative-importance assessment. First, this inference applies only to the incubated high-tech startups. The industrial policy is also likely to positively affect high-tech startups that are not incubated. Second, the increase in startups' innovation activity after the industrial policy, based on the results in Table 5, may be partially caused by confounding factors other than the industrial policy. This issue may bias downwards the estimated contribution of the incubator channel because the denominator—the overall policy effect—may be inflated. In the next section, we conduct analyses at the startup level to explore the variation in policy effect across startups and alleviate the concern of confounding factors.

5. Startup-Level Analysis

In this section, we use the rich startup-level data to further examine the effect of the industrial policy on startup activity as well as the variation in such effect among different types of startups. These analyses can provide more evidence on the specific mechanisms through which the industrial policy affects high-tech industries in China.

5.1. Effect of the Industrial Policy on Startup's Innovation Activity

We first examine the effect of the industrial policy on innovation activity at the startup level, following the specification in Equation (1). Specifically, all variables including the fixed effects are similar to those in Table 5 except that they are constructed at the startup level rather than the incubator level. Panel A of Table 6 presents the results. We find that in all regressions, the DID coefficient β is positive and significant at the 1% level. These results show that, consistent with the incubator-level analysis, startups in the targeted industries, relative to startups in other industries, experience significant increases in their innovation activity after the policy implementation. Interestingly, the coefficients are larger than those in the incubator-level regressions (Table 5), implying that the effect of the industrial policy may be stronger for smaller startups. This is because the incubator-level analysis aggregates the startup activity at the incubator level and therefore puts more weight on larger startups.

[Insert Table 6 Here.]

We then exploit the detailed startup-level data and conduct the regression analysis using several alternative innovation measures in Panel B of Table 6. Specifically, Column (1) examines a dummy variable for startups with positive R&D investment instead of the logarithm of R&D investment. Columns (2) to (5) examine the subcategories of employee backgrounds, including number of employees with doctoral degrees, number of employees with bachelor's degrees, number of employees with overseas educational experience, and number of newly hired employees. Column (6) presents the result using patents granted rather than patent applications filed, and Column (7) examines a dummy variable for startups with positive VC funding (rather than the level of VC funding). The DID coefficient β remains significantly positive in all these robustness regressions.

We further conduct two placebo tests in Table 7 to address the concern that the findings in Table 6 may be driven by fundamental differences between the policy-targeted industries and other industries before or after the policy. Panel A reports the regressions of innovation measures on $Treated_i$, which equals 1 for the startups in the targeted industries and 0 otherwise, using only observations before the policy (i.e., observations in 2016). Since the industrial policy has yet to be implemented in this sample, the coefficient on $Treated_i$ captures the pre-policy differences in the innovation activity unrelated to the policy. The coefficient on $Treated_i$ is insignificant in all the regressions, suggesting that our DID results are unlikely to be explained by cross-sectional differences between targeted industries and other industries prior to the policy.

[Insert Table 7 Here.]

In Panel B of Table 7, we conduct the second placebo test, which is similar to Table 6 but defines $Treated_i$ by randomly assigning three industries that are targeted in other provinces but not in the home province. The premise is that if the results were driven by cross-industry differences post the policy, the same industries that are targeted in one province and display higher innovation outcomes should show similar effects in different provinces even if they are not targeted. Panel B shows that the coefficient of $Treated_i$ is insignificant in all regressions, suggesting that our findings are not driven by certain industries but by the variation of targeted-industry classifications in the localized industrial policies.

5.2. Cross-Sectional Differences

Having established the significant effect of the industrial policy on the innovation activity both at the incubator and startup levels, we explore if and how the industrial policy implemented in 2017 to 2019 through high-tech incubators is different from traditional policies implemented in China in the past decades.

Our first question focuses on the distributional impacts across firms. Traditional policies used by Chinese governments to promote innovation or the manufacturing industries directly target large or SOE firms, for example, the top 1,000 most energy-intensive firms (Chen et al., 2021a). The industrial policy studied in our paper is implemented through market intermediaries—incubators—who provide screening and tutoring services directly to the firms throughout the incubation life cycle. This decentralized approach is likely to affect firms differently from the traditional policy.

We first examine the heterogeneity in the policy effect across officially recognized high-tech firms (HTE) and non-HTE firms. HTE firms, credentialed by MOST agencies, have traditionally received preferential policy treatments via lower tax rates or more subsidies than have the non-HTE firms (e.g., Cai et al., 2018; Chen et al., 2021b; Tian and Xu, 2021). We therefore examine if the decentralized approach through high-tech incubators may be more helpful to the less resourceful non-HTE firms. Panel A of Table 8 presents DID regressions that include an interaction term of $Treat_i \times Post_t$ and its triple interaction with a dummy variable for non-HTE firms. The coefficient of the non-HTE interaction term is positive and significant at the 1% level in Columns (1) to (6), suggesting that the market-based industrial policies yield a more pronounced effect on the innovation outcomes of non-HTE firms than of HTE firms. The magnitude of the coefficient of non-HTE interaction is similar to or larger than that of the $Treat_i \times Post_t$, indicating that the policy effect on non-HTE startups is much larger than the effect on HTE startups. Additionally, the positive policy effect on the patents and sales of startups is primarily driven by non-HTE startups. These results show that, unlike the traditional industrial policy, the market-based industrial policy leads to larger benefits for the less resourceful non-HTE firms.

[Insert Table 8 Here.]

Panel B of Table 8 includes the interaction with a dummy variable for young startups, defined as those aged below five years. The younger startups tend to be more vulnerable and have more uncertainty over their ultimate success. As a result, these startups are less likely to receive policy support or market resources in general. The regression results in Panel B show that the new industrial policies yield a more positive effect on the innovation outcomes of younger startups than of more established ones. These results indicate that, consistent with the results in Panel A, less resourceful firms see larger policy benefits of the market-based industrial policy.

In Panel C of Table 8, we include the interaction with a dummy variable for the firms that are in the same industry as their incubator. Since the industrial policy allocates government support primarily based on the industry the incubators specialize in, it is expected that the incubators may concentrate their resources on firms in their specialized industries. In all six regressions, we find that the coefficient on the same-industry interaction is significantly positive while that on $Treat_i \times Post_t$ is insignificant (marginally significant in the regression of VC funding). This stark contrast indicates that the effect of the new industrial policy is exclusively driven by startups in the industries their incubators specialize in.

Besides the three startup characteristics examined in Table 8, a major difference between the incubator channel and the traditional industrial policy is that the incubator channel is focused on the private sector of the economy. Almost all incubated startups are privately owned (99.6%), so the government support for high-tech incubators is entirely transmitted to the private sector of the economy (privately owned startups). This is a stark contrast with the traditional industrial policies that give strong preference to the state-owned sector.

6. Specific Mechanisms of the Incubator Channel

In this section, we investigate potential mechanisms through which high-tech incubators translate government support into innovation outcomes of the incubated startups and in turn achieve the policy goals. We first examine whether incubators potentially use government supports received to increase the incubation services. We then compare the efficiency of SOE vs. private incubators in terms of carrying out industrial policies.

6.1. The Effect of the Industrial Policy on Incubation Services

Incubators specialize in recruiting and providing services for startups to grow, and their profits depend on the success of incubated startups. Therefore, it is plausible that incubators use government support for increasing incubation services that benefit the incubated startups. We examine this possibility by running DID regressions similar to our baseline regressions but using measures of incubator service (instead of innovation outcomes). We examine the same four measures used in Panel B of Table 3, among which the two measures of professional agents and tutoring sessions directly evaluate an incubator's service to its incubated startups and the two measures of staff education and investment funds reflect an incubator's potential quality of service as well as its ability to provide financial support to the incubated startups.

Table 9 presents the regression results, in which the coefficient on $Treat_i \times Post_t$ is positive and statistically significant in all four regressions except the one of tutoring sessions. Specifically, incubators in targeted industries experience increases in staff education, number of agencies hired, and investment funds of 1.5%, 6.8%, and 52.3%, respectively, following the industrial policy compared to incubators in non-targeted industries. It appears that incubators in targeted industries experience the most rapid growth in investment funds that are available for direct equity investment in either new or existing startups.

[Insert Table 9 Here.]

6.2. The Role of Private Incubators

Existing literature has documented that SOEs or governments tend to be less efficient in converting investment and resources to innovation output than are domestic private firms or foreign-invested firms (Wei et al., 2017). In this section, we examine the role of private as opposed to SOE incubators in carrying out government's industrial policies.

6.2.1. Government Support Allocation

There are reasons to believe that the government may prefer SOE incubators over private ones in terms of government support, leading to potential misallocation of government resources. We first compare the government supports received by SOE and private incubators. We run the DID regressions of government support on $Treat_i \times Post_t$ interacted with a dummy variable for private incubators, where private incubators are defined as those with government ownership less than 50%, which account for 65% to 74% of incubators across different years in our sample period.

Panel A of Table 10 shows that the coefficient of $Treat_i \times Post_t$ is significantly positive in all four regressions, suggesting that SOE incubators in policy-targeted industries receive more government support following the policy relative to their peers in non-targeted industries. More importantly, the coefficient of the interaction term with private incubator is negative and significant at the 1% level in all four regressions, suggesting that among incubators in policy-targeted industries, private incubators receive significantly less government support than do SOE incubators following the policy. For example, in the regression of total government support (Column (4)), the coefficient of $Treat_i \times Post_t$ is 4.359 and that of the private incubator interaction is -1.589, indicating that the private incubators in targeted industries receive about 36% (=1.589/4.359) less government support relative to their SOE peers in targeted industries in the post-policy period. Among the three types of government support, private incubators receive disproportionately fewer tax breaks than SOE incubators do, followed by cash subsidies and government investments.

[Insert Table 10 Here.]

6.2.2. Innovation Activity of Existing Incubated Startups

Next, we examine whether the private incubators, which receive less government support than SOE incubators do after the policy, are more efficient in converting government support into innovation activity. Specifically, we estimate regressions of innovation outcomes on the interaction of $Treat_i \times Post_t$ with a dummy for private incubators at the startup by year level.

The results in Panel B of Table 10 show that the coefficient on the triple interaction term is positive and statistically significant in all six regressions. Therefore, even with less government support allocated, the startups in private incubators experience significantly greater increases in innovation outcomes following the policy, relative to those in SOE incubators. These results are also economically significant. As discussed in the previous subsection, treated private incubators receive 36% less government support than do treated SOE incubators following the policy. However, the results in Panel B show that startups in treated private incubators experience 13.8% to 77.1% greater increase in innovation outcomes than startups in treated

SOE incubators do following the policy.[19] This sharp contrast shows that despite receiving less government support as a result of the industrial policy than do their SOE peers, private incubators are more efficient in carrying out the industrial policy.

6.2.3. Screening of New Startups

Screening startups and selecting high-quality ones is an important task for high-tech incubators as the due diligence process is resource-consuming. In addition to the improvement of existing startups, treated incubators may also use the additional government support to recruit high-quality fresh startups that they could not afford otherwise. We examine this possibility in this subsection.

We first plot the newly incubated startups each year for SOE and private incubators separately. In the left panel of Figure 4, we find that the number of new recruits by SOE incubators does not increase substantially following the policy. More importantly, the share of newly recruited startups in the policy-targeted industries for SOE incubators experience a decrease from 2015. In contrast, the left panel of Figure 4 shows that private incubators overall experience an increase in newly incubated startups after the policy, and the share of newly incubated startups in the post-2015 period is higher than the 2015 level. These results highlight a difference in their industry composition and a greater role played by private incubators in carrying out the industrial policy.

[Insert Figure 4 Here.]

We further examine how the quality of new incubatees changes after the policy for SOE and private incubators. We measure the quality of new incubatees using an indicator of one-year graduation that equals 1 for a newly incubated startup graduating within a year after entering the incubation (i.e., the startup is with the incubator in the year $t+1$ but not $t+2$).

[19] For treated SOE incubators relative to private ones, R&D experiences a 21.8% (=0.622/2.859) lower increase, number of employees experiences a 21.7% (=0.058/0.267) lower increase, patent applications experience a 77.1% (=0.118/0.153) lower increase, sales experience a 46.6% (=0.513/1.100) lower increase, VC funds experience a 20.4% (=0.286/1.401) difference, and graduation rate experiences a 13.8% (=0.039/0.282) lower increase.

This approach is based on the premise that new incubatees with higher quality are more likely to graduate in the following year. We exclude new startups that entered in 2018 or 2019 to require two years of data after entry. The sample for this analysis therefore contains 121,880 startups that entered into incubation in 2015 to 2018.

In Panel C of Table 10, we regress the graduation indicator on the interaction term of $Treat_i \times Post_t$ as well as its triple interaction with an indicator of private incubators to test for their higher efficiency in using government support. We control for a set of startup attributes as well as province-by-industry, industry-by-year, and province-by-year fixed effects in different specifications. In Column (6) with the full specification, the coefficient on $Treat_i \times Post_t$ is statistically insignificant while that on the private incubator is positive and significant at the 1% level, suggesting that the quality of the new startups recruited by SOE incubators does not change in the targeted industries after the policy and that private incubators tend to recruit better startups than do SOEs even before the policy. Moreover, the coefficient on the triple interaction term is significantly positive, suggesting that the quality of those recruited by private incubators increases significantly by 0.7 percentage points relative to self before the policy as well as SOE incubators after the policy. Based on the average graduation rate of 6% for private incubators in the targeted industries prior to the policy, 0.7 percentage points represent an increase of 11.7% from the average.

Overall, the evidence in this section shows that SOE incubators in policy-targeted industries, relative to their private peers, receive more government support after the industrial policy but demonstrate less efficiency in using the government to boost their startups' innovation activity or select quality startups. These results reveal partial resource misallocation during the implementation of the industrial policy, despite the overall positive effect of the industrial policy on innovation.

7. Conclusion

This paper studies a market-based mechanism in carrying out the government's innovation policy through high-tech incubators. Our analysis exploits the variation in SEIs targeted by different provinces as part of China's innovation strategy and is based on a unique data set covering all Chinese high-tech incubators and their startups from 2015 to 2019.

We find that following the implementation of the industrial policy, high-tech incubators in the targeted industries receive significantly more government support in all three forms—cash subsidy, equity investment, and tax reduction—relative to their peers in non-targeted industries. Furthermore, we find evidence that government support to incubators has a significantly positive causal effect on their startups' innovation activity. This finding holds when we address the endogeneity concerns by conducting 2SLS analyses with two instrumental variables for government subsidy.

We estimate that the increase in innovation activity attributed to high-tech incubators accounts for about one-seventh of the overall effect of the industrial policy on startups' innovation activity. Moreover, the hybrid model through high-tech incubators exerts a much greater effect on young and "non-HTE" firms that had been overlooked in traditional direct government policies and are more in need of resources. We also find that treated state-owned incubators receive significantly more government support than do their treated private peers after the policy, although state-owned incubators are less efficient in utilizing government subsidy than their private peers are. This contrast suggests that the state-owned incubators are favored by the government even through the market-based policy mechanism, resulting in potential resource misallocation in carrying out industrial policies.

Because of the various challenges faced by private investments in innovation, many think government support and even intervention are necessary in promoting corporate innovation. Our paper contributes to both the literature on industrial policy and that on high-tech incubators by being the first to study the unique market-based approach to implement industrial policy through high-tech incubators. Our findings show that, unlike traditional industrial policy that directly allocates resources to firms, the hybrid market-based model uses the expertise of high-tech incubators in utilizing the government subsidy, and plays an important role in realizing the policy goal of promoting innovation activity in targeted high-tech industries.

References

Acemoglu, Daron, Ufuk Akcigit, Harun Alp, Nicholas Bloom, and William Kerr, 2018, Innovation, reallocation, and growth, *American Economic Review* 108, 3450–91.

Acs, Z.J., P. Braunerhjelm, and D.B. Audretsch, 2009, The knowledge spillover theory of entrepreneurship, *Small Business Economics* 32, 15–30.

Agrawal, Ajay, Carlos Rosell, and Timothy Simcoe, 2020, Tax credits and small firm R&D spending, *American Economic Journal: Economic Policy* 12, 1–21.

Babina, Tania, and Sabrina T. Howell, 2018, Entrepreneurial spillovers from corporate R&D, NBER Working Paper 25360.

Bloom, Nicholas, Rachel Griffith, and John Van Reenen, 2002, Do R&D tax credits work? Evidence from a panel of countries 1979–1997, *Journal of Public Economics* 85, 1–31.

Bloom, Nicholas, John Van Reenen, and Heidi Williams, 2019, A toolkit of policies to promote innovation, *Journal of Economic Perspectives* 33, 163–184.

Brandt, Loren, and Xiaodong Zhu, 2000, Redistribution in a decentralized economy: Growth and inflation in China under reform, *Journal of Political Economy* 108, 422–439.

Cai, Jing, Yuyu Chen, and Xuan Wang, 2018, The impact of corporate taxes on firm innovation: Evidence from the corporate tax collection reform in China, NBER Working Paper 25146.

Chen, Qiaoyi, Zhao Chen, Zhikuo Liu, Juan Carlos Suárez Serrato, and Daniel Xu, 2021a, Regulating conglomerates in China: Evidence from an energy conservation program, NBER Working Paper 29066.

Chen, Zhao, Zhikuo Liu, Juan Carlos Suárez Serrato, and Daniel Yi Xu, 2021b, Notching R&D investment with corporate income tax cuts in China, *American Economic Review* 111, 2065–2100.

Fang, Hanming, Jing Wu, Rongjie Zhang, and Li-An Zhou, 2022, Understanding the resurgence of the SOEs in China: Evidence from the real estate sector, NBER Working Paper 29688.

Fang, Lily H., Josh Lerner, and Chaopeng Wu, 2017, Intellectual property rights protection, ownership, and innovation: Evidence from China, *Review of Financial Studies* 30, 2446–2477.

Gonzalez-Uribe, Juanita, and Michael Leatherbee, 2018, The effects of business accelerators on venture performance: Evidence from Start-Up Chile, *Review of Financial Studies* 31, 1566–1603.

González-Uribe, Juanita, and Santiago Reyes, 2021, Identifying and boosting "Gazelles": Evidence from business accelerators, *Journal of Financial Economics* 139, 260–287.

Griffin, John M, Clark Liu, and Tao Shu, 2022, Is the Chinese anticorruption campaign authentic? Evidence from corporate investigations, *Management Science* 68, 7248–7273.

Guo, Di, Yan Guo, and Kun Jiang, 2016, Government-subsidized R&D and firm innovation: Evidence from China, *Research Policy* 45, 1129–1144.

Gurley-Calvez, Tami., and Donald. Bruce, 2008, Do tax cuts promote entrepreneurial longevity?, *National Tax Journal* 61, 225–250.

Hall, Bronwyn, and John Van Reenen, 2000, How effective are fiscal incentives for R&D? A review of the evidence, *Research Policy* 29, 449–469.

Hallen, Benjamin L., Susan L. Cohen, and Christopher B. Bingham, 2020, Do accelerators work? If so, how?, *Organization Science* 31, 378–414.

Han, Pengfei, Wei Jiang, and Danqing Mei, 2020, Mapping U.S.-China technology decoupling, innovation, and firm performance, Columbia Business School Research Paper, Available at SSRN 3779452.

Hoberg, Gerard, Bruce Yuan Li, and Gordon M Phillips, 2021, US-China innovation competition, Tuck School of Business Working Paper, Available at SSRN 3294389.

Howell, Sabrina T., 2017, Financing innovation: Evidence from R&D grants, *American Economic Review* 107, 1136–1164.

Hsieh, Chang-Tai, and Zheng Michael Song, 2015, Grasp the large, let go of the small: The transformation of the state sector in China, *Brookings Papers on Economic Activity* 295–366.

Koleski, Katherine, 2017, The 13th five-year plan, U.S.-China Economic and Security Review Commission Staff Research Report.

König, Michael, Zheng Michael Song, Kjetil Storesletten, and Fabrizio Zilibotti, 2020, From imitation to innovation: Where is all that Chinese R&D going?, NBER Working Paper 27404.

Kortum, Samuel, and Josh Lerner, 2000, Assessing the impact of venture capital to innovation, *RAND Journal of Economics* 31, 674–92.

Li, Hongbin, and Li-An Zhou, 2005, Political turnover and economic performance: The incentive role of personnel control in China, *Journal of Public Economics* 89, 1743–1762.

Lu, Yi, Jin Wang, and Lianming Zhu, 2019, Place-based policies, creation, and agglomeration economies: Evidence from China's economic zone program, *American Economic Journal: Economic Policy* 11, 325–360.

Madaleno, Margarida, Max Nathan, Henry Overman, and Sevrin Waights, 2018, Incubators, accelerators and regional economic development, CEP Discussion Paper 1575.

Ru, Hong, 2018, Government credit, a double-edged sword: Evidence from the China Development Bank, *Journal of Finance* 73, 275–316.

Shue, Kelly, and Richard R. Townsend, 2013, Swinging for the fences: Executive reactions to quasi-random option grants, Available at SSRN 2207026.

Song, Zheng, Kjetil Storesletten, and Fabrizio Zilibotti, 2011, Growing like China, *American Economic Review* 101, 196–233.

Stantcheva, Stefanie, 2021, The effects of taxes on innovation: Theory and empirical evidence, NBER Working Papers 29359.

Tian, Xuan, and Jiajie Xu, 2021, Do place-based policies promote local innovation and entrepreneurship?, *Review of Finance* 26, 595–635.

Wei, Shang-Jin, Zhuan Xie, and Xiaobo Zhang, 2017, From "Made in China" to "Innovated in China": Necessity, prospect, and challenges, *Journal of Economic Perspectives* 31, 49–70.

Woetzel, Jonathan, Yougang Chen, James Manyika, Erik Roth, Jeongmin Seong, and Jason Lee, 2015, The China effect on global innovation, McKinsey Global Institute.

Wu, Yonghong, 2005, The effects of state R&D tax credits in stimulating private R&D expenditure: A cross-state empirical analysis, *Journal of Policy Analysis and Management* 24, 785–802.

Wübbeke, Jost, Mirjam Meissner, Max J. Zenglein, Jaqueline Ives, and Björn Conrad, 2016, Made in China 2025: The making of a high-tech superpower and consequences for industrial countries, MERICS Papers on China.

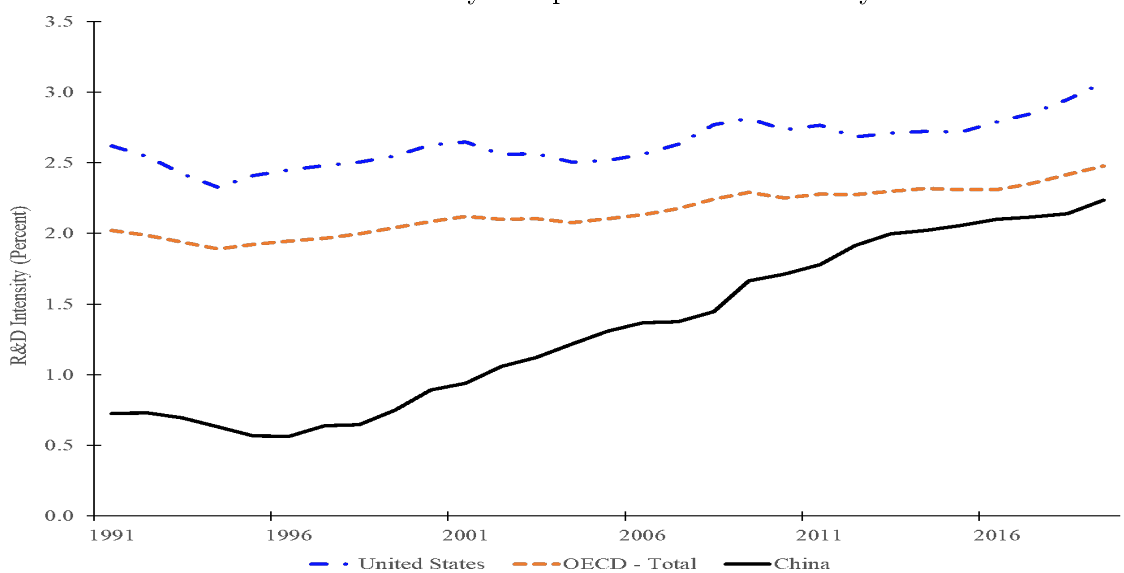
Xiong, Wei, 2018, The Mandarin model of growth, NBER Working Papers 25296.

Yu, Sandy, 2020, How do accelerators impact the performance of high-technology ventures?, *Management Science* 66, 530–552.

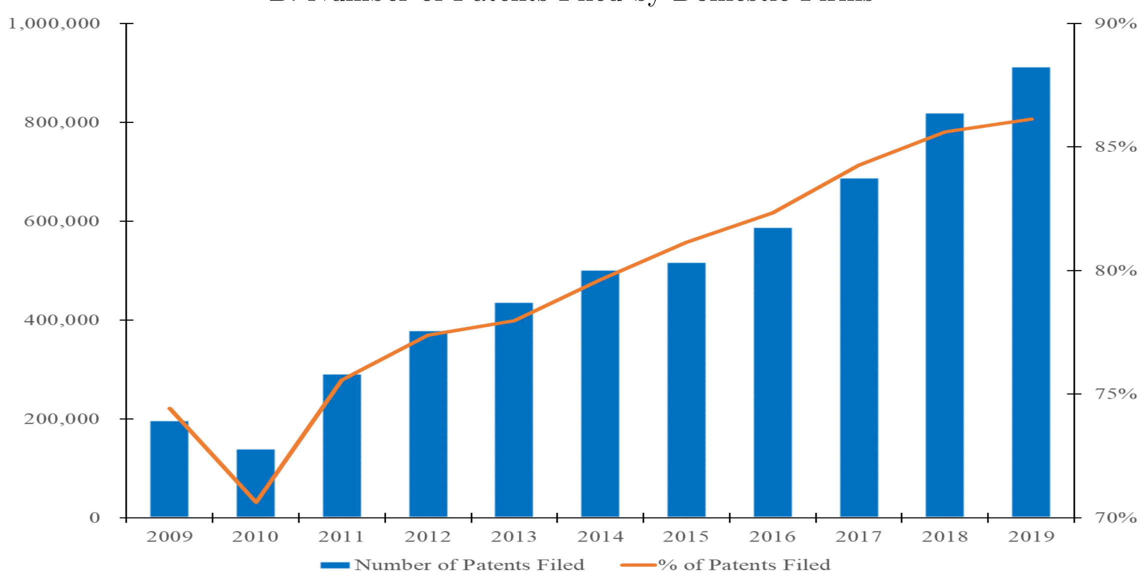
Zheng, Siqi, Weizeng Sun, Jianfeng Wu, and Matthew E. Kahn, 2017, The birth of edge cities in China: Measuring the effects of industrial parks policy, *Journal of Urban Economics* 100, 80–103.

Figure 1. Innovations in China

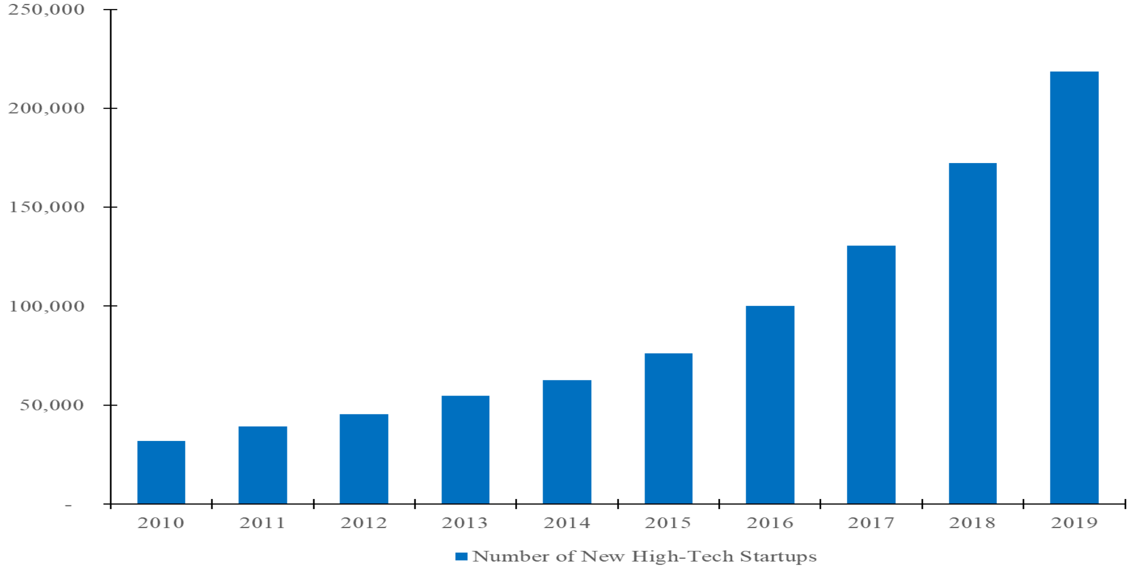
A: Cross-Country Comparison of R&D Intensity



B: Number of Patents Filed by Domestic Firms



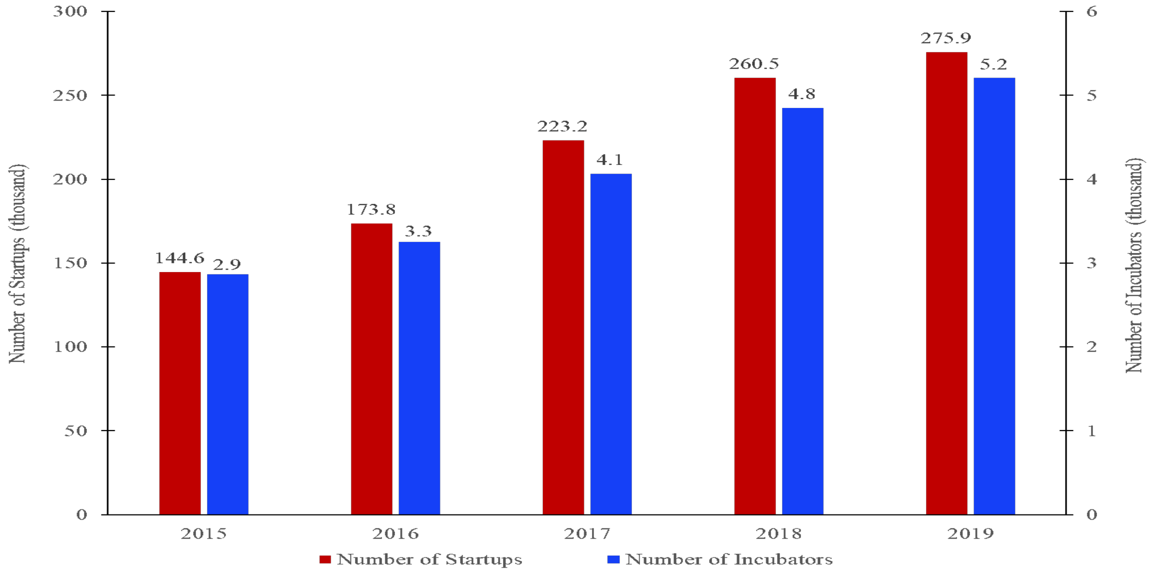
C: Number of New High-Tech Startups



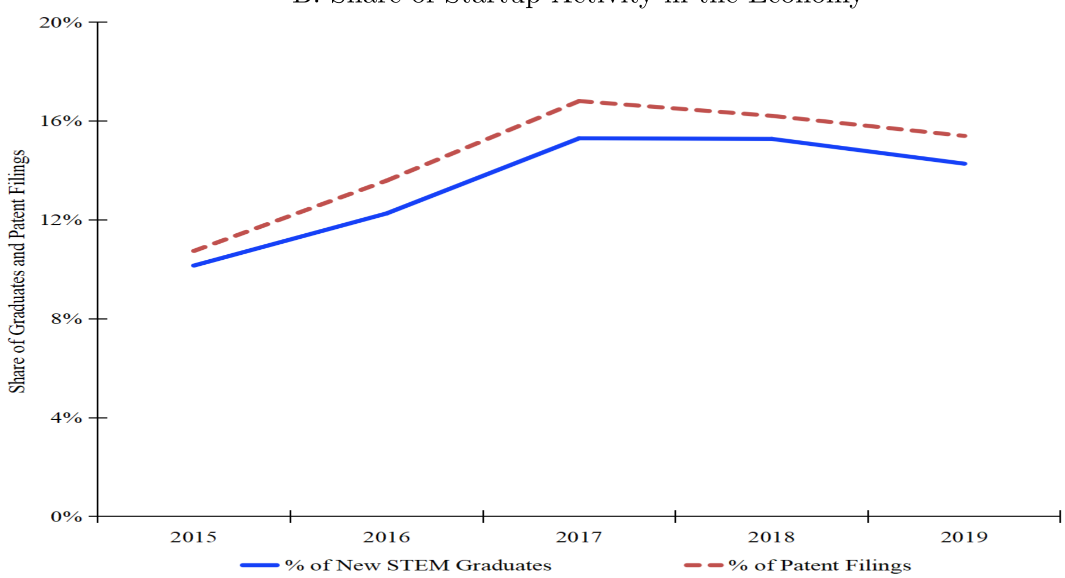
This figure plots the innovation activity in China over time. Panel A plots the R&D intensity for the United States, OECD countries, and China from 1991 to 2019, where R&D intensity of a country is measured as the country's R&D investment as a percentage of GDP. Panel B plots the annual number of patent applications filed in China from 2009 to 2019 as well as the percentage of Chinese patent applications accounted for by domestic firms. Panel C plots the number of new high-tech startups established in China from 2010 to 2019.

Figure 2. High-Tech Incubators and Startups: Number and Economic Activity

A: Numbers of Incubators and Startups

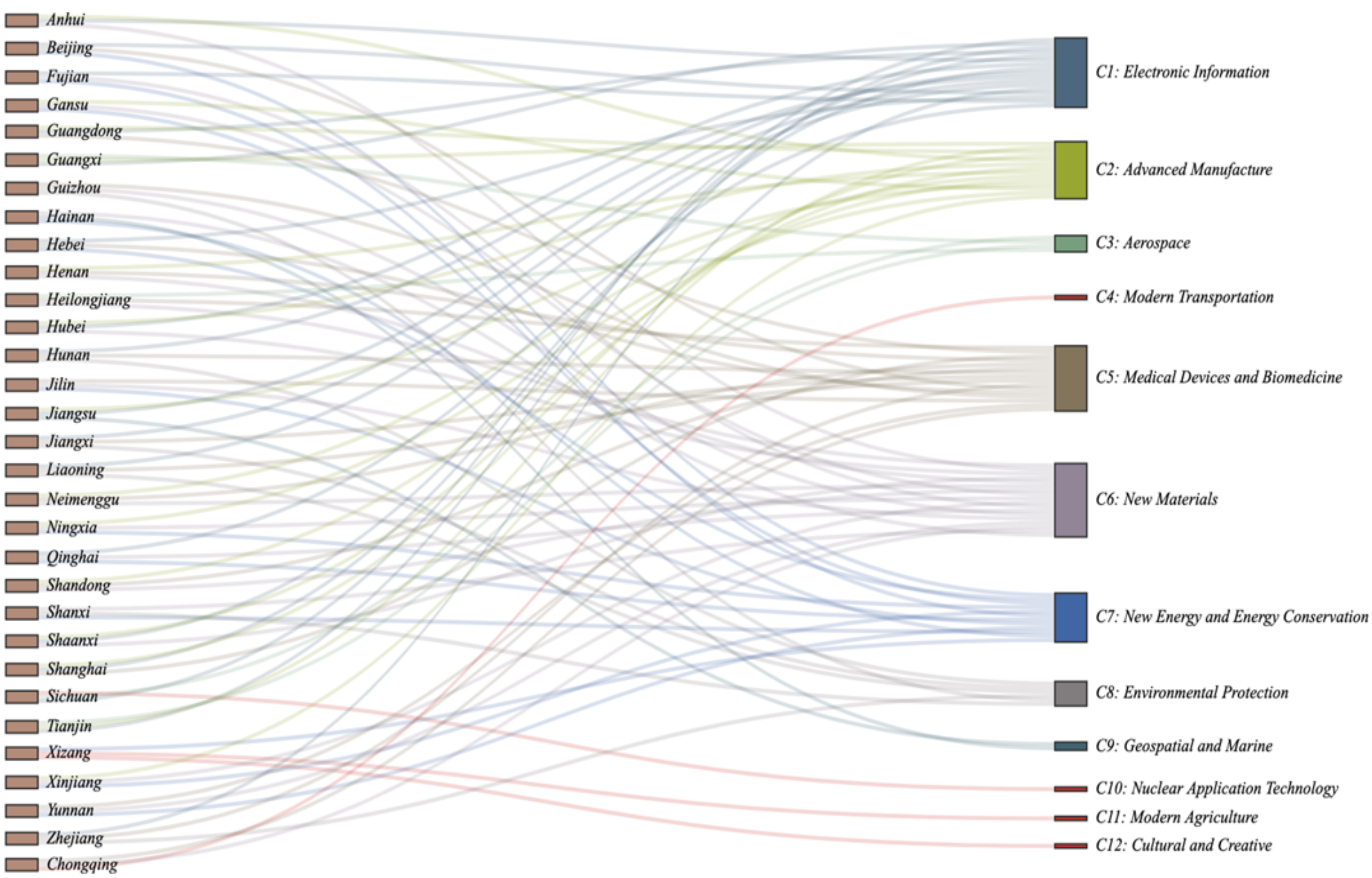


B: Share of Startup Activity in the Economy



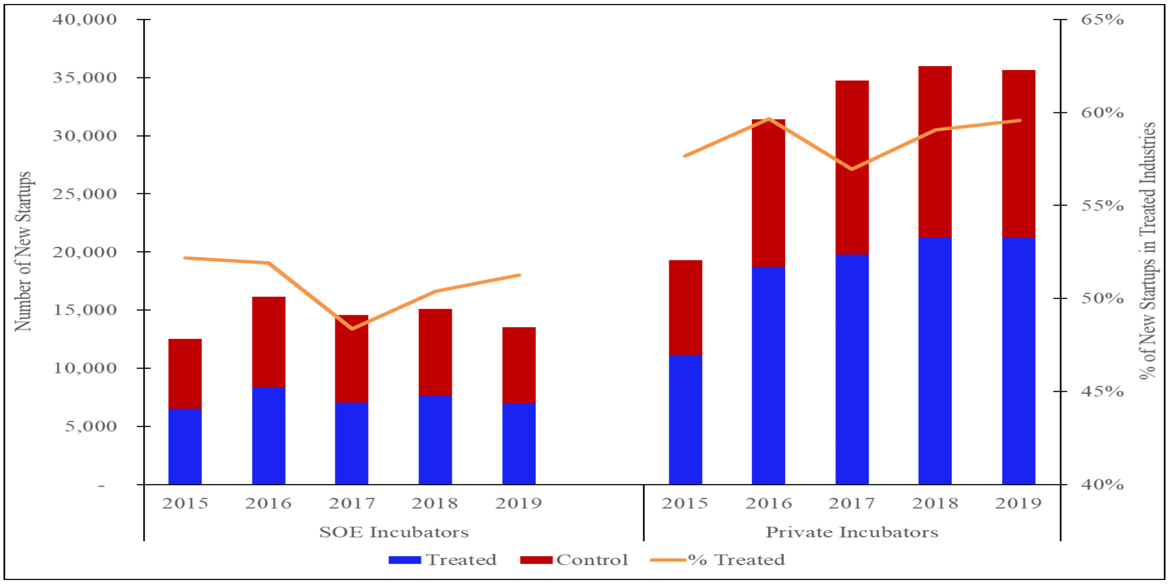
This figure presents the numbers of sample incubators and their incubated startups as well as their share of economic activity in the country. Panel A plots the number of incubators and the number of startups in our database each year from 2015 to 2019. Panel B plots the percentage of the share of sample startups' activity in the Chinese economy over our sample period, including the percentage of new employment of STEM graduates in China and the percentage of new patent applications in China.

Figure 3. Province-Specific Industrial Policy



This figure plots the policy-targeted industries of individual provinces' 13^{th} Five-Year Plans. The left-hand side of the figure lists each of the provinces, and the right-hand side lists each of the targeted industries.

Figure 4. New Incubatees of Treated and Control Incubators: SOE vs. Private Incubators



This figure plots the number of new startups in treated and control industries recruited by SOE and private incubators by year. The left panel plots SOE incubators, where the stacked columns represent numbers of startups newly recruited by SOE incubators each year (treated incubators in blue color and control incubators in red color), and the line indicates the percent of new incubatees in treated industries. The x-axis is the first year when these startups entered the incubators. The right panel is similar to the left panel but plots the new incubatees of private incubators.

Table 1: Summary Statistics

Panel A: Incubator Data

Sample	Treated = 0				Treated = 1			
	Post = 0		Post = 1		Post = 0		Post = 1	
Variables	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Govt Subsidy (RMB mil)	1.631	4.581	1.277	3.537	1.749	4.061	3.681	8.098
Govt Invest (RMB mil)	6.209	31.761	3.636	23.878	2.065	18.505	3.170	22.397
Govt Tax (RMB mil)	0.191	0.868	0.176	0.787	0.092	0.531	0.153	0.875
Govt All (RMB mil)	6.088	17.651	3.935	13.805	3.312	10.409	6.043	14.243
Log(Govt Subsidy)	8.492	6.800	7.856	6.847	8.685	6.848	10.403	6.615
Log(Govt Invest)	3.357	6.375	2.780	5.800	1.731	4.808	2.470	5.602
Log(Govt Tax)	2.090	4.755	2.347	4.929	1.411	3.961	2.972	4.961
Log(Govt All)	9.715	6.874	8.914	6.932	9.305	6.867	11.274	6.319
Log(R&D)	14.201	2.675	12.340	6.381	14.781	2.582	15.424	2.174
Log(Employ)	5.985	1.074	6.160	1.175	6.019	1.047	6.526	1.067
Log(Patents)	2.499	1.851	2.511	1.836	2.844	1.718	3.462	1.435
Log(Sales)	17.448	1.980	17.971	1.733	17.745	1.847	18.449	1.385
Log(VC)	5.715	7.449	8.522	7.700	6.996	7.663	12.288	6.793
Log(Graduate)	1.179	1.032	1.463	1.034	1.244	1.073	2.031	0.704
Log(Capital)	16.502	1.908	16.763	1.870	16.385	1.782	16.471	1.798
I(Old Incubator)	0.405	0.491	0.577	0.494	0.482	0.500	0.654	0.476
I(SOE Incubator)	0.308	0.462	0.334	0.472	0.269	0.444	0.279	0.449
I(HTE Zone)	0.277	0.448	0.381	0.486	0.297	0.457	0.416	0.493
Log(No_Firms)	3.330	0.968	3.653	0.874	3.456	0.941	3.769	0.824
Staff Edu	0.929	0.136	0.937	0.122	0.932	0.128	0.949	0.104
Log(Agents)	1.570	1.059	1.915	1.040	1.709	1.060	2.142	0.963
Log(Tutorships)	2.407	1.088	2.516	1.155	2.437	1.086	2.638	1.088
Log(Invest Funds)	12.076	6.630	11.078	7.316	12.584	6.289	12.586	6.477
N	741		1831		1627		4123	

Panel B: Startup Data

Sample	Treated = 0				Treated = 1			
	Post = 0		Post = 1		Post = 0		Post = 1	
Variables	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Log(R&D)	5.609	6.181	6.187	6.335	6.705	6.257	11.097	2.478
Log(Employ)	2.559	0.855	2.627	0.885	2.620	0.855	3.038	0.719
Log(Patents)	0.361	0.681	0.429	0.761	0.437	0.748	0.732	1.061
Log(Sales)	11.634	5.673	12.366	5.376	11.919	5.642	14.471	2.092
Log(VC)	0.722	3.051	0.792	3.194	0.821	3.283	2.644	5.104
I(Graduate)	0.182	0.386	0.337	0.473	0.194	0.395	0.722	0.448
Log(Capital)	14.315	1.529	14.523	1.578	14.322	1.444	14.580	1.520
I(SOE Firm)	0.002	0.045	0.002	0.045	0.010	0.098	0.011	0.106
I(Non-HTE Firm)	0.905	0.293	0.938	0.241	0.887	0.317	0.920	0.272
I(Young Firm)	0.766	0.423	0.643	0.479	0.742	0.437	0.593	0.491
I(SOE Incubator)	0.554	0.497	0.501	0.500	0.491	0.500	0.443	0.497
N	43552		85099		14482		26244	

Panel C: New Startup Data

Sample	Treated = 0				Treated = 1			
	Post = 0		Post = 1		Post = 0		Post = 1	
Variables	Mean	SD	Mean	SD	Mean	SD	Mean	SD
I(One-Year Graduation)	0.056	0.231	0.063	0.243	0.048	0.215	0.065	0.247
Log(Capital)	13.500	3.384	12.744	4.871	13.646	2.983	13.167	4.240
I(Old Firm)	0.044	0.206	0.052	0.221	0.042	0.201	0.048	0.214
I(SOE Firm)	0.004	0.064	0.004	0.067	0.004	0.062	0.003	0.058
I(Private Incubator)	0.585	0.493	0.646	0.478	0.654	0.476	0.730	0.444
N	23,192		29,862		30,396		38,430	

This table reports summary statistics for all variables used in our analysis for our sample period of 2016–2019. Panel A reports summary statistics for our baseline sample of incubators, which contains the incubators that exist in 2016. Panel B reports summary statistics for our baseline sample of startups, which contains all incubated startups that exist in 2016. Panel C reports summary statistics for the new startup sample, which contains newly incubated startups during 2015–2018. All continuous variables are winsorized at the 1^{st} and 99^{th} percentiles. Variable definitions are provided in Table A.1 in the Appendix.

Table 2: Industrial Policy and Government Support to Incubators

Panel A: Effect of the Industrial Policy on Government Support to Incubators

Dep Var	Log(Govt Subsidy)	Log(Govt Invest)	Log(Govt Tax)	Log(Govt All)
	(1)	(2)	(3)	(4)
$\text{Treated}_i \times \text{Post}_t$	2.673***	2.826***	1.622***	3.310***
	(6.57)	(6.82)	(4.75)	(8.35)
$\text{Log(Capital)}_{i,t-1}$	0.072	-0.463***	-0.039	-0.140*
	(0.80)	(-4.14)	(-0.75)	(-1.73)
$\text{I(Old Incubator)}_{i,t-1}$	-0.141	-0.291	-0.021	-0.409
	(-0.55)	(-0.98)	(-0.09)	(-1.49)
$\text{I(SOE Incubator)}_{i,t-1}$	-0.485	-2.513***	0.424	-1.130***
	(-1.10)	(-5.20)	(1.07)	(-3.19)
$\text{I(HTE Zone)}_{i,t-1}$	0.186	0.436	1.313***	0.222
	(0.43)	(0.91)	(4.73)	(0.49)
$\text{Log(No\_Firms)}_{i,t-1}$	0.416*	-0.110	0.278***	0.480**
	(1.79)	(-0.70)	(2.84)	(2.25)
Province × Industry	Yes	Yes	Yes	Yes
Industry × Year	Yes	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes	Yes
Incubator FE	Yes	Yes	Yes	Yes
N	8322	8322	8322	8322
Adj. R^2	0.362	0.314	0.424	0.369

Panel B: Effect of the Industrial Policy on Non-Government Funding to Incubators

Dep Var	Investments by Corporations	Investments by Non-Corp Org.	Investments by Others
	(1)	(2)	(3)
$\text{Treated}_i \times \text{Post}_t$	0.259	-0.154	0.004
	(0.61)	(-1.16)	(0.02)
$\text{Log(Capital)}_{i,t-1}$	-1.653***	0.001	-0.073
	(-11.93)	(0.03)	(-1.11)
$\text{I(Old Incubator)}_{i,t-1}$	-0.698**	-0.047	-0.356***
	(-2.14)	(-0.58)	(-2.63)
$\text{I(SOE Incubator)}_{i,t-1}$	3.191***	-0.173	0.767***
	(5.55)	(-1.10)	(3.28)
$\text{I(HTE Zone)}_{i,t-1}$	-0.375	0.021	-0.354
	(-0.67)	(0.16)	(-1.32)
$\text{Log(No\_Firms)}_{i,t-1}$	-0.248	0.136	0.095
	(-1.14)	(1.42)	(1.23)
Province × Industry	Yes	Yes	Yes
Industry × Year	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes
Incubator FE	Yes	Yes	Yes
N	8322	8322	8322
Adj. R^2	0.222	0.184	0.162

This table reports the results of the effects of the industrial policy on government support and non-government funding to high-tech incubators. The sample contains all incubators that existed as of 2016 over 2016–2019. Columns (1) to (4) in Panel A present the regressions of the government support measures, including the logarithms of cash subsidy, equity investment, tax reduction, and the sum of the three types of support. Columns (1) to (3) in Panel B present the regressions of the measures of non-government funding for incubators, including the logarithms of investment from corporations, investment from non-corporation organizations, and investment from other parties (mainly individuals). Our main independent variable is the interaction term of $Treated$ and $Post$, where $Treated$ is a dummy variable for incubators in policy-targeted industries, and $Post$ is a dummy variable for the post-policy period. We control for incubator characteristics as well as province-by-industry, industry-by-year, province-by-year and incubator fixed effects in all regressions. All variables are defined in Table A.1. T-statistics using heteroscedasticity-robust standard errors with clustering at the province-by-industry level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Government Support to Incubators and Innovation Activity of Incubated Startups

Panel A: Effect of Government Support on Startups' Innovation Activity

Dep Var	Log(R&D)	Log(Employ)	Log(Patents)	Log(Sales)	Log(VC)	Log(Graduate)
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Govt All)$_{i,t-1}$	0.020***	0.028***	0.025***	0.009***	0.293***	0.007***
	(3.41)	(8.21)	(4.27)	(3.89)	(5.93)	(5.78)
Log(Capital)$_{i,t-1}$	0.095**	0.050**	-0.050**	0.044***	0.198*	0.017*
	(2.24)	(2.42)	(-2.09)	(2.65)	(1.93)	(1.86)
I(Old Incubator)$_{i,t-1}$	-0.026	0.027	0.069	-0.007	-0.540	-0.074**
	(-0.19)	(0.42)	(1.18)	(-0.19)	(-1.40)	(-2.25)
I(SOE Incubator)$_{i,t-1}$	-0.260	-0.075	0.125	0.092	1.143***	0.013
	(-1.41)	(-0.69)	(0.98)	(1.02)	(3.36)	(0.26)
I(HTE Zone)$_{i,t-1}$	0.434**	0.005	-0.135	-0.020	-0.285	-0.292***
	(1.99)	(0.07)	(-1.38)	(-0.33)	(-0.51)	(-4.59)
Log(No_Firms)$_{i,t-1}$	0.322***	0.098**	0.096*	0.455***	1.044***	0.253***
	(2.94)	(2.49)	(1.67)	(10.76)	(3.84)	(8.10)
Province × Industry	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year	Yes	Yes	Yes	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes	Yes	Yes	Yes
Incubator FE	Yes	Yes	Yes	Yes	Yes	Yes
N	8322	8322	8322	8322	8322	8322
Adj. R^2	0.631	0.172	0.298	0.755	0.384	0.653

Panel B: Incubator Service

Dep Var	Staff Edu	Log(Agents)	Log(Tutorships)	Log(Invest Funds)
	(1)	(2)	(3)	(4)
Log(Govt All)$_{i,t-1}$	0.003***	0.005***	0.008***	0.055***
	(3.82)	(4.19)	(4.00)	(4.70)
Log(Capital)$_{i,t-1}$	-0.003**	0.025***	0.022*	0.056
	(-2.02)	(2.75)	(1.72)	(0.70)
I(Old Firm)$_{i,t-1}$	0.003	-0.034	-0.066*	0.046
	(0.59)	(-1.59)	(-1.82)	(0.21)
I(SOE)$_{i,t-1}$	0.008	0.012	0.077	-0.235
	(0.88)	(0.37)	(1.17)	(-0.77)
I(HTE Zone)$_{i,t-1}$	-0.008*	0.022	0.039	0.210
	(-1.68)	(0.50)	(0.78)	(0.60)
Log(No_Firms)$_{i,t-1}$	0.000	0.143***	0.135***	1.033***
	(0.07)	(4.57)	(2.80)	(5.82)
Province × Industry	Yes	Yes	Yes	Yes
Industry × Year	Yes	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes	Yes
Incubator FE	Yes	Yes	Yes	Yes
N	8322	8322	8322	8322
Adj. R^2	0.576	0.816	0.655	0.615

This table reports the results on the effect of government support to incubators on the innovation activity of incubated startups. The sample contains all incubators that existed as of 2016 over 2016–2019. Panel A presents regressions of startup innovation activity at the incubator level. The dependent variable is one of the six measures that reflect startup innovation activity, including the logarithms of R&D expenditure, number of employees, patent applications filed in the year, sales, VC funding received in the year, and the number of startups that graduated in the year. These variables are aggregate values at the incubator level and are reported by the sample incubators. Panel B presents regressions of incubator services to incubated startups, where the dependent variable is one of the four measures that reflect the quantity or quality of incubator services, including the percentage of incubator staff with college degrees or above (Staff Edu), the logarithm of the number of professional agencies hired for startups (Agents), the logarithm of the number of tutoring sessions (Tutorships), and the logarithm of incubator's investment fund (Invest Funds). The main independent variable is the logarithm of total government support (sum of cash subsidy, equity investment, and tax reduction). We control for incubator characteristics as well as province-by-industry, industry-by-year, province-by-year, and incubator fixed effects in all regressions. All variables are defined in Table A.1. T-statistics using heteroscedasticity-robust standard errors with clustering at the province-by-industry level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Government Support and Innovation Activity: 2SLS Regression Analysis

Panel A: Using Local Politician's Tenure as Instrumental Variable

	First Stage	Second Stage					
Dep Var	Log(Govt All)	Log(R&D)	Log(Employ)	Log(Patents)	Log(Sales)	Log(VC)	Log(Graduate)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Political Tenure	3.432***						
	(6.73)						
$Log(\widehat{GovtAll})$		0.054*	0.045***	0.190***	0.020*	0.506***	0.025**
		(1.97)	(4.03)	(6.09)	(1.84)	(3.95)	(2.15)
Log(Capital)$_{i,t-1}$	-0.120	0.100**	0.053**	-0.025	0.046***	0.232**	0.020**
	(-1.47)	(2.27)	(2.54)	(-0.98)	(2.79)	(2.09)	(2.05)
I(Old Incubator)$_{i,t-1}$	-0.524*	-0.010	0.035	0.143*	-0.003	-0.443	-0.066**
	(-1.84)	(-0.08)	(0.53)	(1.76)	(-0.07)	(-1.11)	(-2.05)
I(SOE Incubator)$_{i,t-1}$	-1.032***	-0.219	-0.054	0.323**	0.105	1.398***	0.035
	(-2.92)	(-1.18)	(-0.49)	(2.44)	(1.13)	(3.47)	(0.74)
I(HTE Zone)$_{i,t-1}$	0.315	0.424*	-0.000	-0.187	-0.023	-0.352	-0.298***
	(0.71)	(1.96)	(-0.00)	(-1.59)	(-0.39)	(-0.66)	(-4.88)
Log(No_Firms)$_{i,t-1}$	0.529***	0.306***	0.090**	0.020	0.450***	0.945***	0.244***
	(2.83)	(2.82)	(2.19)	(0.27)	(10.27)	(3.49)	(7.84)
Province × Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Incubator FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	8322	8322	8322	8322	8322	8322	8322
Adj. R^2	0.388	-0.019	-0.004	-0.404	0.015	0.016	-0.019
KP F-stat	45.313						

Panel B: Using Local Exposure to Anti-Corruption Campaign as Instrumental Variable

	First Stage	Second Stage					
Dep Var	Log(Govt All)	Log(R&D)	Log(Employ)	Log(Patents)	Log(Sales)	Log(VC)	Log(Graduate)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Anti-Corruption Exp.	-4.132***						
	(-6.14)						
$Log(\widehat{Govt All})$		0.086*	0.051**	0.121***	0.042**	0.344***	0.035**
		(1.72)	(2.34)	(2.84)	(2.51)	(2.87)	(2.05)
Log(Capital)$_{i,t-1}$	-0.153*	0.105**	0.054**	-0.035	0.049***	0.206*	0.022**
	(-1.87)	(2.40)	(2.50)	(-1.43)	(2.93)	(1.97)	(2.27)
I(Old Incubator)$_{i,t-1}$	-0.416	0.004	0.038	0.112*	0.008	-0.517	-0.061
	(-1.53)	(0.03)	(0.56)	(1.73)	(0.20)	(-1.35)	(-1.59)
I(SOE Incubator)$_{i,t-1}$	-1.308***	-0.181	-0.048	0.240*	0.132	1.204***	0.047
	(-3.59)	(-0.96)	(-0.40)	(1.74)	(1.64)	(3.16)	(0.79)
I(HTE Zone)$_{i,t-1}$	0.290	0.414**	-0.002	-0.165*	-0.030	-0.301	-0.301***
	(0.64)	(1.98)	(-0.02)	(-1.71)	(-0.49)	(-0.54)	(-4.81)
Log(No_Firms)$_{i,t-1}$	0.437**	0.291***	0.087**	0.051	0.439***	1.020***	0.240***
	(2.04)	(2.65)	(2.18)	(0.77)	(9.40)	(3.86)	(7.36)
Province × Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Incubator FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	8322	8322	8322	8322	8322	8322	8322
Adj. R^2	0.368	-0.036	-0.010	-0.143	-0.025	0.048	-0.058
KP F-stat	37.684						

This table presents the 2SLS regressions of incubator-level innovation activity that use two instrumental variables for government support. The sample contains all incubators that existed as of 2016 over 2016–2019. The dependent variables in Columns (2) to (7) are the measures that reflect incubator-level innovation activity of incubated startups, including logarithms of R&D expenditure, number of employees, number of patent applications filed in the year, sales, amount of VC funding received in the year, and number of startups graduated in the year. The main independent variable is the predicted value of the natural logarithm of total government support to an incubator (Log(Govt All)) from the first-stage regression in Column (1). In Panel A, the instrumental variable is predicted political tenure, defined as a dummy variable for the predicted first and second years of the tenure of a city's party secretary (Ru, 2018). In Panel B, the instrumental variable is the local exposure to China's anti-corruption campaign, defined as a dummy variable for the first and the second year after the corruption investigation of a city's party secretary or mayor. We also control for incubator characteristics as well as province-by-industry, industry-by-year, province-by-year, and incubator fixed effects in all regressions. All variables are defined in Table A.1. T-statistics using heteroscedasticity-robust standard errors with clustering at the province-by-industry level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: DID Regressions of Innovation Activity of Incubated Startups

Dep Var	Log(R&D)	Log(Employ)	Log(Patents)	Log(Sales)	Log(VC)	Log(Graduate)
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Treated}_i \times \text{Post}_t$	1.542***	0.462***	0.662***	0.269***	3.437***	0.432***
	(8.25)	(6.68)	(5.26)	(4.42)	(6.40)	(8.06)
$\text{Log(Capital)}_{i,t-1}$	0.099**	0.048**	-0.051**	0.044***	0.170	0.018*
	(2.34)	(2.33)	(-2.06)	(2.61)	(1.61)	(1.97)
$\text{I(Old Incubator)}_{i,t-1}$	-0.014	0.021	0.066	-0.008	-0.626	-0.071**
	(-0.10)	(0.33)	(1.13)	(-0.20)	(-1.65)	(-2.19)
$\text{I(SOE Incubator)}_{i,t-1}$	-0.252	-0.099	0.109	0.086	0.863**	0.014
	(-1.37)	(-0.90)	(0.83)	(0.95)	(2.46)	(0.29)
$\text{I(HTE Zone)}_{i,t-1}$	0.398*	0.001	-0.146	-0.024	-0.287	-0.302***
	(1.83)	(0.02)	(-1.46)	(-0.40)	(-0.46)	(-4.74)
$\text{Log(No\_Firms)}_{i,t-1}$	0.340***	0.113***	0.111**	0.460***	1.199***	0.258***
	(3.09)	(2.88)	(1.99)	(10.82)	(4.29)	(8.20)
Province × Industry	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year	Yes	Yes	Yes	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes	Yes	Yes	Yes
Incubator FE	Yes	Yes	Yes	Yes	Yes	Yes
N	8322	8322	8322	8322	8322	8322
Adj. R^2	0.634	0.159	0.296	0.755	0.347	0.656

This table presents the effect of the industrial policy on innovation outcomes using a DID specification based on the incubator sample. The sample contains all incubators that existed as of 2016 over 2016–2019. The dependent variables are the logarithms of R&D investments, employment, patent applications, sales, VC funding received, and number of startups graduated for all startups in each incubator. Our main independent variable is the interaction term of *Treated* and *Post*, defined as dummy variables for policy-targeted industries and years after 2016, respectively. We control for a number of incubator time-varying attributes as well as province-by-industry, industry-by-year, province-by-year, and incubator fixed effects in all regressions. All variables are defined in Table A.1. T-statistics using heteroscedasticity-robust standard errors with clustering at the province-by-industry level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: DID Analysis of Innovation Activity at Startup Level

Panel A: Main Innovation Outcomes

Dep Var	Log(R&D)	Log(Employ)	Log(Patents)	Log(Sales)	Log(VC)	I(Graduate)
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Treated}_i \times \text{Post}_t$	3.161***	0.296***	0.211***	1.319***	1.546***	0.302***
	(15.74)	(18.33)	(7.90)	(5.89)	(14.67)	(7.10)
$\text{Log(Capital)}_{i,t-1}$	0.028	0.030***	0.006	0.016	-0.011	0.003
	(0.70)	(6.49)	(1.00)	(0.49)	(-0.29)	(0.76)
$\text{I(Old Firm)}_{i,t-1}$	-0.256***	-0.025**	-0.061***	-0.737***	-0.112	0.096***
	(-2.73)	(-2.33)	(-4.55)	(-9.27)	(-1.56)	(8.33)
$\text{I(SOE Firm)}_{i,t-1}$	-0.373	0.024	-0.040	-0.571	-0.571	-0.113**
	(-0.48)	(0.24)	(-0.48)	(-0.87)	(-1.28)	(-1.98)
Province × Industry	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year	Yes	Yes	Yes	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	169377	169377	169377	169377	169377	169377
Adj. R^2	0.581	0.758	0.415	0.524	0.303	0.620

Panel B: Alternative Measures of Innovation Outcomes

Dep Var	I(R&D > 0)	Log(Employ)				Log(Patents Granted)	I(VC > 0)
		Doctor's	Bachelor's	Abroad	New		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{Treated}_i \times \text{Post}_t$	0.360***	0.058***	0.210***	0.043***	0.106***	0.045**	0.134***
	(18.92)	(4.17)	(14.22)	(4.34)	(3.91)	(2.55)	(15.48)
$\text{Log(Capital)}_{i,t-1}$	-0.001	0.005	0.028***	-0.000	0.021***	0.006	-0.002
	(-0.28)	(1.44)	(5.10)	(-0.15)	(3.04)	(1.39)	(-0.61)
$\text{I(Old Firm)}_{i,t-1}$	-0.020***	-0.000	-0.021**	-0.004	-0.013	-0.030***	-0.009
	(-2.73)	(-0.01)	(-2.13)	(-0.86)	(-0.84)	(-3.03)	(-1.63)
$\text{I(SOE Firm)}_{i,t-1}$	-0.062	0.040	0.055	-0.011	0.063	0.026	-0.045
	(-0.97)	(0.94)	(0.56)	(-0.32)	(0.62)	(0.43)	(-1.34)
Province × Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	169377	169377	169377	169377	169377	169377	169377
Adj. R^2	0.576	0.620	0.723	0.561	0.439	0.363	0.269

This table presents the effect of the industrial policy on innovation outcomes using a DID specification based on the startup sample. The sample contains all startups that existed in the data as of 2016 over 2016–2019. The dependent variables in Panel A are the logarithms of R&D investments, employment, patent applications, sales, and VC funding received, and an indicator for graduated startups. Those in Panel B are positive R&D indicator; the logarithms of number of employees with doctor's, bachelor's, and overseas degrees, and number of new hires; the logarithm of patents granted; and positive VC funding indicator. Our main independent variable is the interaction term of *Treated* and *Post*, defined as dummy variables for policy-targeted industries and years after 2016, respectively. We control for a number of startup time-varying attributes as well as province-by-industry, industry-by-year, province-by-year and startup fixed effects in all regressions. All variables are defined in Table A.1. T-statistics using heteroscedasticity-robust standard errors with clustering at the province-by-industry level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: DID Analysis of Innovation Activity at Startup Level: Placebo Tests

Panel A: Cross-Sectional Differences before the Industrial Policy

Dep Var	Log(R&D)	Log(Employ)	Log(Patents)	Log(Sales)	Log(VC)	I(Graduate)
	(1)	(2)	(3)	(4)	(5)	(6)
Treated_i	0.416	0.034	-0.024	0.276	-0.050	-0.019
	(1.22)	(0.68)	(-0.73)	(0.92)	(-0.42)	(-1.47)
$\text{Log(Capital)}_{i,t-1}$	0.236***	0.137***	0.048***	0.109***	0.098***	0.008***
	(11.07)	(37.82)	(15.67)	(4.77)	(8.52)	(5.97)
$\text{I(Old Firm)}_{i,t-1}$	1.189***	0.559***	0.079***	3.225***	-0.131***	0.418***
	(13.71)	(32.33)	(7.42)	(32.34)	(-2.85)	(29.07)
$\text{I(SOE Firm)}_{i,t-1}$	-0.629	0.105*	-0.052	-0.629	-0.066	-0.002
	(-1.16)	(1.89)	(-0.87)	(-1.08)	(-0.33)	(-0.06)
Province × Industry	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year	Yes	Yes	Yes	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No
N	58034	58034	58034	58034	58034	58034
Adj. R^2	0.136	0.203	0.053	0.101	0.015	0.242

Panel B: Randomly Assigned Policy-Targeted Industries

Dep Var	Log(R&D)	Log(Employ)	Log(Patents)	Log(Sales)	Log(VC)	I(Graduate)
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Treated}_i \times \text{Post}_t$	0.202	0.021	0.012	0.072	0.050	0.062
	(0.49)	(0.53)	(0.35)	(0.26)	(0.28)	(1.19)
$\text{Log(Capital)}_{i,t-1}$	0.025	0.030***	0.006	0.015	-0.012	0.002
	(0.63)	(6.38)	(0.97)	(0.46)	(-0.33)	(0.69)
$\text{I(Old Firm)}_{i,t-1}$	-0.252***	-0.025**	-0.060***	-0.736***	-0.111	0.097***
	(-2.74)	(-2.36)	(-4.54)	(-9.22)	(-1.55)	(8.07)
$\text{I(SOE Firm)}_{i,t-1}$	0.514	0.107	0.019	-0.201	-0.138	-0.028
	(0.68)	(1.02)	(0.24)	(-0.31)	(-0.30)	(-0.51)
Province × Industry	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year	Yes	Yes	Yes	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	169377	169377	169377	169377	169377	169377
Adj. R^2	0.572	0.754	0.413	0.522	0.297	0.607

This table reports two placebo tests on the effect of the industrial policy on innovation outcomes based on the startup panel sample. The dependent variables are the logarithms of R&D investments, employment, patent applications, sales, and VC funding received, and an indicator for graduated startups. In Panel A, our main independent variable is *Treated*, defined as a dummy variable for policy-targeted industries, but the sample is restricted to 2016 before the industrial policies took effect. In Panel B, the main explanatory variable is the interaction term of *Treated* and *Post*, with the former being defined as a dummy variable for policy-targeted industries randomly assigned from the policy-targeted industries based on policies in provinces other than home provinces. We control for a number of startup time-varying attributes as well as province-by-industry, industry-by-year, province-by-year, and firm fixed effects in all regressions. The sample used in Panel B contains all startups that existed in the data as of 2016 over 2016–2019. All variables are defined in Table A.1. T-statistics using heteroscedasticity-robust standard errors with clustering at the province-by-industry level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Effect of Industrial Policy on Startups' Innovation Activity: Cross-Sectional Analyses

Panel A: Non-HTE Firms vs. HTE firms

Dep Var	Log(R&D)	Log(Employ)	Log(Patents)	Log(Sales)	Log(VC)	I(Graduate)
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Treated}_i \times \text{Post}_t$	1.360***	0.138***	-0.058	-0.413**	0.765***	0.163***
	(2.76)	(5.03)	(-1.13)	(-1.98)	(2.79)	(3.99)
$\times$ Non-HTE $\text{Firm}_{i,t-1}$	2.076***	0.182***	0.311***	1.996***	0.899***	0.160***
	(4.29)	(6.28)	(4.97)	(10.22)	(2.66)	(3.23)
$\text{Log(Capital)}_{i,t-1}$	0.029	0.030***	0.006	0.017	-0.010	0.003
	(0.74)	(6.50)	(1.04)	(0.54)	(-0.27)	(0.81)
$\text{I(Old Firm)}_{i,t-1}$	-0.260***	-0.025**	-0.061***	-0.741***	-0.114	0.096***
	(-2.81)	(-2.41)	(-4.56)	(-9.37)	(-1.59)	(8.19)
$\text{I(SOE Firm)}_{i,t-1}$	-0.397	0.022	-0.044	-0.594	-0.581	-0.115**
	(-0.50)	(0.22)	(-0.52)	(-0.89)	(-1.30)	(-2.00)
Province $\times$ Industry	Yes	Yes	Yes	Yes	Yes	Yes
Industry $\times$ Year	Yes	Yes	Yes	Yes	Yes	Yes
Province $\times$ Year	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	169377	169377	169377	169377	169377	169377
Adj. R^2	0.582	0.758	0.416	0.525	0.304	0.620

Panel B: Young Firms vs. Old Firms

Dep Var	Log(R&D)	Log(Employ)	Log(Patents)	Log(Sales)	Log(VC)	I(Graduate)
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Treated}_i \times \text{Post}_t$	2.717***	0.227***	0.152***	0.552**	0.629***	0.245***
	(12.48)	(12.35)	(5.40)	(2.54)	(5.42)	(6.92)
$\times$ Young Firm_i	0.777***	0.121***	0.105***	1.343***	1.605***	0.100**
	(5.18)	(6.37)	(3.02)	(7.06)	(9.91)	(2.46)
$\text{Log(Capital)}_{i,t-1}$	0.029	0.030***	0.006	0.018	-0.008	0.003
	(0.74)	(6.56)	(1.04)	(0.58)	(-0.21)	(0.84)
$\text{I(Old Firm)}_{i,t-1}$	-0.095	0.000	-0.039***	-0.459***	0.220*	0.117***
	(-0.80)	(0.01)	(-2.68)	(-3.55)	(1.79)	(10.43)
$\text{I(SOE Firm)}_{i,t-1}$	-0.406	0.019	-0.044	-0.629	-0.639	-0.118**
	(-0.52)	(0.19)	(-0.53)	(-0.95)	(-1.43)	(-2.03)
Province $\times$ Industry	Yes	Yes	Yes	Yes	Yes	Yes
Industry $\times$ Year	Yes	Yes	Yes	Yes	Yes	Yes
Province $\times$ Year	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	169377	169377	169377	169377	169377	169377
Adj. R^2	0.581	0.759	0.415	0.526	0.307	0.621

Panel C: Same Industry as Incubators

Dep Var	Log(R&D)	Log(Employ)	Log(Patents)	Log(Sales)	Log(VC)	I(Graduate)
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Treated}_i \times \text{Post}_t$	-0.369	0.100	-0.097	0.185	0.908*	-0.008
	(-0.30)	(0.60)	(-0.86)	(0.18)	(1.73)	(-0.12)
$\times$ Same $\text{Industry}_{i,t-1}$	3.563***	0.198	0.311***	1.144	0.636	0.314***
	(2.90)	(1.18)	(2.72)	(1.08)	(1.20)	(3.77)
Same $\text{Industry}_{i,t-1}$	0.185	0.004	0.038	0.095	0.308	-0.012
	(0.39)	(0.08)	(0.64)	(0.22)	(1.16)	(-0.35)
$\text{Log(Capital)}_{i,t-1}$	0.028	0.030***	0.006	0.016	-0.011	0.003
	(0.69)	(6.49)	(1.00)	(0.49)	(-0.30)	(0.76)
$\text{I(Old Firm)}_{i,t-1}$	-0.254***	-0.025**	-0.061***	-0.736***	-0.112	0.096***
	(-2.71)	(-2.32)	(-4.54)	(-9.27)	(-1.55)	(8.35)
$\text{I(SOE Firm)}_{i,t-1}$	0.491	0.072	0.035	-0.294	-0.419	-0.037
	(0.67)	(0.81)	(0.40)	(-0.41)	(-0.86)	(-0.62)
Province $\times$ Industry	Yes	Yes	Yes	Yes	Yes	Yes
Industry $\times$ Year	Yes	Yes	Yes	Yes	Yes	Yes
Province $\times$ Year	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	169377	169377	169377	169377	169377	169377
Adj. R^2	0.581	0.758	0.415	0.524	0.303	0.620

This table presents the analyses of the heterogeneous effect of the industrial policy on startups' innovation outcomes using a DID specification based on the startup sample. The sample contains all startups that existed in the data as of 2016 over 2016–2019. The dependent variables are the logarithms of R&D investments, employment, patent applications, sales, and VC funding received, and an indicator for graduated startups. Our main independent variable is the interaction term of *Treated* and *Post*, defined as dummy variables for policy-targeted industries and years after 2016, respectively, along with a triple interaction term with indicators for different types of startups. There are three types of startups identified: non-HTE startups in Panel A, defined as those not formally credentialed by MOST agencies as high-tech startups; young startups in Panel B, defined as those founded in the past five years; and startups in the same industries as incubators in Panel C. We control for a number of startup time-varying attributes as well as province-by-industry, industry-by-year, province-by-year, and firm fixed effects in all regressions. All variables are defined in Table A.1. T-statistics using heteroscedasticity-robust standard errors with clustering at the province-by-industry level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9: DID Regressions of Incubator Service

Dep Var	Staff Edu	Log(Agents)	Log(Tutorships)	Log(Invest Funds)
	(1)	(2)	(3)	(4)
$\text{Treated}_i \times \text{Post}_t$	0.015**	0.068*	-0.009	0.523**
	(2.33)	(1.87)	(-0.18)	(2.18)
$\text{Log(Capital)}_{i,t-1}$	-0.004**	0.024***	0.020	0.050
	(-2.18)	(2.67)	(1.60)	(0.62)
$\text{I(Old Incubator)}_{i,t-1}$	0.002	-0.035	-0.069*	0.028
	(0.43)	(-1.63)	(-1.90)	(0.13)
$\text{I(SOE)}_{i,t-1}$	0.005	0.008	0.067	-0.290
	(0.58)	(0.24)	(1.02)	(-0.94)
$\text{I(HTE Zone)}_{i,t-1}$	-0.008	0.022	0.042	0.213
	(-1.54)	(0.48)	(0.82)	(0.60)
$\text{Log(No\_Firms)}_{i,t-1}$	0.002	0.146***	0.139***	1.061***
	(0.30)	(4.65)	(2.85)	(5.97)
Province × Industry	Yes	Yes	Yes	Yes
Industry × Year	Yes	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	8322	8322	8322	8322
Adj. R^2	0.563	0.816	0.654	0.613

This table presents the results on the effect of the industrial policy on incubator services using a DID specification based on the incubator sample. The sample contains all incubators that existed as of 2016 over 2016–2019. The dependent variables are the percentage of incubator staff with college degrees or above ($StaffEdu$), the logarithm of number of professional agencies hired for startups ($Agents$), the logarithm of number of tutoring sessions to startups ($Tutorships$), and the logarithm of incubator's investment fund ($InvestFunds$). Our main independent variable is the interaction term of $Treated$ and $Post$, defined as dummy variables for policy-targeted industries and years after 2016, respectively. We control for a number of incubator time-varying attributes as well as province-by-industry, industry-by-year, province-by-year, and incubator fixed effects in all regressions. All variables are defined in Table A.1. T-statistics using heteroscedasticity-robust standard errors with clustering at the province-by-industry level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Efficiency in Policy Implementation: SOE vs. Private Incubators

Panel A: Government Supports Received

Dep Var	Log(Govt Subsidy)	Log(Govt Invest)	Log(Govt Tax)	Log(Govt All)
	(1)	(2)	(3)	(4)
$\text{Treated}_i \times \text{Post}_t$	3.746***	3.817***	3.767***	4.359***
	(7.29)	(8.09)	(7.94)	(9.64)
$\times$ I(Private Incubator)$_{i,t-1}$	-1.625***	-1.501***	-3.248***	-1.589***
	(-3.51)	(-4.03)	(-5.97)	(-4.06)
I(Private Incubator)$_{i,t-1}$	1.254**	3.223***	1.113***	1.882***
	(2.40)	(5.33)	(2.85)	(4.29)
Log(Capital)$_{i,t-1}$	0.071	-0.464***	-0.042	-0.141*
	(0.79)	(-4.14)	(-0.81)	(-1.73)
I(Old Incubator)$_{i,t-1}$	-0.099	-0.252	0.062	-0.368
	(-0.38)	(-0.85)	(0.26)	(-1.34)
I(HTE Zone)$_{i,t-1}$	0.176	0.427	1.293***	0.212
	(0.41)	(0.89)	(4.79)	(0.47)
Log(No_Firms)$_{i,t-1}$	0.470**	-0.059	0.387***	0.534**
	(2.02)	(-0.36)	(3.97)	(2.51)
Province $\times$ Industry	Yes	Yes	Yes	Yes
Industry $\times$ Year	Yes	Yes	Yes	Yes
Province $\times$ Year	Yes	Yes	Yes	Yes
Incubator FE	Yes	Yes	Yes	Yes
N	8322	8322	8322	8322
Adj. R^2	0.364	0.316	0.440	0.371

Panel B: Innovation Activity of Incubated Startups

Dep Var	Log(R&D)	Log(Employ)	Log(Patents)	Log(Sales)	Log(VC)	I(Graduate)
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Treated}_i \times \text{Post}_t$	2.859***	0.267***	0.153***	1.100***	1.401***	0.282***
	(10.59)	(14.28)	(4.00)	(3.90)	(10.92)	(6.30)
$\times$ I(Private Incubator)$_{i,t-1}$	0.622*	0.058**	0.118***	0.513**	0.286**	0.039*
	(1.75)	(2.29)	(3.00)	(1.99)	(1.98)	(1.92)
I(Private Incubator)$_{i,t-1}$	-0.484***	-0.031**	-0.037**	-1.487***	-0.013	0.023***
	(-3.40)	(-2.38)	(-2.59)	(-9.84)	(-0.21)	(2.69)
Log(Capital)$_{i,t-1}$	0.027	0.030***	0.006	0.014	-0.011	0.003
	(0.68)	(6.48)	(0.99)	(0.45)	(-0.30)	(0.76)
I(Old Firm)$_{i,t-1}$	-0.260***	-0.025**	-0.061***	-0.750***	-0.112	0.096***
	(-2.80)	(-2.35)	(-4.54)	(-9.32)	(-1.56)	(8.32)
I(SOE Firm)$_{i,t-1}$	-0.347	0.025	-0.041	-0.441	-0.580	-0.117**
	(-0.44)	(0.25)	(-0.49)	(-0.67)	(-1.28)	(-2.05)
Province $\times$ Industry	Yes	Yes	Yes	Yes	Yes	Yes
Industry $\times$ Year	Yes	Yes	Yes	Yes	Yes	Yes
Province $\times$ Year	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	169377	169377	169377	169377	169377	169377
Adj. R^2	0.581	0.758	0.415	0.529	0.303	0.620

Panel C: Graduation Rate of Newly Recruited Startups

Dep Var	I(One-Year Graduation)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Treated}_i \times \text{Post}_t$	0.009*	0.001	0.009*	0.000	0.007	0.002
	(1.96)	(0.25)	(1.95)	(0.14)	(1.58)	(0.74)
$\times$ I(Private Incubator)$_{i,t-1}$		0.008**		0.008**		0.007*
		(2.48)		(2.59)		(2.16)
I(Private Incubator)$_{i,t-1}$		0.027***		0.024***		0.023***
		(7.56)		(6.52)		(5.50)
Log(Capital)$_{i,t-1}$			-0.003***	-0.002***	-0.002***	-0.002***
			(-5.00)	(-9.16)	(-4.23)	(-6.83)
I(Old Firm)$_{i,t-1}$			0.078***	0.077***	0.072***	0.072***
			(9.58)	(22.75)	(8.76)	(21.87)
I(SOE Firm)$_{i,t-1}$			0.007	0.006	0.002	0.002
			(0.48)	(0.64)	(0.13)	(0.20)
Province $\times$ Industry	No	No	No	No	Yes	Yes
Industry $\times$ Year	No	No	No	No	Yes	Yes
Province $\times$ Year	No	No	No	No	Yes	Yes
N	121880	121880	121880	121880	121880	121880
Adj. R^2	0.000	0.004	0.007	0.010	0.028	0.030

This table reports results on the heterogeneous effect of the industrial policy on government supports and innovation outcomes between private and SOE incubators. Panel A presents DID regressions of government support. The sample contains all incubators in services as of 2016 over 2016–2019. The dependent variables are the logarithms of government subsidies, government incremental investments, tax breaks, and the sum of the three forms of support. Our main independent variable is the interaction term of *Treated* and *Post*, defined as dummy variables for policy-targeted industries and years after 2016, respectively, along with a triple interaction term with an indicator for private incubators. We control for a number of incubator time-varying attributes as well as province-by-industry, industry-by-year, province-by-year, and incubator fixed effects. Panel B presents DID regressions of innovation activity of startups. The sample contains all startups in incubators as of 2016 over 2016–2019. The regression design is similar to Panel A except it is at the startup level and the dependent variables are measures of startup innovation activity, including the logarithms of R&D investments, employment, patent applications, sales, and VC funding received, and an indicator for graduated startups that equals 1 if the startup graduate one year after entering incubator and 0 otherwise. We control for a number of startup time-varying attributes as well as province-by-industry, industry-by-year, province-by-year, and firm fixed effects. Panel C is similar to Panel B except the dependent variable is the graduation rate of newly incubated startups. The sample contains startups entering into incubators in each year from 2015 to 2018 in order to define their one-year graduation rate. The dependent variable is an indicator variable that equals 1 if the newly incubated startup graduates in the next year, and zero otherwise. All variables are defined in Table A.1. T-statistics using heteroscedasticity-robust standard errors with clustering at the province-by-industry level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix

Table A.1: Variables Definition

Variable	Definition
	Incubator-Level Government Support Variables
Log(Govt Subsidy)	Natural logarithm of subsidies granted by the government for each incubator-year.
Log(Govt Invest)	Natural logarithm of increasing investments from the government for each incubator-year.
Log(Govt Tax)	Natural logarithm of tax breaks received for each incubator-year.
Log(Govt All)	Natural logarithm of sum of subsidies, investments, and tax breaks from the government for each incubator-year.
	Incubator-Level Startup Performance Variables
Log(R&D)	Natural logarithm of total R&D investments of all startups for each incubator-year.
Log(Employ)	Natural logarithm of total employees of all startups for each incubator-year.
Log(Patents)	Natural logarithm of total patents applied of all startups for each incubator-year.
Log(Sales)	Natural logarithm of total sales amounts of all startups for each incubator-year.
Log(VC)	Natural logarithm of total VC funding received of all startups for each incubator-year.
Log(Graduate)	Natural logarithm of total graduated startups for each incubator-year.
	Key Independent Variables and Instrument Variables
Treated	An indicator that equals one for incubators in the industries which were encouraged by the industrial policies in different provinces.
Post	An indicator that equals one for the years 2017–2019, and zero for 2016.
Anti-Corruption Exp.	An indicator that equals one when the incubator-located cities' secretaries or mayors are investigated by the CPC in year t or year t-1.
Political Tenure	An indicator that equals one for the first and second years in secretaries' tenure in the incubator-located cities.
	Incubator-Level Control Variables
Log(Capital)	Natural logarithm of total shareholders' investments for each incubator-year.
I(Old Firm)	An indicator that equals one for incubators founded five years prior to year t.
I(SOE)	An indicator that equals one for state-owned incubators (that is, government shareholding > 50%).
I(HTE Zone)	An indicator that equals one for national incubators.
Log(No_Firms)	Natural logarithm of the number of startups that are incubated for each incubator-year.
	Startup-Level Performance Variables
Log(R&D)	Natural logarithm of R&D investments in year t.
Log(Employ)	Natural logarithm of employees in year t.
Log(Patents)	Natural logarithm of patents applied for in year t.
Log(Sales)	Natural logarithm of total revenue in year t.
Log(VC)	Natural logarithm of VC funding received in year t.
I(Graduate)	An indicator that equals one for graduated startups.
I(R&D>0)	An indicator that equals one for startups with positive R&D investment in year t.
Log(Employ_Doctor)	Natural logarithm of employees with Ph.D. degrees in year t.
Log(Employ_Bachelor)	Natural logarithm of employees with bachelor's degrees in year t.
Log(Employ_Abroad)	Natural logarithm of employees who ever studied abroad in year t.
Log(Employ_New)	Natural logarithm of employees who freshly graduated in year t.
Log(Patents Granted)	Natural logarithm of patents granted in year t.
I(VC>0)	An indicator that equals one for startups that received VC funding in year t.

Variable	Definition
	Startup-Level Control Variables
Log(Capital)	Natural logarithm of registered capital when startups were founded.
I(Old Firm)	An indicator that equals one for startups founded five years prior to year t.
I(SOE)	An indicator that equals one for state-owned startups.
	Incubator-Level Incubating Services Variables
Staff Edu	The percentage of staff with college degrees or above over total staff for each incubator-year.
Log(Agents)	Natural logarithm of agencies signing contracts with incubators and providing services to startups, such as accounting firms and law firms, for each incubator-year.
Log(Tutorships)	Natural logarithm of the number of training sessions for startups for each incubator-year.
Log(Platform)	Natural logarithm of incubators' investments in internal sharing tech service platforms for each incubator-year.
Log(Invest Funds)	Natural logarithm of funds that are sponsored by incubators and for investing in startups, for each incubator-year.
	Variables in Heterogeneity Analyses
Young Firm	An indicator that equals one for startups founded within five years prior to year t. In other words, Young Firm equals one if I(Old Firm) equals zero.
Non-HTE Firm	An indicator that equals one for startups that are certified as high-tech enterprises in the year 2016.
I(SOE Incubator)	An indicator that equals one for state-owned incubators.
	Variables in New Startup Regressions
I(One-Year Graduation)	An indicator that equals one for startups graduated in the second year after entering incubators.
Log(Capital)	Natural logarithm of registered capital when startups were founded.
I(Old Firm)	An indicator that equals one for startups founded five years prior to the years entering incubators.
I(SOE Firm)	An indicator that equals one for state-owned startups.
I(Private Incubators)	An indicator that equals one for startups incubated in the non-SOE incubators.