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

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Abstract

Using proprietary data on all high-tech incubators in China, this paper examines a market-based implementation of industrial policy under Made in China 2025 (MIC2025), whereby the government channels support through incubators rather than directly to high-tech firms. Exploiting cross-provincial variation in localized targeting of "strategic emerging industries," we find that incubators in targeted industries receive significantly more government support post-policy. Additionally, government support to incubators has a positive causal effect on their startups' innovation activity. Although privately owned incubators receive less government support than state-owned incubators, they deploy it far more efficiently in fostering innovation. Over all, the MIC2025 hybrid, market-intermediated model enhances innovation outcomes and improves the allocation efficiency of industrial policy relative to traditional direct-subsidy approaches.

Keywords: Industrial policy, Made in China 2025, Entrepreneurship, Incubators, High-tech startups, Innovation

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

After four decades of rapid growth, the Chinese economy has reached a crossroads and faces an innovation imperative as its two main growth engines—labor force expansion and capital accumulation—gradually lose momentum (Woetzel et al., 2015; Wei et al., 2017). As early as 2010, Chinese policymakers declared their ambition to transform the nation from a low-cost manufacturer into a technology-driven global powerhouse. This ambition materialized in the Made in China 2025 (MIC2025) initiative, unveiled in 2015, which places innovation and high-tech upgrading at the core of China's next growth phase. By many conventional indicators, China has already emerged as a global innovation leader: its research and development (R&D) intensity now rivals that of major advanced economies, and patent filings by Chinese firms have quadrupled in the past decade, surpassing those in the United States (Panels A and B of Figure 1).[1] Recent trade wars reveal that China is no longer merely catching up but overtaking the United States in key frontier technologies, including artificial intelligence (AI), electric batteries, robotics, and advanced materials—a phenomenon describe as a "China Shock 2.0," in which China contests global leadership across the innovation frontier (Lee, et al. 2023; Li and Branstetter, 2024; Autor and Hanson, 2025).

While a large literature examines China's industrial policies in traditional manufacturing sectors (e.g., Brandt and Zhu, 2000; Li and Zhou, 2005; Song et al., 2011; Hsieh and Song, 2015; Song and Xiong, 2024), much less attention has been paid to the mechanisms driving China's rise in high-tech domains. Lerner et al. (2024) show that China's integrated model of venture capital, incubator networks, and state-guided innovation has been highly successful domestically and is diffusing to other developing economies. Building on this perspective, this paper examines one critical yet understudied channel: the use of high-tech business incubators as market intermediaries for implementing MIC2025. These incubators play a pivotal role in connecting policy design and firm-level innovation, channeling

[1] Panel C of Figure 1 shows that the number of new high-tech startups established rises from around 30,000 in 2010 to over 200,000 in 2019.

government support, technical expertise, and private capital into strategic emerging industries (SEIs). By evaluating their impact on start-up performance and regional innovation outcomes, we provide new empirical evidence on how China leverages a hybrid system of state-directed industrial policy and entrepreneurial dynamism to consolidate its position as a global technology leader.

High-tech incubators specialize in screening and nurturing startups at their earliest stages, serving as vital intermediaries between government policy, private capital, and entrepreneurial innovation (Hausberg and Korreck, 2020). In China, their growth and scale are unparalleled globally: by 2019, the country had established over 5,000 high-tech incubators supporting more than 200,000 startups, compared with approximately 1,400 incubators and accelerators in the United States and fewer than 1,000 across the European Union (NBIA, 2020; OECD, 2021). While roughly 70% of Chinese incubators are privately owned and 30% are state-owned, nearly all incubated firms are privately owned. These incubators offer a comprehensive range of services—office space, mentorship, professional consulting, technical support, and venture financing—to help startups "graduate" after achieving sustainable growth. Their profitability depends not only on service fees but, more importantly, on equity investments in their incubatees, aligning their success directly with that of the startups they cultivate. This structure gives Chinese incubators an outsized role in translating industrial policy into entrepreneurial outcomes, distinguishing them from their counterparts in the U.S. and Europe, where incubators typically play a more limited facilitative role.[2]

A central feature of MIC2025 is the establishment of national targets for SEIs (see Table 1, left panel) to accelerate China's rise as a global technology powerhouse. As China seeks to promote innovation-driven growth, the traditional industrial policy approach—which directly channels resources to firms, especially state-owned enterprises (SOEs)—has proven increasingly inefficient, as

[2] We discuss more details about the institutional background of Chinese high-tech incubators in Section 1.2.

SOEs tend to be less effective in converting R&D investment into genuine innovation output (Wei et al., 2017). In response, China has turned to a hybrid implementation model that leverages high-tech incubators as market-based intermediaries for policy delivery. Equipped with specialized expertise in screening, mentoring, and financing early-stage firms, these incubators enable the government to allocate resources more efficiently to high-potential startups. Under this system, the state provides targeted support, such as direct subsidies, tax incentives, and equity co-investments, to incubators, which are then responsible for fostering the innovation activity and commercialization performance of the startups they host. This model blends state guidance with entrepreneurial selection, representing a key institutional mechanism through which MIC2025 translates national industrial policy into firm-level technological advancement.

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. Sourced from China's Ministry of Science and Technology (MOST), this data includes 20,243 incubator-years and 1,032,383 startup-years from 2015 to 2019, accounting for a considerable fraction of China's high-tech industries. During our sample period, startups in these incubators employ 11%–16% of new STEM graduates and file 10%–14% of patent applications in China. The dataset includes detailed characteristics for both incubators and firms, such as year of establishment and incubation, location, industry, entrepreneur characteristics, investments received from different sources, employment, operating performance, and intellectual property (e.g., patents filed and granted).

Our empirical design exploits cross-provincial variation in industrial policies that target different SEIs under MIC2025. We focus on a highly localized industrial policy implemented under the 13th Five-Year Plan (FYP, 2016–2020), which operationalizes MIC2025 objectives by providing cash subsidies, equity investments, and tax benefits to provincially prioritized SEIs. Provincial 13th FYP

documents, released in late 2016 or early 2017 and implemented thereafter, identify each province's priority SEIs. We manually review these documents and code the top three SEIs in each province as its targeted industries. These priorities vary substantially across provinces. For instance, electronic information is prioritized in Anhui but not in Yunnan; thus, incubators in this sector are considered treated in Anhui but untreated in Yunnan. To estimate the policy's causal effect on incubators' government support and their startups' innovation outcomes, we employ a difference-in-differences (DID) framework that compares differential changes in targeted and non-targeted industries before and after policy implementation.

Our analyses yield several important findings. First, we find that high-tech incubators in the targeted industries ("treated incubators"), relative to those in the control industries, receive 3.3 times more government support than their pre-policy levels following the policy.[3] This result holds across all three forms of government support: cash subsidy, equity investment, and tax reduction. The finding remains robust after we control for incubator, province-by-year, industry-by-year, and province-by-industry fixed effects and time-varying incubator characteristics. In contrast, treated incubators experience little change in funding from non-government sources (e.g., corporations, nonprofit organizations, or individuals) relative to control incubators after the policy, suggesting that the increased government support is driven by the industrial policy rather than by broader economic or market-wide factors.

Second, we find that government support for incubators has a significantly positive effect on the innovation activity of incubated startups. We use six measures of startups' innovation activity—R&D investment, number of employees, patent applications, sales, VC funding received, and an

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

indicator variable for startup "graduation"—as the dependent variables. We estimate incubator-level OLS regressions of these innovation measures on the government support received by incubators. For all six measures, innovation activity is significantly positively associated with government support, consistent with a positive effect of government support on incubated startups' innovation. Government support also significantly enhances 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 both secure greater government subsidies and enhance its startups' innovation. 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, following Ru (2018), who shows that local officials tend to increase public investments early in their tenure. Accordingly, we expect higher government subsidies to incubators in the earlier years of local politicians' tenure. The second IV is local exposure to China's anti-corruption campaign. Since Fang et al. (2022) find that the campaign deters government officials from engaging with private firms, we expect greater exposure to the campaign to reduce government support to incubators. The 2SLS estimates continue to indicate a significantly positive effect of incubator government subsidies on incubated startups' innovation activity.

Third, we assess the contribution of the incubator channel to the overall impact of the industrial policy on startup innovation. Combining our first two findings, we estimate that the incubator approach generates post-policy increases among incubated startups in targeted industries, relative to peers in other industry, of 6.6% in R&D investment, 9.3% in employment, 8.3% in patent applications,

3.0% in sales, 97.0% in VC funding, and 2.3% in graduation rates. We then assess the overall industrial policy effect on startups' innovation estimate the share attributable to the incubator channel. The incubator approach accounts for 4.3% of the total policy effect on startups' R&D, 20.1% on employment, 12.5% on patent applications, 11.1% on total revenue, 28.2% on VC funding, and 5.4% on the probability of startup graduation. Overall, 13.6%, or about one-seventh, of the industrial policy impact on high-tech startups operates through incubators.

Fourth, using granular startup-level data, we examine heterogeneity in the policy's effects across different types of startups. In startup-level analysis, we find that, consistent with our incubator-level results, startups in the targeted industries experience significant growth in innovation activity. Placebo tests show that our finding is not driven by the pre-policy differences across incubators by industry or location. More importantly, unlike traditional policies that directly target large firms or SOEs, this high-tech industrial policy generates significantly more growth in less resourceful startups, such as non-high-tech (non-HTE) and younger startups.[4]

Lastly, we compare the efficiency of private incubators and SOE incubators in implementing the industrial policy. In the absence of a counterfactual policy, SOE incubators could behave similarly to the government, because their executives share career concerns with government officials (Li and Zhou, 2005; Ru, 2018), while private incubators have incentives to act as efficient market intermediaries, maximizing profits by promoting their startups' innovation. We find that treated SOE incubators receive disproportionately greater government support after the policy than do their private counterparts. However, startups hosted by treated SOE incubators exhibit significantly lower post-policy growth in innovation output relative to those in treated private incubators. Moreover, treated SOE incubators tend to recruit fewer and lower-quality startups than their private peers. These results

[4] 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.

suggest that, despite the market-based implementation approach under MIC2025, resource allocation remains distorted toward less efficient state-owned actors, potentially dampening overall policy effectiveness.

Our paper contributes to the literature on industrial and innovation policy, particularly how government interventions shape firm-level innovation. Prior studies show mixed evidence on whether public spending effectively promotes innovation. While government support can address market failures in R&D (Hall and Van Reenen, 2000; Bloom et al., 2002; Howell, 2017; Acemoglu et al., 2018), inefficient targeting often limits its impact. In China, Wei et al. (2017) find that subsidies disproportionately favor SOEs, even though private and foreign firms exhibit stronger innovation outcomes. Related studies on place-based and programmatic policies, such as Tian and Xu (2021) on high-tech zones, Guo et al. (2016) on the Innofund, and Chen et al. (2021) on InnoCom, highlight the diversity of policy instruments but also their uneven effectiveness.

Lerner (2009) cautions that many government efforts to stimulate entrepreneurship and venture capital fail because they crowd out private initiative or lack proper incentive alignment. However, he emphasizes that public interventions can be effective when they complement rather than replace market mechanisms. We extend this literature by documenting a new institutional mechanism for implementing industrial policy: high-tech incubators. Unlike the traditional top-down model that directly channels funds to firms—often SOEs—MIC2025 embeds innovation promotion within a market-based allocation system. The government provides fiscal subsidies, tax incentives, and equity co-investments to incubators, which then select and nurture startups with the highest growth and innovation potential. This incubator-based toolkit represents a novel hybrid approach that combines state coordination with entrepreneurial selection and nurturing, addressing the long-standing issue of R&D misallocation in China's industrial policy while aligning with Lerner's insight that effective

innovation policy must leverage private-sector discipline and incentives.

Our study also contributes to the literature on incubators and entrepreneurship, which has focused mainly on private-sector models of startup support. Previous research shows that accelerators and incubators can improve venture performance by providing funding, mentorship, and networks (Gonzalez-Uribe and Leatherbee, 2018; Madaleno et al., 2018; Yu, 2020; Hallen et al., 2020; Gonzalez-Uribe and Reyes, 2021). We differ by showing that incubators can function as policy intermediaries, transmitting state innovation incentives to the private sector. This perspective highlights a previously unexplored channel through which governments can leverage existing entrepreneurial infrastructure to achieve industrial upgrading at scale.

Finally, our paper offers new empirical evidence on the effectiveness and heterogeneity of this hybrid policy system. Using detailed data on incubators and startups, we find that the incubator channel significantly increases innovation outcomes, but private incubators are more effective than state-owned ones at transmitting policy effects, underscoring the efficiency of decentralized, market-driven allocation relative to direct government intervention. By demonstrating how incubators bridge the gap between policy design and firm-level innovation, our paper introduces a new framework for understanding how industrial policy can be implemented through entrepreneurial intermediaries, providing insights for both emerging and advanced economies.

1. INSTITUTIONAL BACKGROUND

1.1. Made in China 2025

Despite the marketization reform, China has largely maintained its tradition of Soviet-style five-year plans (FYPs) to align the economy with top policy goals and communicate this directive throughout the government bureaucracy. Targets 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 broad economic and social behavior, and it was not until the 11th FYP (2006–2010) that China began implementing an industrial policy aimed at revitalizing targeted traditional manufacturing industries. These megaprojects were financed by billions of RMBs from the government's annual budget.

Beginning with the 12th FYP (2011–2015), Chinese policymakers publicly articulated plans to upgrade the economy from traditional industries toward a more advanced, technology-driven model by introducing the concept of SEIs. The MIC2025 Action Plan, unveiled in 2015, marked a historic turning point in this transformation. It laid out a technical roadmap for innovation-driven growth and industrial upgrading by identifying ten priority SEIs (see Table 1, left panel) and establishing quantifiable performance benchmarks (Wübbeke et al., 2016).

Unlike earlier industrial policies, such as the 863 Program or the Torch Program, which targeted specific technologies or sectors, MIC2025 is China's first comprehensive, national-level strategy to modernize the entire manufacturing ecosystem. It integrates technological innovation, industrial upgrading, digital transformation, and sustainability into a unified national framework, signaling a shift from "Made in China" to "Created in China." This strategic consolidation not only redefines China's approach to industrial policy but also lays the foundation for the country's pursuit of global leadership in high-value manufacturing.

The 13th FYP (2016–2020), adopted in March 2016, operationalized MIC2025 by providing the legal, fiscal, and administrative framework for its implementation—through national budget allocations, targeted tax incentives, and coordinated provincial action (Koleski, 2017). To support this shift, the government mobilized massive public investment, directed subsidies, R&D support, and tax incentives to firms aligned with these SEIs. For example, in November 2016, the China Development Bank pledged at least $44.8 billion (RMB 300 billion) in credit to support the initiative's rollout.

Additional funding mechanisms included the $20 billion (RMB 139 billion) National Integrated Circuit Fund, the $3 billion (RMB 20 billion) Advanced Manufacturing Fund, and the $6 billion (RMB 40 billion) Emerging Industries Investment Fund, each designed to strengthen strategic sectors and accelerate industrial upgrading.

This wave of state-led resource mobilization enabled Chinese firms to rapidly expand technological capabilities and industrial scale. By 2025, MIC2025 had profoundly reshaped China's manufacturing landscape, propelling the nation from a low-cost producer to a global leader in high-tech industries. Through sustained public investment and coordinated local implementation, China consolidated dominance in electric vehicles, renewable energy, advanced batteries, high-speed rail, and industrial robotics. Chinese firms now account for the majority of global production in solar panels, lithium-ion batteries, and EVs, while gaining competitiveness in aerospace, semiconductors, and biomedicine. MIC2025's focus on innovation, digitalization, and supply-chain self-reliance has reduced dependence on foreign technology and moved domestic manufacturers up the global value chain. Although progress in areas such as advanced chips and aircraft engines remains incomplete, the initiative laid the groundwork for greater technological sovereignty and global industrial leadership.

Unlike previous, largely top-down innovation policies, the 13th FYP decentralized implementation to local governments, which played a pivotal role in executing MIC2025 through fiscal co-funding and targeted subsidies. Provincial and municipal authorities pledged unprecedented financial support to firms in prioritized sectors, reflecting close alignment between national objectives and local development agendas. Variation in industrial priorities and fiscal commitments across provinces provides a valuable empirical setting to study the heterogeneous effects of industrial policy on firm-level innovation. The interplay between central planning and local experimentation under MIC2025 offers unique insights into how China's policy-driven innovation model reshapes the

geography of technological upgrading.

1.2. High-Tech Incubators

High-tech business incubators play a central role in implementing MIC2025 by translating national industrial policy into firm-level innovation. As the initiative emphasizes innovation-driven growth and technological upgrading, incubators provide the critical infrastructure to nurture start-ups in SEIs. They bridge the gap between R&D and commercialization and help overcome regional disparities in technological capacity. Acting as intermediaries between governments and firms, incubators channel fiscal incentives, R&D grants, and tax breaks funded through MIC2025 and the 13th FYP, while also enhancing firm capabilities through training, mentorship, and R&D collaboration. By clustering firms in priority sectors, they foster spillovers and industrial synergies, accelerating local specialization in SEIs.

Although China's first high-tech incubator was established in 1987, the 2014 "Mass Entrepreneurship and Innovation" initiative dramatically expanded the system by offering substantial funding, tax incentives, and policy support. By 2019, China hosted over 5,000 incubators serving more than 200,000 start-ups. All incubators are registered, credentialed, and evaluated by the Ministry of Science and Technology (MOST), which determines their classification and eligibility for policy support such as free space, tax reductions, and direct subsidies. For example, a district-level MOST office in Shenzhen provides up to $300,000 (RMB 2 million) in one-time funding, as well as annual performance bonuses for qualified incubators.

Chinese incubators operate under diverse ownership and business models, ranging from state-owned and municipal incubators to private and corporate-led programs run by firms like Tencent, Alibaba, and Microsoft. While their services—training, workspace, capital access—mirror international norms, their function is far more strategic: they act as policy catalysts that integrate

national planning with market-driven innovation. By combining public guidance with private entrepreneurship, high-tech incubators serve as micro-level engines of MIC2025, transforming China's industrial modernization agenda into a self-sustaining, innovation-based growth model.

1.3. Case Studies of Incubators

Case 1: Sinovation Ventures

Founded by Dr. Kai-Fu Lee, a pioneering AI scientist and former president of Google China, Sinovation Ventures is one of China's most influential AI-focused incubators and venture investors, operating under a hybrid model of "top-tier incubation + venture capital funding." [5] Sinovation identifies frontier technologies and promising scientific teams, provides strategic guidance and financing, and deeply engages in commercialization. Since its founding, it has incubated and invested in numerous technology leaders in AI robotics, and enterprise software. Supported by policy incentives, Sinovation Ventures received average annual government subsidies of approximately RMB 3 million before the 13th FYP (2015-2016), and this amount increased to about RMB 5.8 million per year during the 13th FYP (2017–2019). It has partnered with over 20 intermediary service agencies, organized nearly 100 innovation and entrepreneurship training programs annually, and managed incubation funds exceeding RMB 300 million.

Among its most successful incubatees is AInnovation Technology Group (stock code: 02121.HK), which went public on the Hong Kong Stock Exchange on January 27, 2022, debuting at a market capitalization exceeding HKD 14 billion. AInnovation launched China's first large-scale AI model focused on the manufacturing industry. The company has filed nearly 1,400 patents, more than 80% of them invention patents, and serves over 1,200 enterprise clients, with manufacturing customers accounting for over 70%. Its AI solutions cover eight major industrial domains, including

[5] The company was founded as "Innovation Works" and rebranded as "Sinovation Ventures" in 2016.

steel metallurgy, panel display, and semiconductors. According to IDC, AInnovation ranks among the top three in China's computer vision and machine learning platform markets and holds the largest market share in AI-powered industrial inspection.

Sinovation played a decisive role in incubating and scaling AInnovation from inception to IPO, remaining one of its major shareholders. Sinovation provided continuous strategic, technological, and financial support, guiding AInnovation from early-stage concept to commercialization and global expansion. This approach exemplifies the MIC2025 vision of fostering innovation-driven industrial transformation in high-value sectors such as artificial intelligence and advanced manufacturing. By combining venture capital, policy support, and scientific talent, Sinovation Ventures shows how private-sector incubators, when aligned with national innovation strategies, can serve as powerful catalysts for technological upgrading and global competitiveness.

Case 2: Nanhu Science & Technology Entrepreneurship Service Center (Nanhu S&T)

Established in 2005 in the Yangtze River Delta innovation corridor, the Nanhu S&T is wholly owned by the Jiaxing municipal government. It specializes in the electronic information industry, one of the three SEIs (alongside biomedicine and medical devices) designated by Zhejiang Province during the 13th FYP. In line with national and provincial industrial policies, Nanhu received annual government subsidies of about RMB 5.3 million between 2017 and 2019, up from RMB 0.6 million in 2015-2016 (before the 13th FYP). As public support increased, Nanhu significantly expanded its services and capacity: professionally trained staff grew from 4 in 2015 to 20 in 2019; contracted intermediary service agencies increased from zero to 5; startup training sessions rose from 200 to 270; and the number of innovation and entrepreneurship events doubled from 5 to 10. Moving beyond simply offering space before 2016, the center evolved into a comprehensive platform for talent development, financing, and technology transfer, accelerating commercialization for early-stage firms.

One of Nanhu's most successful incubatees, Zhejiang StarPower Semiconductor Co., Ltd. (StarPower, ticker: 603290.SH), is now a leading Chinese power semiconductor manufacturer specializing in insulated-gate bipolar transistor (IGBT) chips and modules for electric vehicles and industrial power electronics. Founded in 2005, StarPower relocated from Shanghai to Jiaxing in 2008, entering the Nanhu incubator the same year to leverage its resources for rapid growth. Between 2015 and 2019, the company's R&D investment doubled from RMB 25 million to RMB 50 million, its R&D personnel and patent applications also doubled; and sales revenue climbed from less than RMB 300 million to nearly RMB 700 million. In 2020, StarPower graduated from Nanhu and was listed on the Shanghai Stock Exchange's Main Board with a market capitalization of about RMB 25 billion. According to Omdia's 2023 report, StarPower ranked among the world's top five suppliers of IGBT modules, marking it a signature success stories of MIC 2025 initiative and showcasing how targeted government support and effective incubation can convert regional innovation into global competitiveness.

The experiences of Sinovation Ventures and Nanhu S&T highlight how the integration of venture capital, government policy, and incubation services can translate policy ambition into measurable industrial outcomes. Both AInnovation and StarPower achieved rapid technological and commercial breakthroughs, moving from concept to IPO, by leveraging the resources, networks, and sustained guidance provided by their incubators. Their success underscores the effectiveness of China's hybrid innovation system in bridging the gap between research and market application. Absent incubator-based mechanisms and MIC2025's targeted incentives, these startups would likely have faced prolonged commercialization timelines, limited financing access, and weaker global competitiveness. Together, the cases illustrate how China's institutional architecture for innovation transforms policy design into scalable entrepreneurial success.

2. DATA AND SAMPLE CONSTRUCTION

2.1. Incubator and Startup Data

We obtained data on all Chinese high-tech incubators from 2015 to 2019 from the MOST of China. This database, constructed under the "Torch Program" to promote high-tech industry development, requires all high-tech incubators to report detailed information about themselves and their incubated startups 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 sample period, showing rapid growth in both. For example, the number of high-tech incubators grows 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 sector, we plot in Panel B of Figure 2 the sample startups' activity as a share of the overall economy. Over the sample period, incubated startups employ 10%–14% of all new STEM graduates nationwide and file 11%–16% of all new patent applications. These results demonstrate that high-tech incubators and incubated startups represent a considerable share of China's high-tech industry and innovation activity.

The dataset includes characteristics of both incubators and startups: year of establishment; incubator level (national, provincial, or municipal incubators); ownership (SOE vs. private); registered capital; location; technology area (industry); year of incubation (for startups); and HTE status (for startups). It also contains annual financial information for startups, including shareholder information, employment, R&D expenditure, exports, taxes, intellectual property (e.g., patent applications, patents granted, technology transactions), sales, operating costs, profit, and VC funding received. For incubators, the dataset records services provided to incubated startups, such as the number of tutorial

sessions, the number of agencies hired for the startups, and equity investments in startups.

2.2. Classifications of Policy-Targeted Industries

To identify provincial-level policy-targeted industries, we collect information from the 13th FYP documents released by provincial governments in 2016 or early 2017. Consistent with the SEIs in MIC2025, each provincial designates at least two "key development industries" to be prioritized in the next five years, typically listed in order of importance. For empirical implementation, we treat the first three industries listed in each province's 13th FYP as that province's policy-targeted industries. As shown in Table 1, these policy-targeted industries align closely with the SEIs defined in MIC2025.[6]

Figure 3 plots each province's policy-targeted industries, showing a highly diversified portfolio. 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 SEIs, there is large variation in provincial priorities.

We classify each high-tech incubator as treated (*Treated* =1) or control (*Treated* =0) based on whether its industry is policy-targeted in its provinces. There are two types of incubators: general and specialized. Specialized incubators focus on a single MIC2025 industry, and thus we use their reported industries. General incubators serve multiple industries, so we assign them to industries with the largest number of incubated startups. Note that the same industry can be treated in some provinces and not in others. For example, electronic information is policy-targeted in Anhui but not in Yunnan. Accordingly, incubators in this industry are treated in Anhui and control in Yunnan.

[6] The only exception is "cultural and creative", which is a provincial-level policy-targeted industry but not an SEI in MIC2025.

2.3. Sample Construction and Summary Statistics

Although our data starts in 2015, the test period starts in 2016 because the regression analysis requires lagged incubator and startup attributes. We set 2016 as the pre-policy year (*Post* = 0) and 2017 onward as the post-policy period (*Post* = 1), since the provincial 13th FYPs take effect in 2017. We further restrict the incubator sample to those existing in 2016 to evaluate policy effects on incumbent 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 measure innovation activity of incubated startups: R&D investment, number of employees, number of patent applications, sales, VC funding received, and a graduation indicator that equals 1 if the startup graduates in the year and 0 otherwise. Among these six measures, R&D investment and patent applications directly measure innovation. Number of employees, sales, and VC funding proxy for the growth of these high-tech startups. Graduation indicates that a startup's progression beyond the incubation stage following successful development.[7] All outcome variables are available at both the incubator and startup levels.

Governments channel three forms of support to high-tech incubators: cash subsidies (*Govt Subsidy*), equity investments (*Govt Invest*), and tax reduction (*Govt Tax*). We sum these to construct total government support (*Govt All*), capturing the aggregate government subsidies received by incubators. For incubators, we track four outcomes that gauge the amount and quality of services rendered to startups each year: share of incubator staff with a college degrees or higher (*Staff Edu*), number of professional agencies hired for startups (*Agents*), number of tutoring sessions provided to startups

[7] A startup graduates from its incubator after a period of successful growth and meeting other requirements. After graduation, it may pursue an IPO, secure VC funding, be acquired by another firm or investor, or continue operating independently.

(*Tutorships*), and the incubator's investment fund size (*Invest Funds*).[8]

Panels A and B of Table 2 present summary statistics for the incubator and startup samples, respectively. Each panel reports means and standard deviations for the variables used in our analysis across 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 from pre- to post-policy years, likely reflecting the broader slowdown in China's economic growth. In contrast, treated incubators experience increases across these dimensions. For example, average annual government support (*Govt All*) for untreated incubators declines from RMB 6.09 million pre-policy to RMB 3.64 million post-policy, while support for treated incubators rises from RMB 3.31 million to RMB 6.04 million over the same period. Panel B shows similar patterns for startups. The logarithm of R&D for startups in untreated incubators decreases from 14.201 to 12.340, while it increases from 14.781 to 15.424 for treated incubators. These univariate results provide preliminary evidence of a shift of government resources towards policy-targeted industries.

Panel C of Table 2 presents summary statistics for the new startup sample, which includes startups newly incubated during 2015–2018. As discussed later, we use this sample examine how the policy affects the quality of newly incubated startups.

3. INCUBATOR-LEVEL ANALYSIS

We take three steps to assess high-tech incubators as a market-based mechanism for implementing industrial policy. First, we examine whether industrial policy increases government support for treated incubators. Second, we examine whether greater government support for incubators translates into higher innovation activity among their startups. Third, we evaluate the relative contribution of the incubator channel to the overall policy effect on high-tech startups.

[8] An incubator's investment funds are the total capital it has available to invest in startups.

3.1. Industrial Policy and Government Support to Incubators

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

$$Govt_Support_{i,t} = \beta \times Target_{i,t} + \gamma' \times X_{i,t-1} + \eta_i + \eta_{l,s} + \eta_{l,t} + \eta_{s,t} + \varepsilon_{i,t} \quad (1)$$

where $Govt_Support_{i,t}$ is a measure of government support received by incubator i in time t; $Target_{i,t}$ is an indicator variable that equals 1 if incubator i is in a policy-targeted industry, and year t is in the post-policy period (2017–2019), and zero otherwise. $X_{i,t-1}$ includes a set of lagged incubator attributes, including incubator size, number of incubated startups, an indicator variable for old incubators (aged ≥ 5 years), an SOE incubator indicator, and an indicator for location in a high-tech zones.[9] These controls capture observable factors that may influence government support. η 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 the coefficient of interest, capturing the change in government support for treated incubators, relative to their peers, after policy implementation. 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.

Panel A of Table 3 presents the regression results. Columns (1) to (3) present estimates for the three forms of government support: cash subsidy, equity investment, and tax reduction, while Column (4) uses their sum. We find that β is positive and significant at the 1% level in all four regressions, indicating that in the post-policy period, government support increases for incubators in policy-

[9] 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.

targeted industries relative to peers. The magnitudes are also economically large. For example, the coefficient in Column (4) indicates that total government support for a treated incubator increases by 3.31 times from the pre-policy level relative to a control incubator.

One concern is that increased government support for policy-targeted incubators might simply reflect broader resource inflows to cutting-edge industries rather a policy effect. To address this concern, we examine three measures of non-government funding received by incubators, including investments from corporations, nonprofit organizations, and other sources (mainly individuals). We re-estimate regressions similar to Panel A of Table 3 using these non-government funding measures. Panel B of Table 3 shows that the DID coefficient β is small and insignificant across all three regressions. Therefore, in a sharp contrast to the large increase in government support for treated incubators, there is little increase in non-government funding to these incubators. These results suggest that the observed increase in government support to treated incubators is driven by the industrial policy rather than by an economy-wide reallocation of resources.

3.2. Government Support and Innovation of Incubated Startups

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

3.2.1. OLS Analysis

We estimate the following incubator-level OLS regression of startups' innovation activity on government support received by incubators:

$$Innovation_{i,t} = \beta \times Govt_All_{i,t-1} + \gamma' \times X_{i,t-1} + \eta_i + \eta_{l,s} + \eta_{l,t} + \eta_{s,t} + \varepsilon_{i,t} \qquad (2)$$

where $Innovation_{i,t}$ is one of the six measures that reflect the 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, VC funding received, and the number of incubated startups that graduate in the year. We take the natural logarithm of these 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 their startups. We report t-statistics using robust standard errors with clustering at the industry-province level.

Panel A of Table 4 presents the regression results, in which β is positive and significant at the 1% level in all six regressions, suggesting that government support significantly boosts incubated startups' innovation activity. The elasticities imply that doubling government support is associated with an increase of 2.0% in R&D, 2.8% in employment, 2.5% in patent applications, 0.9% in total sales, 29.3% in VC funding, and 0.7% in graduation rate.[10] From Table 3, treated incubators experience a 3.31-fold increase in government post-policy. Combining the results in Tables 3 and 4, the implied policy effect through the incubator channel corresponds to increases of 6.6% in R&D, 9.3% in employment, 8.3% in patent applications, 3.0% in total sales, 97.0% in VC funding, and 2.3% in graduation rate for startups in the treated incubators.

We also examine whether government support to incubators enhances the services they provide to startups, shedding light on the mechanism linking government support to startup innovation. We re-estimate Equation (2) using one of the four service measures as independent variables: the share of incubator staff with college degrees or higher (*Staff Edu*), the number of professional agencies hired for startups (*Agents*), the number of tutoring sessions (*Tutorships*), and the size of incubator

[10] We repeat the analysis using each government support component separately (i.e., cash subsidy, equity investment, and tax reduction) and find similarly positive effects, with stronger impacts for cash subsidy and equity investment than tax reduction.

investment funds available for making equity investments in startups (*Invest Funds*). Panel B of Table 4 shows the coefficient of government support is positive and statistically significant at the 1% level across all four regressions. These results corroborate the analysis in Panel A and provide further evidence that industrial policy boosts high-tech startup performance via improvements in incubator services.

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

While the OLS results point to a positive effect of government support on incubated startups' innovation, these results are subject to endogeneity concerns because omitted variables may drive both government support and startup innovation. For example, better managed incubators might both secure more government support and foster greater innovation. To address the endogeneity concerns, we conduct a 2SLS analysis using two instrumental variables for government support.

Our first instrument follows Ru (2018), who finds that local politicians increase public investment early in their tenure because such investments take time to yield 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. We obtain party secretaries' tenure data from the Chinese Research Data Services Platform (CNRDS). Given a typical five-year tenure, 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.[11] Because these predetermined municipal turnover cycles are not affected by current economic factors (Shue and Townsend, 2017), using predicted rather than actual tenure mitigate concerns that political turnovers are themselves driven by economic factors.

[11] 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.

Our second instrument exploits local exposure to China's anti-corruption campaign. Launched in 2012, it is the largest anti-corruption campaign in China's history, with millions prosecuted or disciplined (Griffin et al., 2022). Fang et al. (2022) show that the campaign discourages government officials from engaging with private firms, either due to reduced career incentives or "playing it safe" by passive policies. As a result, higher local exposure to the anti-corruption campaign may reduce government support to incubators. Using investigation records from the websites of the Central Commission for Discipline Inspection and National Supervisory Commission, we identify city-years in which a city's party secretary or mayor is investigated. We then construct a dummy variable for the first and second years after such an investigation. We expect this instrument to be negatively related to government support to incubators.

Panel A of Table 5 presents the 2SLS regressions using predicted political tenure as the instrument. Column (1) shows a significantly positive first-stage coefficient on predicted tenure, consistent with Ru's (2018) finding of increased public investment early in local officials' terms. Columns (2) to (7) present the second-stage regressions for the six innovation measures, and the coefficient on government support is significantly positive in all regressions. Most 2SLS coefficients are similar in magnitude to the OLS estimates in Table 4, with the exception of the patent applications regression, where the coefficient is larger than the baseline. The Kleibergen-Paap weak instrument F-statistic is 45.3, indicating that predicted political tenure is unlikely to be a weak instrument. Overall, the results in Panel A corroborate the OLS analysis and alleviate the endogeneity concerns.

Panel B of Table 5 presents the 2SLS results using local corruption investigations as the instrument. As predicted, Column (1) shows a significantly negative first-stage coefficient of the investigation dummy, consistent with Fang et al.'s (2022) finding that the anti-corruption campaign induces more cautious government behavior and reduces support. In the second stage, the coefficient

on the fitted value of government support is significantly positive across all six innovation measures. Taken together, the 2SLS results from both instruments, each providing an exogenous shock to government support, consistently indicate a positive causal effect of incubators' government support on their startups' innovation activity.

3.3. Contribution of the Incubator Channel in Overall Policy Effect

Our evidence shows that the industrial policy increases government support to incubators in policy-targeted industries and, in turn, that such support increases startups' innovation activity. Together, these findings indicate that incubators serve as an effective market-based mechanism for the Chinese government to carry out the industrial policy aiming at MIC2025. However, industrial policy may also influence startup innovation through other channels, such as direct support to startups, improvements in the business environment, or greater non-government funding such as bank loans or VC/PE funds. In this subsection, we assess the contribution of the incubator channel in the industrial policy's overall impact on startups' innovation.

As estimated in Section 3.2.1, the incubator channel increases R&D by 6.6%, employment by 9.3%, patent applications by 8.3%, sales by 3.0%, VC funding by 97.0%, and graduation rate by 2.3% for incubators in targeted industries post-policy. To assess the relative importance of the incubator channel, we first estimate the policy's overall impact on startup innovation by re-running the DID Equation (1) at the startup level (rather than the incubator level), using startup-level innovation measures as dependent variables.

Table 6 presents the regression results. The DID coefficient is significantly positive across all regressions, indicating a positive overall effect of industrial policy on startup innovation in targeted industries. In terms of magnitude, the coefficients indicate that the industrial policy leads to increases of 154.2% in R&D, 46.2% in employment, 66.2% in patent applications, 26.9% in sales, 343.7% in

VC funding, and 43.2% in the graduation rate.

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

We acknowledge two caveats to this relative-importance assessment. First, the inference applies only to incubated high-tech startups, while the industrial policy likely also benefits non-incubated high-tech startups. Second, the post-policy increase in startup innovation (Table 6) may partly reflect confounding factors unrelated to the policy. This would bias downwards the incubator channel's estimated share if the denominator—the overall policy effect—is inflated. In the next section, we turn to startup-level to examine heterogeneity in policy effects and alleviate concerns about confounding factors.

4. STARTUP-LEVEL ANALYSIS

In this section, we use rich startup-level data to examine the industrial policy's impact on startup activity and how this impact varies among startup types. These analyses shed light on the specific mechanisms through which the industrial policy influences China's high-tech industries.

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

We begin by estimating the policy's effect on start-up level innovation using the DID specification in Equation (1). All variables including the fixed effects are similar to those in Table 6 except that they are constructed at the startup (rather than incubator) level. Panel A of Table 7 presents the results. In all regressions, the DID coefficient is positive and significant at the 1% level, indicating that startups in targeted industries experience significant post-policy increases in innovation relative

to their peers. Notably, the coefficients are larger than in the incubator-level regressions (Table 6), suggesting that the industrial policy may have stronger effects on 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.

We then exploit the detailed startup-level data and re-estimate the regressions using several alternative innovation measures. In Panel B of Table 7, Column (1) uses an indicator variable for startups with positive R&D investment (instead of the logarithm of R&D). Columns (2) to (5) use the numbers of employees with doctoral degrees, employees with bachelor's degrees, employees with overseas educational experience, and newly hired employees, respectively. Column (6) uses patents granted (instead of patent applications), and Column (7) uses an indicator variable for startups with positive VC funding (instead of VC funding level). The DID coefficient remains significantly positive in all these regressions, reinforcing the robustness of our findings.

We further conduct two placebo tests to address concerns that the results in Table 7 may reflect fundamental differences between policy-targeted industries and other industries, either before or after policy. Panel A of Table 8 reports the regressions of innovation measures on $Treated_i$, an indicator variable that equals 1 for startups in targeted industries and 0 otherwise, using only pre-policy observations (i.e., observations in 2016). Since the policy had not been implemented in this sample, the coefficient on $Treated_i$ captures pre-policy differences unrelated to the industry policy. This coefficient is insignificant across all regressions, suggesting that our DID results are unlikely to be explained by pre-existing differences between targeted and non-targeted industries.

We conduct a second placebo test similar to Table 7 and define *Pseudo Target* similarly as *Target* except using pseudo policy-targeted industries (rather than actual policy targeted industries). Pseudo policy-targeted industries are defined by randomly selecting three industries that are targeted in other

provinces, not in the startup's home province. The premise is that if post-policy results were driven by inherent cross-industry differences, industries targeted elsewhere (and exhibiting higher innovation) would show similar effects even when not locally targeted. Panel B of Table 8 shows that the coefficient of *Pseudo Target* is insignificant in all regressions, suggesting that our findings are not driven by particular industries but by the localized variation in targeted-industry designations under provincial industrial policies.

4.2. Cross-Sectional Differences

Having established that industrial policy significantly boosts innovation at both the incubator and startup levels, we next examine whether and how the implementation approach of MIC2025 through high-tech incubators differs from traditional industrial policies in China over past decades.

Our first question concerns distributional impacts across firms. Traditional Chinese policies promoting innovation or manufacturing have often targeted large or SOE firms directly, for example, the top 1,000 energy-intensive firms (Chen et al., 2025). By contrast, MIC2025 is at least partially implemented through market intermediaries—incubators—that screen, mentor, and support startups throughout the incubation lifecycle. This decentralized, hybrid approach is likely to produce different distributional effects across firms than traditional top-down targeting.

We first examine heterogeneity between officially recognized high-tech firms (HTEs) and non-HTE firms. HTEs, credentialed by MOST agencies, have traditionally received preferential policy treatments such as lower tax rates and larger subsidies (e.g., Cai et al., 2018; Chen et al., 2021; Tian and Xu, 2021). We therefore examine whether the hybrid approach disproportionately benefits the less resourceful non-HTE firms. Panel A of Table 9 presents DID regressions that include an interaction term between *Target* and a non-HTE indicator. The coefficient of the interaction is positive and significant at the 1% level across all models, suggesting that the incubator approach has a more

pronounced effect on non-HTE startups' innovation outcomes than on HTEs. Moreover, the magnitude of the interaction coefficient is either similar to or larger than that of *Target*, indicating a much larger policy effect for non-HTE startups. The positive policy effects on patents and sales are primarily driven by non-HTE startups. Overall, these results show that, unlike traditional industrial policies, the hybrid approach through high-tech incubators delivers larger benefits to less resourceful non-HTEs.

Panel B of Table 9 includes an interaction between *Target* and an indicator for young startups, defined as those younger than five years. Younger startups are typically more vulnerable and face greater uncertainty, making them less likely to attract policy support or market resources. The coefficient is significantly positive across all regressions, showing that the incubator channel has a stronger positive impact on the innovation outcomes of younger startups. Consistent with Panel A, these results indicate that less resourceful firms derive larger policy benefits from MIC2025's hybrid implementation model.

In Panel C of Table 9, we interact *Target* with an indicator for startups operating in the same industry as their incubator. Because policy-driven support is allocated according to incubators specializations, incubators are expected to focus resources on firms in their own specialty. Across all six regressions, the same-industry interaction is significantly positive, whereas *Target* is insignificant (marginally significant for VC funding). This stark contrast indicates the policy effects are concentrated among startups aligned with their incubators' specialized industries.

Besides the three startup characteristics examined in Table 9, a key distinction between the incubator channel and the traditional industrial policy is its focus on the private sector. Almost all incubated startups are privately owned (99.6%), so government support to high-tech incubators flows almost entirely to privately owned startups. This is a sharp contrast to traditional industrial policies,

which have intended to favor the state-owned sector.

5. SPECIFIC MECHANISMS

In this section, we investigate the mechanisms through which high-tech incubators translate government support into startups' innovation outcomes and thereby advancing MIC2025's policy objectives. We first examine whether incubators use received government support to expand or enhance incubation services. We then compare the effectiveness of SOE versus private incubators in implementing industrial policy.

5.1. The Effect of the Industrial Policy on Incubation Services

Incubators specialize in recruiting and supporting startups, and their profits depend on the success of incubated startups. It is therefore plausible that incubators deploy government support to expand services that benefit incubated startups. We examine this possibility by estimating DID regressions analogous to our baseline but using incubator-service measures as outcomes. We use the four incubator-service measures from Panel B of Table 4: professional agencies hired and tutoring sessions (directly service intensity), and staff education and investment funds (service quality and financial support capacity). Table 10 presents the regression results, in which the DID coefficient is significantly positive in most regressions except tutoring sessions. It appears that the largest effect is on investment funds (increase by 52.3%), indicating especially raid growth in capital available for direct equity investments in new or existing startups.

5.2. The Role of Private Incubators

Prior research finds that SOEs or governments are typically less efficient than domestic private or foreign-invested firms at converting inputs into innovation output (Wei et al., 2017). We therefore examine the relative roles of private versus SOE incubators in implementing MIC2025 policy goals.

5.2.1. Government Support Allocation

There are reasons to suspect the government may favor SOE incubators over privately owned ones in allocating government support, potentially misallocating resources. To assess this possibility, we compare government support received by SOE versus privately owned incubators. Specifically, we estimate DID regressions of government support on the interaction between *Target* and an indicator variable for privately owned incubators. Private incubators are defined as those with government ownership below 50%, comprising 65% to 74% of incubators across sample years.

Panel A of Table 11 shows that *Target* is significantly positive in all four regressions, suggesting that SOE incubators in targeted industries receive more government support after the policy. More importantly, the coefficient of the interaction term is negative and significant at the 1% level in all specifications, indicating that within targeted industries, privately owned incubators receive significantly less government support than SOE incubators post-policy. For example, in the total support regression (Column 4), the coefficient of *Target* is 4.359 and that of the interaction is -1.589, implying that private incubators receive about 36% (=1.589/4.359) less government support than SOE peers post-policy. Among the three types of government support, the shortfall is largest for tax breaks, followed by cash subsidies and government equity investments.

5.2.2. Innovation Activity of Existing Incubated Startups

We next test whether private incubators, despite receiving less government support than SOE incubators, are more efficient at converting government support into startup innovation. We estimate startup-level regressions of innovation outcomes on the interaction between *Target* and an indicator for private incubators. Panel B of Table 11 shows that the interaction is positive and statistically significant across all six outcomes. Therefore, even with less allocated government support, startups in private incubators see significantly larger post-policy gains in innovation than those in SOE incubators. These effects are also economically significant. As discussed in the previous subsection,

treated private incubators receive 36% less government support than treated SOE incubators post-policy. Yet startups in treated private incubators experience 13.8% to 77.1% greater increases in innovation outcomes than their counterparts in treated SOE incubators.[12] This contrast indicates that private incubators are more efficient implementers of the MIC2025 industrial policy.

5.2.3. Screening of New Startups

Beyond efficiency in generating innovation, we compare private and SOE incubators' ability to use government support to enhance screening of new startups. We plot annual cohorts of newly incubated startups separately for SOE and private incubators. For SOE incubators (Figure 4, left panel), the number of new recruits does not increase substantially following the policy, and the share of newly recruited startups in policy-targeted industries declines relative to 2015. In contrast, for private incubators (Figure 4, right panel), the number of newly incubated startups increases after the policy, and the share of newly incubated startups in the post-2015 period exceed the 2015 level. These results point to a greater role for private incubators in executing the MIC2025 industrial policy through improved screening.

We next assess how the quality of new incubatees changes post-policy for SOE versus private incubators. We proxy the quality of new incubatees using an indicator for one-year graduation that equals 1 if a newly incubated startup graduates within a year of entry, i.e., the startup entering in year t is with the incubator in year t + 1 but not in t + 2. The premise is that higher-quality entrants are more likely to graduate quickly. To ensure two years of post-entry observation, we exclude startups entering in 2018 or 2019. The resulting sample includes 121,880 startups that enter incubation between 2015 to 2017.

[12] 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.

Panel C of Table 11 regresses the one-year graduation indicator on the interaction term between *Target* and a private-incubator indicator to test relative efficiency in deploying government support. We include controls for startup attributes and, across specifications, province-by-industry, industry-by-year, and province-by-year fixed effects. In the full model (Column 6), the coefficient on the private-incubator indicator is positive and significant at the 1% level, suggesting that private incubators recruit higher-quality startups than their SOE peers even before policy. More importantly, the coefficient on *Target* is statistically insignificant, while that on the private-indicator interaction is significantly positive, suggesting that while there is no quality change for SOE recruits post-policy, the quality of newly incubated startups by private incubators increases significantly post-policy. The coefficient indicates 0.7 percentage point increase in recruits' quality for private incubators relative to SOE incubators after the policy. Given a pre-policy average graduation rate of 6% for private incubators in targeted industries, this represents an 11.7% increase.

Overall, the evidence shows that, within policy-targeted industries, SOE incubators receive more government support than private incubators post-policy but are less efficient at translating such support into startup innovation or in selecting higher-quality entrants. These results reveal partial resource misallocation in the policy's implementation, despite its overall positive effect on innovation.

6. CONCLUSION

This paper studies a market-based mechanism for implementing the government's innovation policy through high-tech incubators. Our analysis exploits the variation in SEIs targeted by different provinces under MIC2025 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 policy's implementation, high-tech incubators in targeted industries receive significantly more government support—cash subsidy, equity investment, and tax reduction—

than those in non-targeted industries. This support has a strong causal impact on incubated startups' innovation activity. The results are robust when we address endogeneity concerns using 2SLS analysis with two instrumental variables for government subsidy. We further estimate that the innovation channel accounts for about one-seventh of the policy's effects on startups' innovation outcomes. The effects are especially pronounced among young and non-HTEs, groups often overlooked by traditional direct-subsidy programs and more likely to face financing constraints.

We also find that, post-policy, treated SOE incubators receive disproportionately greater government support than treated private incubators, despite being less efficient at deploying these resources. This indicates that, even within a market-based framework, resource misallocation persists in favor of state-owned entities.

Compared with prior literature on direct subsidy policies, which finds limited effects on innovation quality and firm productivity due to targeting inefficiencies and rent-seeking distortions, our results demonstrate that a market-intermediated approach through high-tech incubators generates stronger and more efficient innovation outcomes. By embedding fiscal support within entrepreneurial intermediaries, this hybrid model better aligns public objectives with market incentives, channeling resources toward dynamic, high-potential firms.

Overall, our study contributes to the literature on industrial and innovation policy by providing the first large-scale empirical evidence that a market-based implementation mechanism—rather than direct fiscal allocation—can enhance policy effectiveness. High-tech incubators serve not merely as passive recipients of government support but as active agents that translate policy intent into entrepreneurial innovation, making the MIC2025 initiative a distinctive and more efficient model of state-led innovation.

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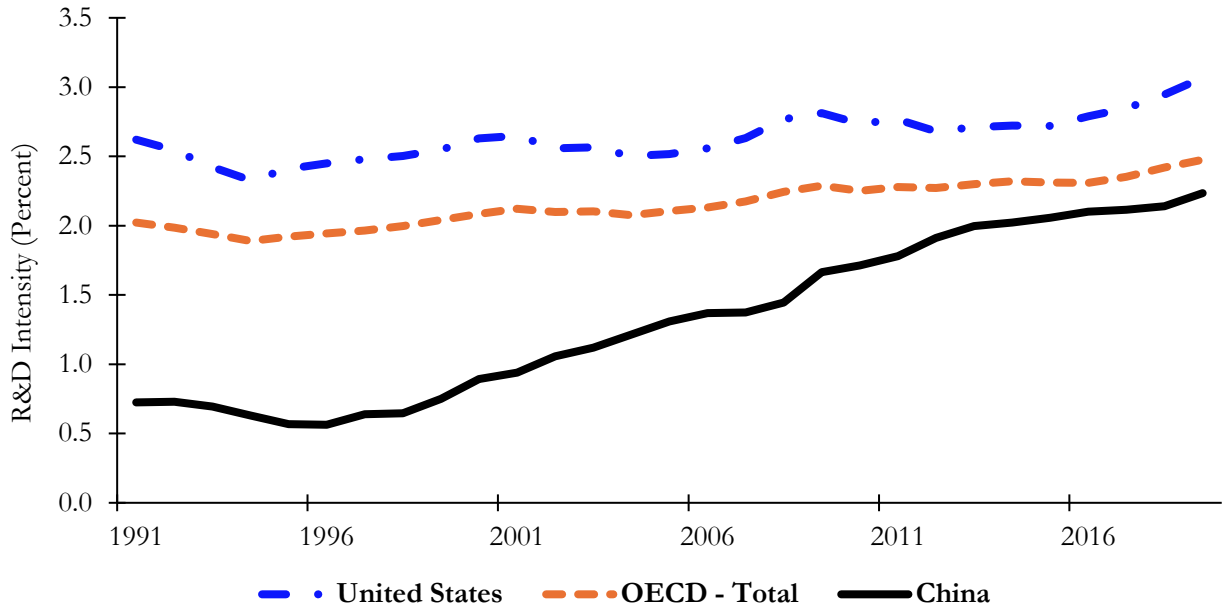
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Yu, Sandy, 2020, How do accelerators impact the performance of high-technology ventures? *Management Science* 66, 530–552.

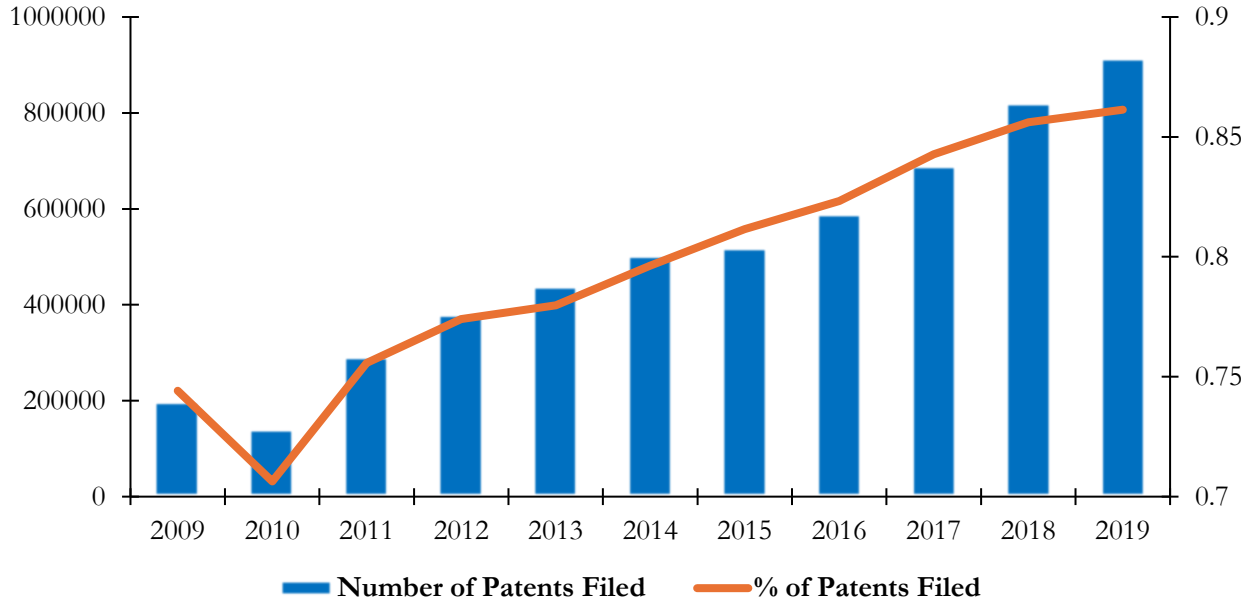
Figure 1
Innovations in China

This figure presents trends in China's innovation activity over time. Panel A shows 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 R&D expenditure as a percentage of GDP. Panel B shows the annual number of patent applications filed in China from 2009 to 2019, as well as the share accounted for by domestic firms. Panel C plots the number of new high-tech startups established in China from 2010 to 2019.

Panel A: Cross-Country Comparison of R&D Intensity



Panel B: Number of Patents Filed by Domestic Firms



Panel C: Number of New High-Tech Startups

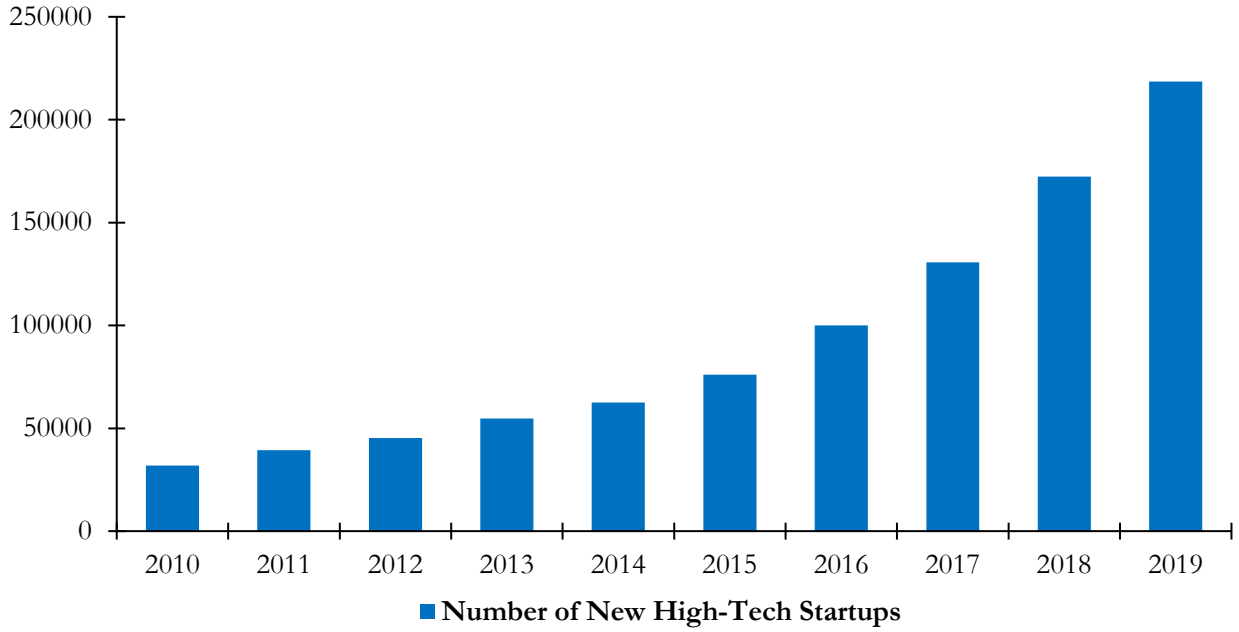
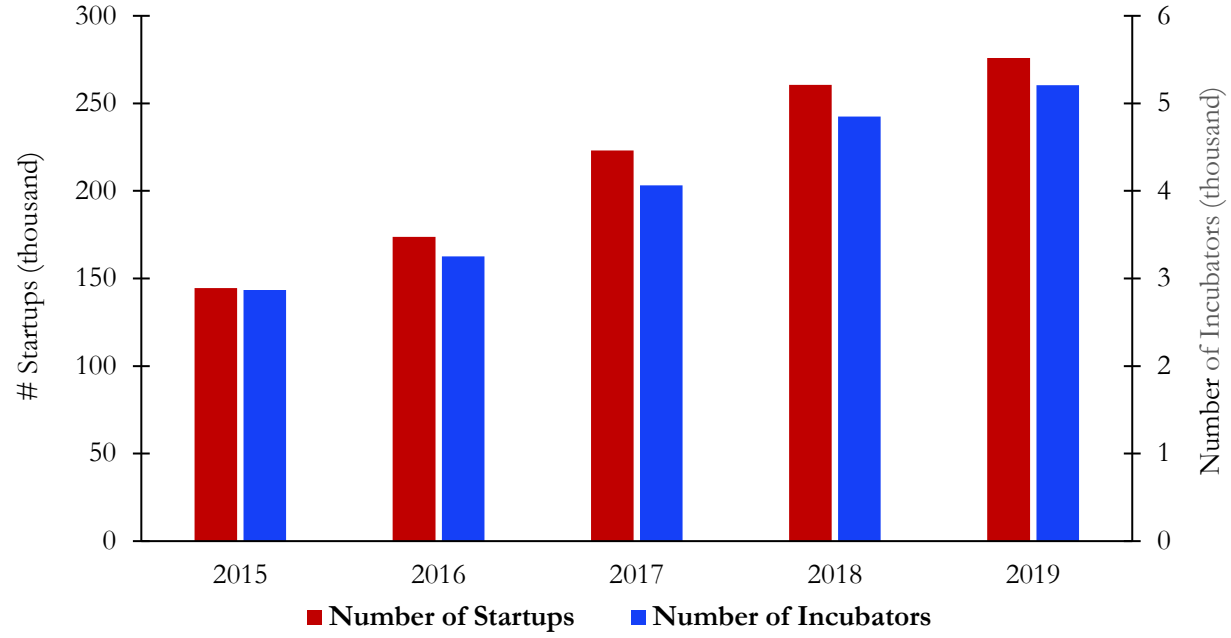


Figure 2
High-Tech Incubators and Startups: Number and Economic Activity

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.

Panel A: Numbers of Incubators and Startups



Panel B: Share of Startup Activity in the Economy

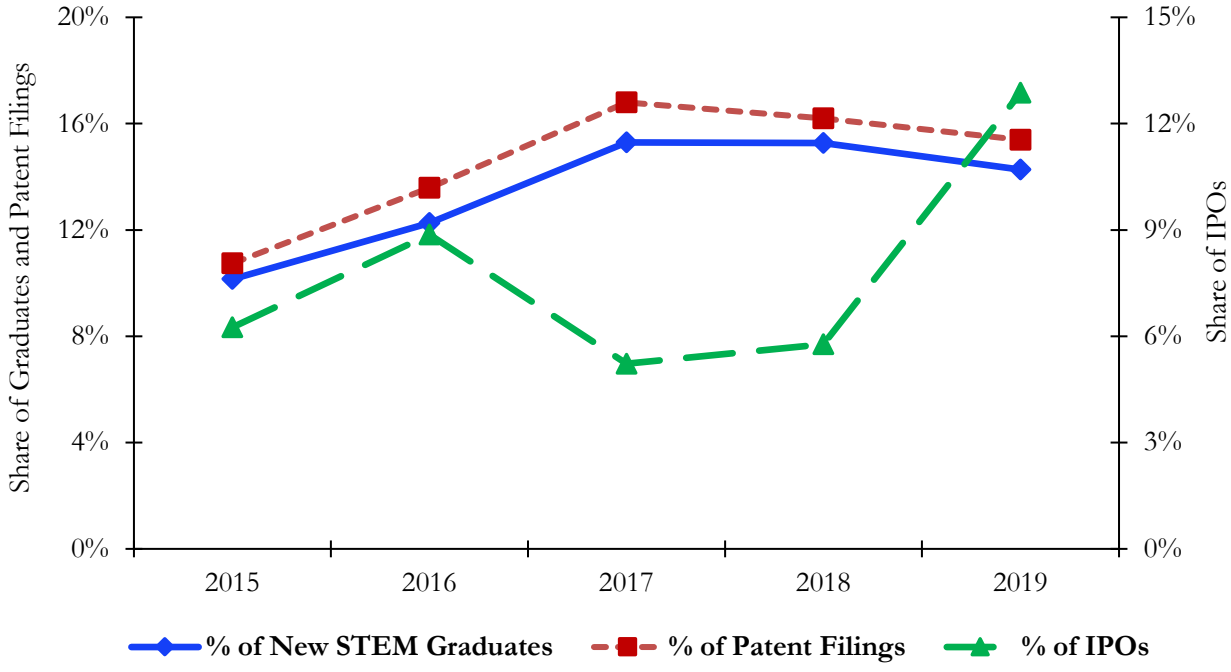


Figure 3
Province-Specific Industrial Policy

This figure plots the policy-targeted industries of individual provinces' 13th 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.

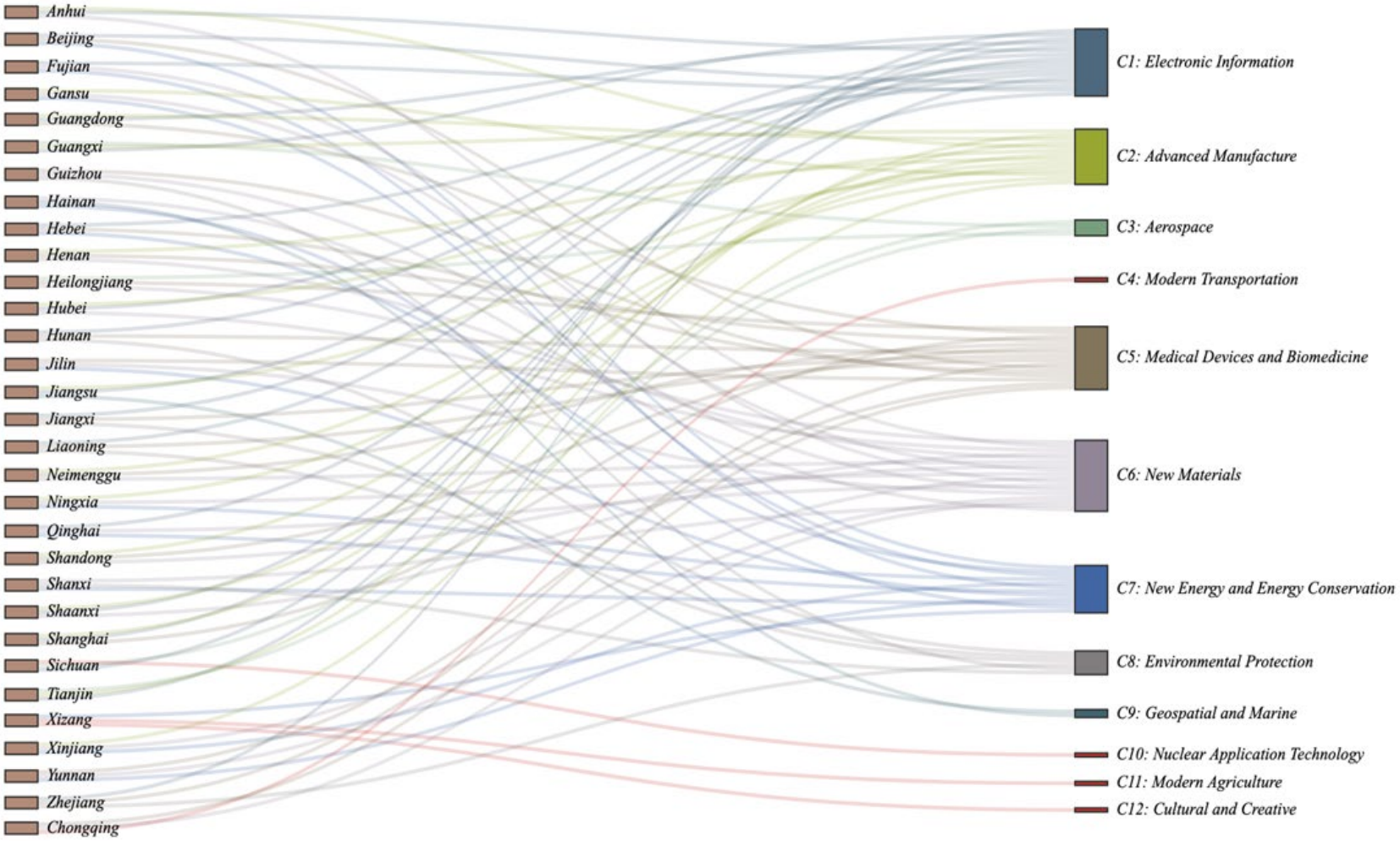


Figure 4

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.

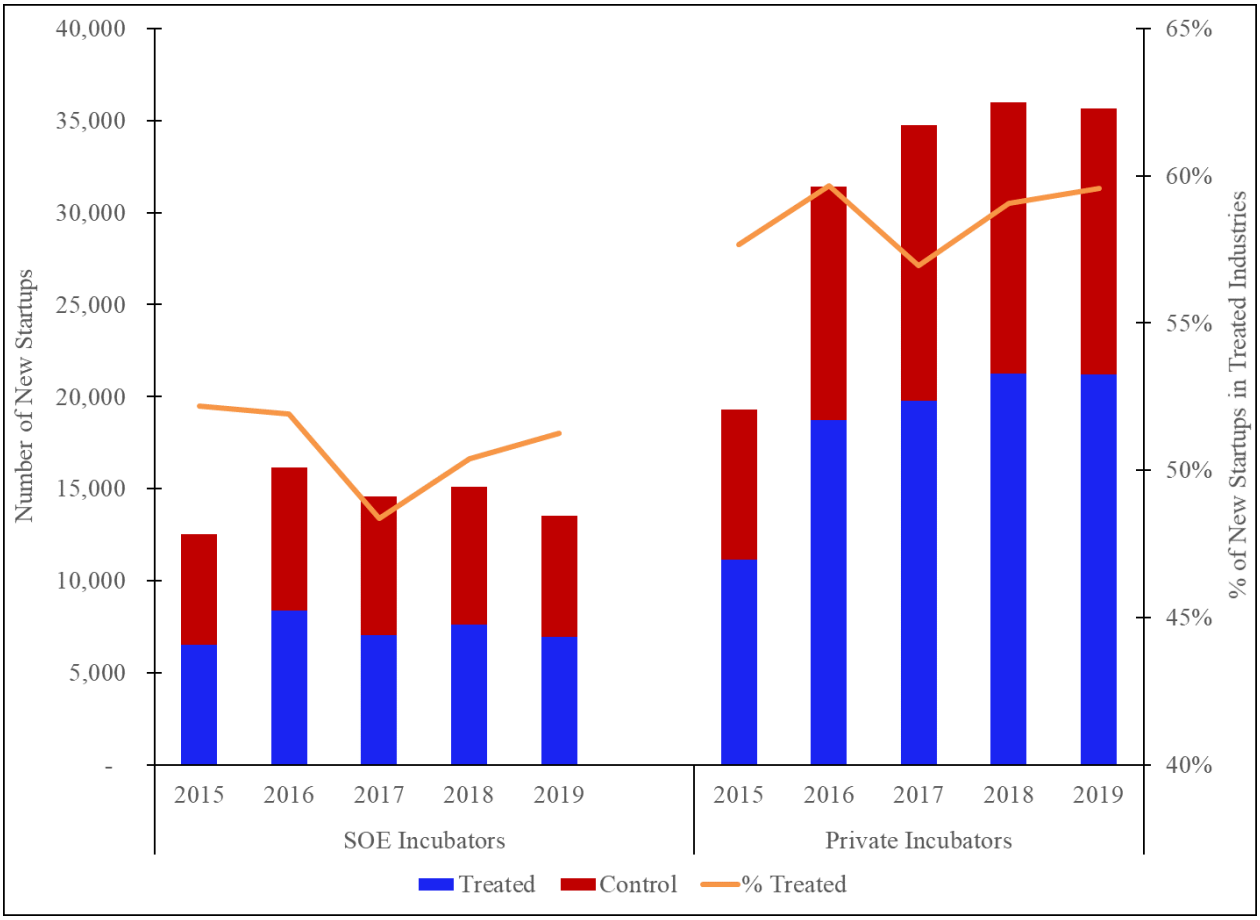


Table 1

Mapping Strategic Emerging Industries between Made In China 2025 and Provincial 13th Five-Year Plans

This figure presents the mapping of strategic emerging industries (SEIs) between Made in China 2025 (MIC2025) and local 13th Five-Year Plans (FYP). The left panel lists the SEIs identified in MIC2025. The right panel presents the corresponding policy-targeted industries in provincial 13th Five-Year Plans (FYPs, 2016-2020), which also align with the industries of the high-tech incubators in our sample.

SEIs in MIC2025	**Corresponding SEIs in Provincial 13th FYPs**
Next-Generation Information Technology	Electronic Information
High-End Computerized Numerical Control Machine Tools and Robotics	Advanced Manufacture
Aerospace and Aviation Equipment	Aerospace and Aviation Geospatial and Marine
Maritime Engineering Equipment and High-Tech Shipbuilding	Geospatial and Marine Modern Transportation
Advanced Rail Transportation Equipment	Modern Transportation
Energy-Saving and New Energy Vehicles	Modern Transportation New Energy and Energy Conservation Environmental Protection
Electrical Equipment	Environmental Protection Nuclear Application Technology
Agricultural Machinery and Equipment	Modern Agriculture
New Materials	New Materials
Biomedicine and High-Performance Medical Devices	Biomedicine and Medical Devices
N/A	Cultural and Creative

Table 2
Summary Statistics

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 1st and 99th percentiles. Variable definitions are provided in the Appendix.

Panel A: Incubator Data

	Treated = 0				Treated = 1			
Sample	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

	Treated = 0				Treated = 1			
Sample	Post = 0		Post = 1		Post = 0		Post = 1	
Variables	Mean	SD	Mean	SD	Mean	SD	Mean	SD
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
#Obs	741		1831		1627		4123	

Panel B: Startup Data

	Treated = 0				Treated = 1			
Sample	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

	Treated = 0				Treated = 1			
Sample	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	

Table 3
Industrial Policy and Government Support to Incubators

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 *Target*, a dummy variable for incubator-years in policy-targeted industries and post-policy period (2017-2019). 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 the Appendix. 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.

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)
Target	**2.673*** **	**2.826*** **	**1.622*** **	**3.310*** **
	(6.57)	**(6.82)**	**(4.75)**	**(8.35)**
$Log(Capital)_{i,t-1}$	0.072	-0.463***	-0.039	-0.140*
	(0.80)	(4.14)	(0.75)	(1.73)
$I(Old\ Incubator)_{i,t-1}$	-0.141	-0.291	-0.021	-0.409
	(0.55)	(0.98)	(0.09)	(1.49)
$I(SOE\ Incubator)_{i,,t-1}$	-0.485	-2.513***	0.424	-1.130***
	(-1.10)	(-5.20)	(1.07)	(-3.19)
$I(HTE\ Zone)_{i,t-1}$	0.186	0.436	1.313***	0.222
	(0.43)	(0.91)	(4.73)	(0.49)
$Log(No^{-}Firms)_{i,t-1}$	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.	Investment by Corporations	Investment by Non-Corp Org	Investment by Others
	(1)	(2)	(3)
Target	**0.259**	**-0.154**	**0.004**
	(0.61)	**(-1.16)**	**(0.02)**
Log(Capital)$_{i,t-1}$	-1.653***	0.001	-0.073
	(-11.93)	(0.03)	(-1.11)
I(Old Incubator)$_{i,t-1}$	-0.698**	-0.047	-0.356***
	(-2.14)	(-0.58)	(-2.63)
I(SOE Incubator)$_{i,,t-1}$	3.191***	-0.173	0.767***
	(5.55)	(-1.10)	(3.28)
I(HTE Zone)$_{i,t-1}$	-0.375	0.021	-0.354
	(0.67)	(0.16)	(-1.32)
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

Table 4

Government Support to Incubators and Innovation Activity of Incubated Startups

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 the Appendix. 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.

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)

Dep Var.	Log(R&D)	Log(Employ)	Log(Patents)	Log(Sales)	Log(VC)	Log(Graduate)
	(1)	(2)	(3)	(4)	(5)	(6)
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

Table 5
Government Support and Innovation Activity: 2SLS Regression Analysis

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 the Appendix. 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.

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

Dep Var.	First Stage	Second Stage					
	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($\widehat{Govt All}$)		**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

Dep Var.	First Stage	Second Stage					
	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						

Table 6
DID Regressions of Innovation Activity of Incubated Startups

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 *Target*, a dummy variable for incubator-years in policy-targeted industries and post-policy period (2017-2019). 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 the Appendix. 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.

Dep Var.	Log(R&D)	Log(Employ)	Log(Patents)	Log(Sales)	Log(VC)	Log(Graduate)
	(1)	(2)	(3)	(4)	(5)	(6)
Target	**1.542*** **	**0.462*** **	**0.662*** **	**0.269*** **	**3.437*** **	**0.432*** **
	(8.25)	**(6.68)**	**(5.26)**	**(4.42)**	**(6.40)**	**(8.06)**
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)
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)
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)
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)
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

Table 7
DID Analysis of Innovation Activity at Startup Level

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 *Target*, a dummy variable for sartup-years in policy-targeted industries and post-policy period (2017-2019). 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 the Appendix. 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.

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)
Target	**3.161*** **	**0.296*** **	**0.211*** **	**1.319*** **	**1.546*** **	**0.302*** **
	(15.74)	**(18.33)**	**(7.90)**	**(5.89)**	**(14.67)**	**(7.10)**
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)
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)
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)	Doctor's	Bachelor's	Abroad	New	Granted	I(VC>0)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Target	**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)**
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)
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)
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

Table 8
DID Analysis of Innovation Activity at Startup Level: Placebo Tests

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 incubators in policy-targeted industries, but the sample is restricted to 2016 before the industrial policies took effect. In Panel B, the main explanatory variable *Pseudo Target*, a dummy variable for startup-years in pseudo policy-targeted industries and post-policy period (2017-2019). Pseudo policy-targeted industries for incubators are randomly selected from the policy-targeted industries in provinces other than incubators' 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 the Appendix. 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.

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)**
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)
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)
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)
Pseudo Target	**0.202**	**0.021**	**0.012**	**0.072**	**0.050**	**0.062**
	(0.49)	**(0.53)**	**(0.35)**	**(0.26)**	**(0.28)**	**(1.19)**
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)
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)
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

Table 9

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

This table presents the analyses of the heterogeneous effect of the industrial policy on startups' innovation out- comes 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. *Target* is a dummy variable for startup-years in policy-targeted industries and post-policy period (2017-2019). We further include interaction term of *Target* 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 the Appendix. 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.

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)
Target × Non-HTE	**2.076*** **	**0.182*** **	**0.311*** **	**1.996*** **	**0.899*** **	**0.160*** **
	(4.29)	**(6.28)**	**(4.97)**	**(10.22)**	**(2.66)**	**(3.23)**
Target	**1.360*** **	**0.138*** **	**-0.058**	**-0.413** **	**0.765*** **	**0.163*** **
	(2.76)	**(5.03)**	**(-1.13)**	**(-1.98)**	**(2.79)**	**(3.99)**
$Log(Capital)_{i,t-1}$	0.029	0.030***	0.006	0.017	-0.010	0.003
	(0.74)	(6.50)	(1.04)	(0.54)	(-0.27)	(0.81)
$I(Old\ Firm)_{i,t-1}$	-0.260***	-0.025**	-0.061***	-0.741***	-0.114	0.096***
	(-2.81)	(-2.41)	(-4.56)	(-9.37)	(-1.59)	(8.19)
$I(SOE\ Firm)_{i,t-1}$	-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 × 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	0.582	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)
Target × Young Firm	**0.777*** **	**0.121*** **	**0.105*** **	**1.343*** **	**1.605*** **	**0.100** **
	(5.18)	**(6.37)**	**(3.02)**	**(7.06)**	**(9.91)**	**(2.46)**
Target	**2.717*** **	**0.227*** **	**0.152*** **	**0.552** **	**0.629*** **	**0.245*** **
	(12.48)	**(12.35)**	**(5.40)**	**(2.54)**	**(5.42)**	**(6.92)**
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)
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)
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 × 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	0.759	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)
Target × Same Industry	**3.563*** **	**0.198**	**0.311*** **	**1.144**	**0.636**	**0.314*** **
	(2.90)	**(1.18)**	**(2.72)**	**(1.08)**	**(1.20)**	**(3.77)**
Target	**-0.369**	**0.100**	**-0.097**	**0.185**	**0.908***	**-0.008**
	(-0.30)	**(0.60)**	**(-0.86)**	**(0.18)**	**(1.73)**	**(-0.12)**
Same 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)
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)
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)
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 × 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

Table 10
DID Regressions of Incubator Service

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 *Target*, a dummy variable for incubator-years in policy-targeted industries and post-policy period (2017-2019). 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 the Appendix. 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.

Dep Var.	Staff Edu	Log(Agents)	Log(Tutorships)	Log(Invest Funds)
	(1)	(2)	(3)	(4)
Target	**0.015****	**0.068***	**-0.009**	**0.523****
	(2.33)	**(1.87)**	**(-0.18)**	**(2.18)**
Log(Capital)$_{i,t-1}$	-0.004**	0.024***	0.020	0.050
	(-2.18)	(2.67)	(1.60)	(0.62)
I(Old Incubator)$_{i,t-1}$	0.002	-0.035	-0.069*	0.028
	(0.43)	(-1.63)	(-1.90)	(0.13)
I(SOE)$_{i,t-1}$	0.005	0.008	0.067	-0.290
	(0.58)	(0.24)	(1.02)	(-0.94)
I(HTE Zone)$_{i,t-1}$	-0.008	0.022	0.042	0.213
	(-1.54)	(0.48)	(0.82)	(0.60)
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

Table 11
Efficiency in Policy Implementation: SOE vs. Private Incubators

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. *Target* is a dummy variable for incubator-years in policy-targeted industries and post-policy period (2017-2019). We further include an interaction term of *Target* 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 the Appendix. 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.

Panel A: Government Supports Received

Dep Var.	Log(Govt Subsidy)	Log(Govt Invest)	Log(Govt Tax)	Log(Govt All)
	(1)	(2)	(3)	(4)
Target × I(Private Incubator)	**-1.625*** **	**-1.501*** **	**-3.248*** **	**-1.589*** **
	(-3.51)	**(-4.03)**	**(-5.97)**	**(-4.06)**
Target	**3.746*** **	**3.817*** **	**3.767*** **	**4.359*** **
	(7.29)	**(8.09)**	**(7.94)**	**(9.64)**
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 × 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	0.364	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)
Target × I(Private Incubator)	**0.622***	**0.058****	**0.118*****	**0.513****	**0.286****	**0.039***
	(1.75)	**(2.29)**	**(3.00)**	**(1.99)**	**(1.98)**	**(1.92)**
Target	**2.859*****	**0.267*****	**0.153*****	**1.100*****	**1.401*****	**0.282*****
	(10.59)	**(14.28)**	**(4.00)**	**(3.90)**	**(10.92)**	**(6.30)**
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 × 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	0.529	0.303	0.620

Panel C: Graduation Rate of Newly Recruited Startups

Dep Var.	I(One-Year Graduation)					
	(1)	(2)	(3)	(4)	(5)	(6)
Target × I(Private Incubator)		**0.008****		**0.008****		**0.007***
		(2.48)		**(2.59)**		**(2.16)**
Target	**0.009***	**0.001**	**0.009***	**0.000**	**0.007**	**0.002**
	(1.96)	**(0.25)**	**(1.95)**	**(0.14)**	**(1.58)**	**(0.74)**
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 × Industry	No	No	No	No	Yes	Yes
Industry × Year	No	No	No	No	Yes	Yes
Province × 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

Appendix
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.
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	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.