The “Demons” in Demonstration: Unintended Consequences of Superstar-oriented R&D Subsidy Policy in China

Zeyu Chen *

March 23, 2025

Abstract

This paper investigates the unintended consequences of selective R&D subsidy policies targeting leading firms on the innovation activities of non-subsidized competitors and new entrants. While such subsidies are typically designed to stimulate innovation, the paper employs a Schumpeterian model to argue that they can discourage innovation among competitor firms and deter new entrants, ultimately undermining aggregate innovation. Empirical evidence from the “National Technological Innovation Demonstration Enterprise (NTIDE)” policy in China supports these predictions, revealing a 30% increase in R&D spending by subsidized firms, but a 13.3% reduction in R&D by competitor firms and a 5.9% decline in the entry of private firms. Furthermore, the policy results in a 13.5% decrease in patent outputs at the corresponding industry and city levels where the certified demonstration enterprises are located. The paper underscores the importance of considering competitive dynamics when designing innovation policies and provides new insights into the effects of selective subsidies on market competition and innovation.

*School of Economics, Renmin University of China; rucczy@ruc.edu.cn. I thank Zhiyuan Chen, Ting Jiang, Zhi Li, Ruiming Liu, Angdi Lu, Haosheng Yan, and Qiong Zhang for helpful comments. I also thank participants at China's Economic Transition Workshop at Renmin University of China.

1 Introduction

Innovation is a critical driver of long-term economic growth (Romer, 1990; Aghion and Howitt, 1992). Owing to its pronounced externalities, innovation frequently necessitates government intervention, with selective R&D subsidies being one of the most widely used policy instruments (Edler and Fagerberg, 2017). A substantial body of literature has demonstrated the positive effects of subsidy policies on recipient firms (Mamuneas and Ishaq Nadiri, 1996; Feldman and Kelley, 2006; Howell, 2017; Pallante et al., 2023; Dong et al., 2024). In recent years, the focus has increasingly shifted toward knowledge spillovers, suggesting that subsidies may confer benefits to other firms by influencing the recipients (Moretti et al., 2023; Pallante et al., 2023; Giroud et al., 2024). Overall, much of the existing research adopts a favorable perspective on these policies, often emphasizing the need to enhance *efficiency* by better targeting firms with higher potential for innovation and spillovers.

In contrast to the prevailing emphasis on the positive effects of selective R&D subsidies, this paper underscores the potential negative consequences that may arise when such policies alter innovation competition. Drawing on Schumpeter's insights on creative destruction, the incentive for new or lagging firms to engage in R&D stems from displacing industry leaders and capturing monopoly profits through innovation (Schumpeter, 1934). When subsidies are allocated to leading firms, this may reduce the likelihood that new or competitor firms can displace these leaders, thereby diminishing the expected returns from engaging in R&D activities. Consequently, such selective subsidies may encourage leading firms at the expense of discouraging innovation among these firms, leading to unintended negative spillovers and ambiguous aggregate effects. This implies that the selection of subsidized firms is not merely a matter of *efficiency* but also potentially one of *effectiveness*.

To illustrate these firm dynamics, I develop a simplified two-period Schumpeterian model. In this theoretical framework, the leading firm captures monopolistic profits and invests in R&D to increase its expected profits in the second period. The model suggests that an increase in government-provided subsidies incentivizes the leading firm to raise its total R&D expenditures, thereby achieving higher expected productivity in the subsequent period. Competitor firms or new entrants, represented by a representative firm, also engage in R&D activities during the first period to develop new technologies for the second period. If the productivity derived from the new technology surpasses that of the leading firm, they enter the market and capture the monopolistic profits. The model indicates that, with the expectation that the leading firm will achieve higher productivity in the second period, the optimal strategy for competitor firms or new entrants lagging behind the productivity frontier is to reduce their R&D expenditures.

The policy practices in China provide a suitable case study to test this theoretical prediction. Since 2011, the Chinese government has implemented the "National Technological Innovation Demonstration Enterprise (NTIDE)" policy, which annually certifies local "superstar firms" as "demonstration enterprises" and subsidizes their innovation activities, without reducing subsidies to other firms. Empirical findings reveal that the policy encourages listed demonstration enterprises to increase their R&D expenditures by 30%. However, it has had a negative effect on the R&D expenditures of other listed competitor firms, reducing them by 13.3%. These negative effects are more pronounced for incumbent firms that lag further behind the productivity frontier. Additionally, the policy has led to a significant decrease in the entry of private firms and foreign firms by 5.9% and 13.8%, respectively.

The divergent influences on demonstration enterprises and other firms suggest an ambiguous overall effect on aggregate innovation. Accordingly, I conduct an estimation at the city–industry level to investigate the change in the citation-weighted number of invention patents after an industry in a city experiences its first subsidized demonstration enterprises. The estimation reveals a gradually exacerbated negative effect over time, resulting in a decrease in patent outputs by approximately 13.5% (or 4% based on the most conservative estimates). Furthermore, this study finds that such negative overall effects are more pronounced in industries characterized by more intense market competition and higher rates of firm entry, which aligns with the narrative of discouraging effects on competitors.

Furthermore, to estimate the overall effects nationwide, I assess the inter-industry spillovers and spatial spillovers of the NTIDE policy by reclassifying the control group. The estimation reveals negligible spillover effects across industries and regions, suggesting that the policy results in a net negative effect on national innovation. Additionally, I investigate whether the policy promotes local knowledge spillovers by supporting industry leaders. However, the findings again indicate that such influences are small in magnitude.

Taken together, this study sheds light on the potential pitfalls of selectivity subsidies, or more broadly, selective innovation policies. Since firms' incentives to engage in R&D activities stem from the expected profits derived from innovation, interventions affecting any single firm can influence the entire market through competitive interactions among firms. Consequently, selective innovation policies must carefully evaluate their impacts on innovation competition within industries; otherwise, the overall effects may be undermined or even counterproductive.

This study contributes to and extends three strands of the literature. First, as discussed in the opening paragraph, it relates to the broad body of research on R&D subsidy policies, which has gradually shifted its focus from subsidized firms to exploring knowledge spillovers and spatial interactions (Mamuneas and Ishaq Nadiri, 1996; Feldman and Kelley, 2006; Howell, 2017; Moretti et al., 2023; Pallante et al., 2023; Dong et al., 2024; Giroud et al., 2024). This study enriches the literature by documenting the negative aspects of selective subsidy policies, a relatively underexplored dimension. Among the few studies examining negative effects, Acemoglu et al. (2018) theoretically demonstrate that subsidies to incumbent firms can increase factor prices, thereby raising entry costs for potential entrants. Similarly, Aghion et al. (2019) find that easing financing constraints for incumbent firms in France led to the persistence of less efficient firms. In contrast to subsidizing all incumbents, the NTIDE policy exhibits greater selectivity by targeting "superstar" firms. By modeling and estimating its effects on both incumbent competitors and new entrants, this study offers a new perspective on the negative consequences of altering the innovation competition dynamics among firms, which may inadvertently result in adverse effects on aggregate innovation.

Secondly, this study contributes to the ongoing discourse on the relationship between innovation and competition. Previous research has primarily utilized cross-industry variations to identify this relationship, with some studies uncovering an "inverted-U" shaped relationship (Blundell et al., 1999; Aghion et al., 2005, 2009). However, it has increasingly been acknowledged that innovation and market structure are endogenously determined, implying that their relationship cannot be adequately captured by a universal function (Gilbert, 2020). Recent studies have shifted the focus towards examining the effects of specific competition shocks, such as mergers of large firms and the exogenous entry of competitors, and have identified heterogeneous effects across different market environments and industries (Goettler and Gordon, 2011; Gutiérrez and Philippon, 2017; Autor et al., 2020; Liu and Ma, 2020). This study enriches the existing literature by considering selective subsidies as another type of shock affecting innovation competition among firms. Furthermore, it contributes to the understanding of heterogeneous effects of competition shocks across industries by revealing the divergent impacts on different innovation agents. Specifically, this study finds that industries characterized by more intense competition and higher rates of firm entry are more likely to experience adverse effects from subsidizing leading firms.

Finally, this study contributes to the literature on the role of different innovation agents, with a particular focus on the relationship between innovation and firm size, a central debate in the field. Earlier studies on this topic have been comprehensively surveyed in Cohen (2010). Recent research continues to provide mixed evidence: some argue that the contributions of leading firms to nationwide total factor productivity growth are declining (Gutiérrez and Philippon, 2019), and that younger firms play a more significant role in exploring new products (Akcigit and Kerr, 2018) and generating high-quality inventions (Arora et al., 2023). Conversely, others emphasize the increasingly dominant role of large firms in driving innovation (Garcia-Macia et al., 2019; König et al., 2022; Braguinsky et al., 2023). In this study, the negative overall effects of the NTIDE policy on aggregate innovation suggest that new firms and small-to-medium enterprises, which typically lag behind the productivity frontier, may play a more substantial role in driving aggregate innovation in China. This finding provides new empirical evidence to this ongoing debate.

The remainder of this paper is structured as follows. Section 2 summarizes the background and key characteristics of the NTIDE policy. Section 3 develops a theoretical framework to formulate the propositions. Section 4 conducts an enterprise-level investigation to empirically examine the propositions. Section 5 estimates the overall effects at the city–industry level to uncover the aggregate impacts of divergent influences on different firms. Section 6 further investigates the spillover effects of the NTIDE policy, encompassing inter-industry, spatial, and local knowledge spillovers. Section 7 concludes the study.

2 Policy background

In September 2010, the Ministry of Industry and Information Technology (MIIT) of China issued an official document to launch the "National Technological Innovation Demonstration Enterprise (NTIDE)" policy.[1] The document emphasizes that the NTIDE policy is designed to encourage the innovation activities of industrial enterprises, thereby facilitating the national transition to innovation-driven growth. Specifically, the policy seeks to support "enterprises with strong technological innovation capabilities, significant innovation performance, and an important role in demonstrating and guiding key industrial sectors."

Demonstration enterprises are certified annually, with the first batch identified at the end of 2011. The certification process typically begins in the first half of each year, with enterprises submitting applications to provincial government departments.[2] These departments conduct preliminary audits, generate recommendation lists, and forward them to the MIIT. The MIIT usually publishes a proposed list between August and October, followed by the final list in November or December. Figure 1 shows the accumulative number of demonstration enterprises from 2011 to 2017, with an average of 71 enterprises being awarded the title nationwide each year. Demonstration enterprises are required to undergo a re-evaluation every three years, and those that no longer meet the criteria lose this title. Between 2014 and 2017, an average of only 0.75 enterprises failed the re-evaluation annually, resulting in an average passing rate of 99.2%. [3]

Based on the requirements outlined in the policy documents, the certification process and subsequent subsidy policies can be summarized by the following three characteristics.[4] First, the policy establishes minimum standards for the size and status of the applicant enterprises, ensuring that only those with a certain number of years in operation, scale of production, and innovation output are initially eligible. For instance, one of the basic requirements stipulated in the policy is that applying enterprises must "have a certain scale of production and operation, with more than 300 employees, annual sales revenue exceeding 30 million CNY, and total assets greater than 40 million CNY." Additionally, the policy requires that enterprises possess innovation-related titles at the provincial level or above when submitting their appli-

[1] This document is available at `https://www.miit.gov.cn/gyhxxhb/jgsj/kjs/wzpz/ztzl/gjjscxsfqy/tzgg/art/2020/art_1cd6b9bf44444bedb642f08a52f3eaba.html` (accessed February 2025).

[2] A few enterprises governed by the central government submit their application materials directly to the MIIT.

[3] A detailed summary of the number of certified enterprises, re-evaluated enterprises, and pass rate is provided in the Appendix Table A.1.

[4] Further details and background on the policy can be found in the Appendix.

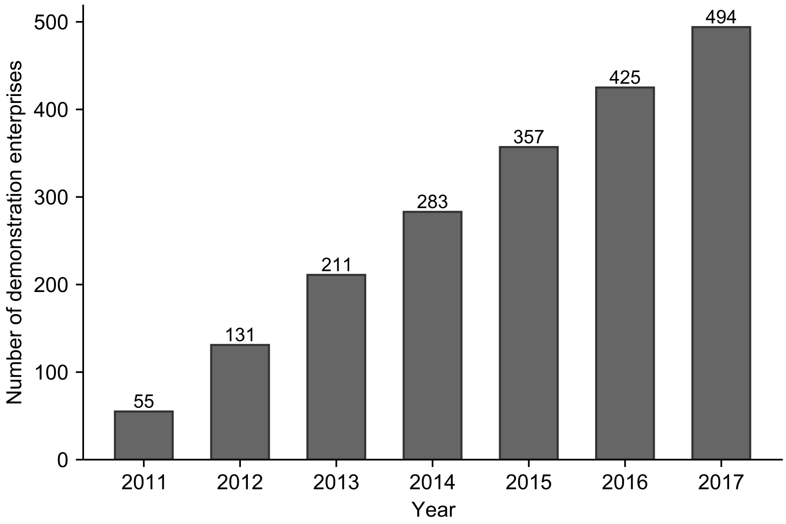

Figure 1: Accumulated number of demonstration enterprises by year

Notes: This figure presents the accumulated number of demonstration enterprises by year from 2011 to 2017. From 2011 to 2013, the accumulated number is the sum of newly certified enterprises in all preceding years. In 2014, demonstration enterprises certified in 2011 underwent their first re-evaluation, a process that continued annually for subsequent cohorts over the following years. Consequently, from 2014 to 2017, the accumulated number reflects the sum of newly certified enterprises in all preceding years, adjusted by subtracting the number of enterprises that failed the re-evaluation and consequently lost the policy title.

cations. As a result, the policy prevents small and medium-sized enterprises, as well as startups, from qualifying for the demonstration enterprise title to a significant extent.

Second, during the annual certification process, the government places a strong emphasis on specific financial indicators and innovation output from the previous year. Enterprises are required to submit detailed materials to the government, including reports on key financial indicators (such as total assets, main business income, total profit, and market share of major products), R&D investment, and the number of patent applications filed in the last year. Local governments conduct a preliminary review, complete a "recommended enterprise summary table," and forward it to the MIIT along with the materials submitted by the enterprises. In addition to the enterprise name, the summary table includes information on the type and industry of the enterprise, as well as details on R&D investment, main business revenue, new product sales revenue, and the number of patent applications for each recommended enterprise. Given that the number of enterprises awarded the demonstration enterprise title is small each year, it is typically "star enterprises" with outstanding business performance and significant patent output that are granted the policy title.[5]

Third, once enterprises are granted the policy title, both central and local governments commit to providing innovation support to the demonstration enterprises. The policy document stipulates that "the MIIT shall provide guidance and support to the demonstration enterprises in industrial technological innovation." Local-level policy documents further elaborate on this commitment. For instance, the policy document from Chongqing, released in October 2014, specifies that "the Municipal Economy and Infor-

[5]In the Appendix, I analyze the number of patents, R&D expenditures, and total assets of the listed demonstration enterprises in the year preceding their application and calculate their rankings among all listed firms in the corresponding industries within their respective provinces. I find that the average ranking for each variable falls between the 70th and 80th quartiles. In industries where there are no more than three listed demonstration enterprises nationwide, the average ranking of demonstration enterprises in terms of invention patent applications approaches the 85th percentile, and their average ranking in R&D investment reaches the 87th percentile. Given that listed companies generally have larger production scales, R&D expenditures, and productivity levels compared to the broader enterprises population, this observation supports the conclusion that demonstration enterprises are clear leaders in their respective local markets.

mation Commission and the Municipal Bureau of Finance shall prioritize support for the technological innovation of demonstration enterprises, offering preferential funding for innovation projects of these enterprises through municipal industrial revitalization special funds."[6] Additionally, the title of demonstration enterprise, as an intangible asset, provides enterprises with enhanced access to financing facilities.[7]

Taken together, in this paper, I treat the NTIDE policy as a mechanism for certifying and subsidizing "innovation star firms."

3 Theoretical framework

In this section, I develop a theoretical framework to analyze the impact of the NTIDE policy on the dynamics of innovation competition among firms. The framework is simplified to focus on a two-period price game and innovation competition between a leading firm and other incumbents or potential entrants, where the latter is represented by a single representative firm for tractability. First, I model the R&D expenditure decision of the monopolistic leading firm in response to government innovation subsidies during the first period, with the objective of maximizing its total profits over the two periods. Subsequently, I model the R&D expenditure decision of the representative competitor firm in the first period, which determines its productivity distribution in the second period. If the competitor achieves higher productivity than the leading firm in the second period, it enters the market and captures the monopolistic profits.

To begin, consider an economy composed of multiple industries, indexed by $i \in \mathscr{I}$, and a single final goods sector characterized by a Dixit–Stiglitz aggregator with a constant elasticity of substitution $\eta > 1$. The production of the final good is expressed as:

$$Y_t = \left(\sum_{i \in \mathscr{I}} Y_{i,t}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}, \tag{1}$$

where $Y_{i,t}$ represents the output of goods in industry i in period t. The CES aggregation structure implies that the total demand faced by firms in industry i is given by:

$$Y_{i,t} = \left(\frac{P_{i,t}}{P_t} \right)^{-\eta} Y_t, \tag{2}$$

where $P_{i,t}$ denotes the price of goods produced in industry i, and $P_t \equiv \left(\sum_{i \in \mathscr{I}} P_{i,t}^{1-\eta} \right)^{1/(1-\eta)}$ is the aggregated price index.

Assume that goods produced by different firms within the same sector are perfect substitutes. Firms within each sector are heterogeneous in productivity and compete on prices to capture market share. Following the framework proposed by Akcigit et al. (2023), I adopt the assumption of a two-stage pricing game in each period. In the first stage, firms decide whether to pay an arbitrarily small entry fee to participate in price competition in the second stage. In the second stage, only those firms that have paid the fee compete by setting prices. This assumption ensures that only the leading firmthe one with the

[6]This document is available at `https://www.miit.gov.cn/gyhxxhb/jgsj/kjs/wzpz/ztzl/gjjscxsfqy/dfwj/art/2020/art_7a52a81b572f462aab00db3735240142.html` (accessed February 2025).

[7]Although there are no definitive statistics detailing the strength of the policy's benefits or the effectiveness of its implementation, some local media reports offer insights into the policy's impact. For example, a report by Shanxi Daily on February 20, 2023, mentioned that "In 2022, China Merchants Bank granted a total of 4.56 billion CNY in credit to 37 technological innovation demonstration enterprises and provided 3.07 billion CNY in financial support." The report also highlighted that the Provincial Department of Industry and Information Technology would provide comprehensive and multi-level support to these enterprises, including industrial policy assistance, technological reform funds, industry–finance integration, and production–demand cooperation. This reflects the local governments' policy intention to foster the development of local industries by supporting technology innovation enterprises.

highest productivitypays the fee, proceeds to the second stage, and ultimately sets the monopoly price. Accordingly, the subscript i is also used to denote the sole firm in industry i.

Firm i's production technology is characterized by a constant-returns-to-scale Cobb–Douglas production function:

$$Y_{i,t} = A_{i,t} K_{i,t}^{\alpha} L_{i,t}^{1-\alpha}, \tag{3}$$

where $\alpha \in (0,1)$, $K_{i,t}$ represents capital input, $L_{i,t}$ represents labor input, and $A_{i,t}$ denotes the productivity level. Given the assumption of constant returns to scale, it can be proved that the unit cost of product for firm i is constant and given by

$$C_{i,t} = \frac{\alpha^{-\alpha}(1-\alpha)^{\alpha-1} r_t^{\alpha} w_t^{1-\alpha}}{A_{i,t}}, \tag{4}$$

where r_t and w_t are the exogenous prices of capital and labor, respectively. Let $C_t \equiv \alpha^{-\alpha}(1-\alpha)^{\alpha-1} r_t^{\alpha} w_t^{1-\alpha}$. The unit cost $C_{i,t} = C_t / A_{i,t}$ is thus determined by firm i's productivity and an exogenous term. Consequently, the profit of firm i in period t is

$$\pi_{i,t} = P_{i,t} Y_{i,t} - C_{i,t} Y_{i,t}. \tag{5}$$

Using Equations (2) and (5), the profit maximization problem yields the optimal price and maximum profit. The latter is given by

$$\pi_{i,t}^{*} = \tilde{\Pi}_t A_{i,t}^{\eta-1}, \tag{6}$$

where $\tilde{\Pi}_t \equiv \eta^{-\eta}(\eta-1)^{\eta-1} Y_t P_t^{\eta} C_t^{1-\eta}$ represents a combination of all macroeconomic factors. This formulation underscores a monotonic relationship between productivity and profits: firms endowed with higher productivity levels ($A_{i,t}$) achieve greater equilibrium profits.

In the two-period model, the leading firm in period t allocates a portion of its profit on R&D activities to enhance its productivity and, consequently, its profit in period $t+1$. The resulting productivity in period $t+1$ is given by

$$A_{i,t+1} = (1+\lambda) A_{i,t}, \tag{7}$$

where $\lambda \geq 0$ denotes the productivity growth rate. This growth rate is non-negative, as the leading firm retains the option to revert to the old technology in the event of unsuccessful innovation. To capture the inherent uncertainty of innovation, I assume that λ is drawn from a distribution $F_{\lambda}\left(x \mid I_{i,t}\right)$, where $I_{i,t}$ represents the firm's total R&D expenditure in period t. It is natural to assume that for any $I_{i,t}^{1} > I_{i,t}^{0}$, $\lambda \mid I_{i,t}^{1}$ first-order stochastically dominates $\lambda \mid I_{i,t}^{0}$. This assumption reflects the intuitive notion that higher R&D expenditure increases the probability of a larger draw of productivity in the second period. The leading firm's total R&D expenditure includes private R&D investments $R_{i,t}$ and exogenous government-provided innovation subsidies $S_{i,t}$. Following the extensive literature suggesting that public funding does not entirely crowd out private R&D investments (e.g., Feldman and Kelley, 2006; Falk, 2007; Pallante et al., 2023), I assume that total R&D expenditure is a CES aggregation of private R&D investments and subsidies, expressed as:

$$I_{i,t} = \left(R_{i,t}^{\frac{\sigma-1}{\sigma}} + S_{i,t}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{8}$$

where $\sigma > 0$ captures the degree of substitutability between private R&D investments and subsidies. In the limit as $\sigma \to \infty$, $I_{i,t} = R_{i,t} + S_{i,t}$, representing the case where they are perfectly substitutable.

Suppose firms are risk-neutral and denote the discount rate as $\beta \in (0,1)$. The leading firm's intertemporal profit maximization problem involves selecting the optimal level of private R&D investments to maximize its total expected discounted profit. This maximization problem can be expressed as:

$$\begin{aligned}\max_{R_{i,t}} \Pi_i &= \mathbb{E}\left[\pi^*_{i,t} - R_{i,t} + \frac{1}{1+\beta}\pi^*_{i,t+1} \mid I_{i,t}\right] \\ &= \tilde{\Pi}_t A_{i,t}^{\eta-1} - R_{i,t} + \frac{1}{1+\beta}\tilde{\Pi}_{t+1} A_{i,t}^{\eta-1}\mathbb{E}\left[(1+\lambda)^{\eta-1} \mid I_{i,t}\right].\end{aligned} \tag{9}$$

Solving this maximization problem necessitates the specification of $\mathbb{E}\left[(1+\lambda)^{\eta-1} \mid I_{i,t}\right]$. Here, I adopt a logarithmic assumption, assuming that this expectation value is

$$\mathbb{E}\left[(1+\lambda)^{\eta-1} \mid I_{i,t}\right] = \tau \ln I_{i,t}, \tag{10}$$

where $\tau > 0$ is a parameter controlling for the measurement units. This assumption implies that expected productivity increases with higher R&D expenditure, while the marginal gains diminish. Based on this, the following two propositions can be derived (see the Appendix for proofs):

Proposition 1. *As government-provided innovation subsidies to the leading firm increase, the direction of the change in its private R&D investments depends on the degree of substitutability between private R&D investments and subsidies σ.*

Proposition 2. *As government-provided innovation subsidies to the leading firm increase, its total R&D expenditure rises, regardless of the value of σ.*

Subsequently, for analytical tractability, I model other competitor firms as a representative firm and analyze its decision regarding R&D expenditure in response to the NTIDE policy. It is common knowledge that the leading firm received higher innovation subsidies in the first period. Consequently, the representative firm anticipates a rightward shift in the productivity distribution of the leading firm in the subsequent period. The representative firm's optimization problem involves maximizing its profits by determining the optimal level of R&D investments.

Let the R&D investments of the representative firm in the first period is $R_{o,t}$, which brings a new technology in the second period. Suppose that the derived productivity $A_{o,t+1}$ is drawn from a distribution $F_A\left(x \mid R_{o,t}\right)$, where for any $R^1_{o,t} > R^0_{o,t}$, $A_{o,t+1} \mid R^1_{o,t}$ first-order stochastically dominates $A_{o,t+1} \mid R^0_{o,t}$. To simplify the subsequent analysis, two additional assumptions are imposed on $F_A\left(x \mid R_{o,t}\right)$. First, the probability density is unimodal, a property implicitly adopted in many studies where researchers employ log-normal or Fréchet distributions to model productivity distributions. Second, an increases in $R_{o,t}$ shifts the productivity density to the right without altering its shape; in other words, $R_{o,t}$ affects the first-order moment of the distribution but leaves higher-order moments unchanged. This two assumptions are used to ensure that $\partial^2 f_A\left(x \mid R_{o,t}\right) / \left(\partial R_{o,t} \partial x\right)$ only has one zero point, a property used in the proof of Proposition 3.

If this productivity exceeds the leader's productivity $(1+\lambda) A_{i,t}$, the representative firm enters the market and capture the entire market share originally held by the leader firm. Otherwise, it refrains from entering the market and receives no payoffs. Accordingly, given the realization of productivity is x, the probability that it enters the market is $\Pr\{x > (1+\lambda) A_{i,t}\} = F_\lambda\left(x/A_{i,t} - 1 \mid I_{i,t}\right)$. Based on Equation (6), the expected profits is given by

$$\Pi_o = -R_{o,t} + \frac{1}{1+\beta}\int_0^\infty F_\lambda\left(\frac{x}{A_{i,t}} - 1 \mid I_{i,t}\right)\tilde{\Pi}_{t+1} x^{\eta-1} \mathrm{d}F_A\left(x \mid R_{o,t}\right). \tag{11}$$

Denote the integral in Equation (11) as $\delta\left(R_{o,t}, I_{i,t}\right)$, which represents the expected payoffs of the representative firm. Given that $F_A\left(x \mid R_{o,t}\right)$ exhibits first-order stochastic dominance with respect to $R_{o,t}$

and the integrand is strictly increasing in x, it follows that $\partial\delta\left(R_{o,t}, I_{i,t}\right)/\partial R_{o,t} > 0$. To ensure the existence and uniqueness of the solution to the first-order condition, I further impose the Inada conditions to this integral. Specifically, I assume that $\partial^2\delta\left(R_{o,t}, I_{i,t}\right)/\partial R_{o,t}^2 < 0$, $\lim_{R_{o,t}\to 0}\partial\delta\left(R_{o,t}, I_{i,t}\right)/\partial R_{o,t} = \infty$, and $\lim_{R_{o,t}\to\infty}\partial\delta\left(R_{o,t}, I_{i,t}\right)/\partial R_{o,t} = 0$. Under these assumptions, the following proposition can be derived (see the Appendix for proof):

Proposition 3. *As government-provided innovation subsidies to the leading firm increase, firms exhibiting larger productivity lag relative to the leading firm will decrease their total R&D expenditure, thereby leading to a decline in their probability of firm entry.*

Taken together, this theoretical model suggests that the NTIDE policy, which subsidizes leading firms without reducing subsidies to other firms, increases the total R&D expenditure of the leading firm but reduces the R&D expenditure of other firms and the entry of new firms.

4 Firm dynamics: How the policy works and how enterprises react?

This section examining the propositions suggested by the theoretical framework by exploring different firm dynamics, including the policy effects on government-provided R&D subsidies and R&D expenditure of demonstration enterprises and other incumbent competitors, as well as firm entries.

4.1 Policy effects on subsidies and R&D expenditures

The primary challenge in identifying firm-level treatment effects lies in finding the appropriate control group for the treated firms. To address this, I restrict the sample to listed firms during 2008 to 2018, as this ensures accessibility to a wide range of financial and innovation indicators. I then employ a matching strategy based on specific financial and innovation indicators that are emphasized in the certification process of the NTIDE policy. This approach aims to identify a control group of firms that exhibit comparable levels of competitiveness in pursuing the policy title relative to treated firms, thereby constructing a more credible counterfactual.[8]

I first obtain the announcements of certified demonstration enterprises over the years from the official website of the Ministry of Industry and Information Technology (MIIT), which provides the name and province of each firm. The list of firm names is then matched with a comprehensive business registration record database provided by the commercial database "Tianyancha" (`https://www.tianyancha.com`) to identify the city and industry of each demonstration enterprise.[9] Since the firms are certified and publicized in November or December, I consider them to be first treated in the year immediately following the certification year. Consequently, as my sample spans from 2008 to 2018, this study includes seven batches of demonstration enterprises certified from 2011 to 2017 and treated from 2012 to 2018.

Subsequently, I obtain financial and innovation indicators of listed firms from two databases: the China Stock Market & Accounting Research Database (CSMAR, `https://data.csmar.com/`) and the Chinese Research Data Services Platform (CNRDS, `https://www.cnrds.com`). All demonstration enterprises are matched with these databases, retaining 212 listed firms out of the 494 demonstration enter-

[8] Inspired by the approach of Greenstone et al. (2010) in which "winners" and "runner-up losers" are compared for identification, a more ideal control group would consist of firms that are recommended by local governments but ultimately not certified by the central government. Moreover, another potential method is to use province-level demonstration enterprises as the control group, as the province-level title is typically a prerequisite for firms to be recommended by local governments. Unfortunately, these two methods are infeasible in practice, as local governments seldom publicize the recommended list or the list of province-level title holders.

[9] In China, the industrial classification system follows the *Industrial Classification for National Economic Activities* (GB/T 4754-2017), which organizes industries into a hierarchical structure with four levels: 20 sectors (*menlei*), 97 divisions (*dalei*), 473 groups (*zhonglei*), and 1,382 classes (*xiaolei*). In this study, industries refer to the 97 divisions (*dalei*).

prises. Based on the city and industry of each demonstration enterprise, listed firms that are in the same city and industry but did not receive the policy title are identified as local competitor firms. This yields two groups of firms influenced by the policy: one treatment group consists of demonstration enterprises directly affected by the policy, and the other treatment group consists of local competitors of the demonstration enterprises, which, according to the theoretical model, may experience negative effects due to the alteration of innovation competition resulting from the policy.

To ensure comparability between the treatment and control groups in the identification, I first exclude firms that did not file any patent applications in the first sample year (i.e., 2008) and firms with missing data during the sample period, resulting in a balanced panel dataset. Next, I employ propensity score matching (PSM) within each "stack" (explained in detail later) to identify the four nearest control group firms for each treated firm in the year immediately preceding the application. The covariates used in the PSM include the number of patent applications, main business revenue, R&D investment, industry, and government-provided R&D subsidies in the year prior to the application. The first four variables are key indicators highlighted in the summary table of recommended enterprises submitted to the central government by local governments (see Appendix Table A.3), while the last variable serves as a proxy for potential political connections.

To address staggered treatment adoption across cohorts, I employ the stacked difference-in-differences (stacked DD) estimator (also see in Deshpande and Li (2019) and Johnson et al. (2023)). This approach involves constructing a separate quasi-experimental design (referred to as a "stack") for each treatment cohort by pooling observations from the treated group with all never-treated samples. The seven stacks—one for each cohort—are subsequently combined into a unified dataset. The empirical specification is estimated as follows:

$$y_{f,i,t,s} = \beta \times \mathbb{1}\{Treated\}_{f,t} + X_f^{2008\prime}\lambda_{t,s}\gamma + \eta_{f,s} + \rho_{i,t,s} + \varepsilon_{f,i,t,s}, \tag{12}$$

where the subscript f, i, t, and s refer to firm, industry, year, and stack, respectively. When examining the policy effects on demonstration enterprises, $\mathbb{1}\{Treated\}_{f,t}$ takes the value of 1 if firm f holds the policy title in year t. Conversely, when evaluating the policy effects on competitor firms, $\mathbb{1}\{Treated\}_{f,t}$ equals 1 if there is at least one demonstration enterprise in the same city and industry as non-demonstration enterprise f in year t. The vector $X_f^{2008\prime}$ represents firm f's characteristics in the initial sample year (i.e., 2008), including the logarithm of total assets, return on assets, and the logarithm of operating revenue. To avoid the issue of "bad control variables"—where control variables themselves may be influenced by the treatment—I interact this vector with stack-specific year fixed effects $\lambda_{t,s}$ (Lu et al., 2019; Xu, 2022). Additionally, $\eta_{f,s}$ represents stack-specific firm fixed effects, $\rho_{i,t,s}$ denotes stack-specific industry–year interactive fixed effects, and $\varepsilon_{f,i,t,s}$ is the error term. In this model, the coefficient β can be interpreted as a weighted average of the seven average treatment effects estimated for each stack. Standard errors are clustered at the firm level.

Furthermore, the following event-study specification is estimated to examine pre-trends and investigate the dynamic effects of the policy:

$$y_{f,i,t,s} = \sum_{m=-4}^{6} \beta^m \times \mathbb{1}\{Treatment\ group\}_f \times \mathbb{1}\{T^R = m\}_{t,s} + X_f^{2008\prime}\lambda_{t,s}\gamma + \eta_{f,s} + \rho_{i,t,s} + \varepsilon_{f,i,t,s}, \tag{13}$$

where $\mathbb{1}\{T^R = m\}_{t,s}$ represents a dummy variable that captures the relative timing of the policy treatment. This variable is contingent on both the absolute time period t and the treatment timing specific to the corresponding stack. The fourth period prior to the treatment and all earlier periods are aggregated into a single period, while the sixth period following the treatment and all subsequent periods are similarly consolidated. The reference period is the year immediately preceding the treatment year within each stack.

4.1.1 Subsidies

I first estimate the policy effects on firms' government-provided R&D subsidies. On one hand, the analysis for demonstration enterprises evaluates whether the government's commitment to providing R&D subsidies following certification is effectively implemented. On the other hand, if the policy leads to an increase in R&D subsidies for demonstration enterprises, examining changes in subsidies for their local competitors allows for testing a key competitive hypothesis in this section: the government may reallocate R&D subsidies by reducing subsidies for other local firms, thereby diminishing their total R&D expenditures. This channel introduces confounding influences that diverge from the competitive effects outlined in the theoretical model.

To calculate the amount of R&D subsidies received by listed firms each year, the CSMAR database provides information on government grants from each listed firm's notes to the financial statements, which includes the amount and a brief description of each government subsidy. I then define eight innovation-related keywords and check whether the description contains one of them.[10] Using this method, I identify 29.1% of the subsidies as R&D subsidies and calculate the annual R&D subsidies received by each listed firm.

Figure 2 presents the estimation results from the event study analysis. The figure demonstrates that, prior to the implementation of the policy, both demonstration enterprises and competitor firms exhibited trends consistent with those of the control group, suggesting the absence of pre-existing trends. Following the policy treatment, the R&D subsidies received by demonstration enterprises display a clear upward trend. However, the subsidies received by competitor firms do not exhibit a declining trend; in fact, they show a slight increase in the fourth and fifth years post-treatment. This finding indicates that the NTIDE policy provides additional subsidies to leading firms without reducing the subsidies allocated to other firms.

The estimation results of Equation (12), with the dependent variable being the logarithm of R&D subsidies, are reported in Table A.3. A consistent pattern is observed in the results. On average, the policy increases the government subsidies received by demonstration enterprises by 47.4% and does not reduce subsidies for competitor firms; in fact, positive point estimates are derived for these firms.

4.1.2 R&D expenditures

Next, I investigate the policy effects on firms' R&D expenditures. Figure 3 demonstrates significantly divergent trajectories for demonstration enterprises and competitor firms. The NTIDE policy incentivizes demonstration enterprises to enhance their investments in R&D activities. Conversely, it appears to discourage competitor firms from engaging in innovation, as evidenced by the persistent negative effects depicted in the figure, despite the absence of a reduction in their resource allocations. This finding is consistent with the discouraging effects anticipated by the theoretical framework.

Estimation results from the stacked DD estimator, as detailed in Appendix Table A.4, suggests that the NTIDE policy encourages demonstration enterprises to increase their R&D expenditure by 30%. This helps clarify the substitutive or complementary relationship between government subsidies and private R&D expenditures. On average, the R&D subsidies received by demonstration enterprises accounted for 13.2% of their total R&D expenditures. Assuming this proportion remains unchanged and simplifying

[10] The eight keywords are "innovation (*chuangxin*)," "research (*yanjiu*)," "R&D (*yanfa*)," "scientific research (*keyan*)," "patent (*zhuanli*)," "talent (*rencai*)," "technology (*keji*)," and "technical (*jishu*)."

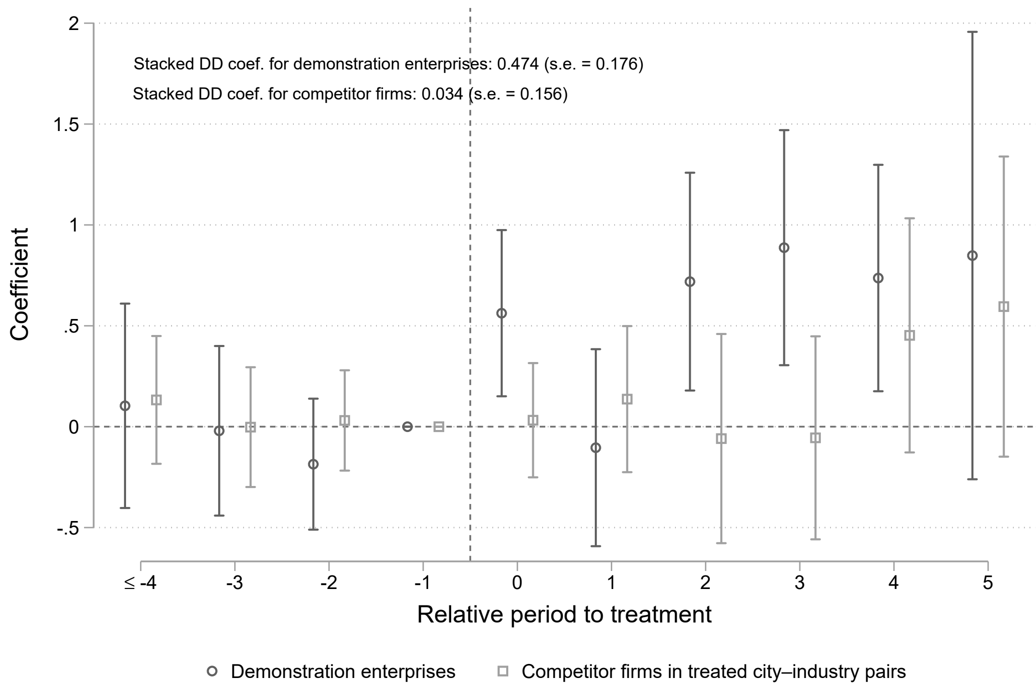

Figure 2: Event study of R&D subsidies

Notes: This figure presents the estimated coefficients obtained from the event study on government-provided R&D subsidies of demonstration enterprises and competitors firms located in the same city and industry as the demonstration enterprises. The circles represent the point estimates, and the lines indicate the 95% confidence intervals. The figure also reports the average treatment effects for the two treatment groups, calculated from the estimation of Equation (12). Additional details of the stacked DD estimates are provided in Appendix Table A.3.

total R&D expenditures as the sum of R&D subsidies and private investment, the policy effects of 47.4% increase in R&D subsidies and 30% increase in R&D expenditures implies that the policy encourages a 27.4% increase in private investment. Therefore, government R&D subsidies not only did not crowd out private R&D investment but also encouraged demonstration enterprises to undertake more, indicating a complementary relationship between the two.

On the contrary, the NTIDE policy may result in a 13.3% reduction in the total R&D expenditures of competitor firms, although this effect lacks statistical significance. This point estimate is somewhat smaller than that observed for demonstration enterprises. However, given that the number of demonstration enterprises in each city and industry rarely exceeds one, while there are multiple listed firms acting as competitors, this finding implies the potential for negative overall effects.

It is crucial to emphasize that the theoretical model anticipates heterogeneous responses among competitor firms. Specifically, competitor firms with a larger productivity gap are expected to face diminished incentives for R&D investment, as they anticipated future productivity advancements of the leading firm. Conversely, the responses of competitor firms with a smaller productivity gap remain theoretically indeterminate. In other words, the competitive effect is inherently heterogeneous across markets with different productivity distributions. As a result, the above estimates is essentially an average of treatment effects across different market structures.

To uncover this heterogeneity, I estimate the annual total factor productivity (TFP) for each listed firm using the methodology proposed by Olley and Pakes (1996), thereby deriving the TFP distribution of listed firm for each city–industry pair in which the demonstration enterprises are located. Subsequently, I calculate the Gini coefficient of each distribution to quantify the degree of productivity dispersion among firms. A higher Gini coefficient signifies that a larger proportion of firms lag behind the technological

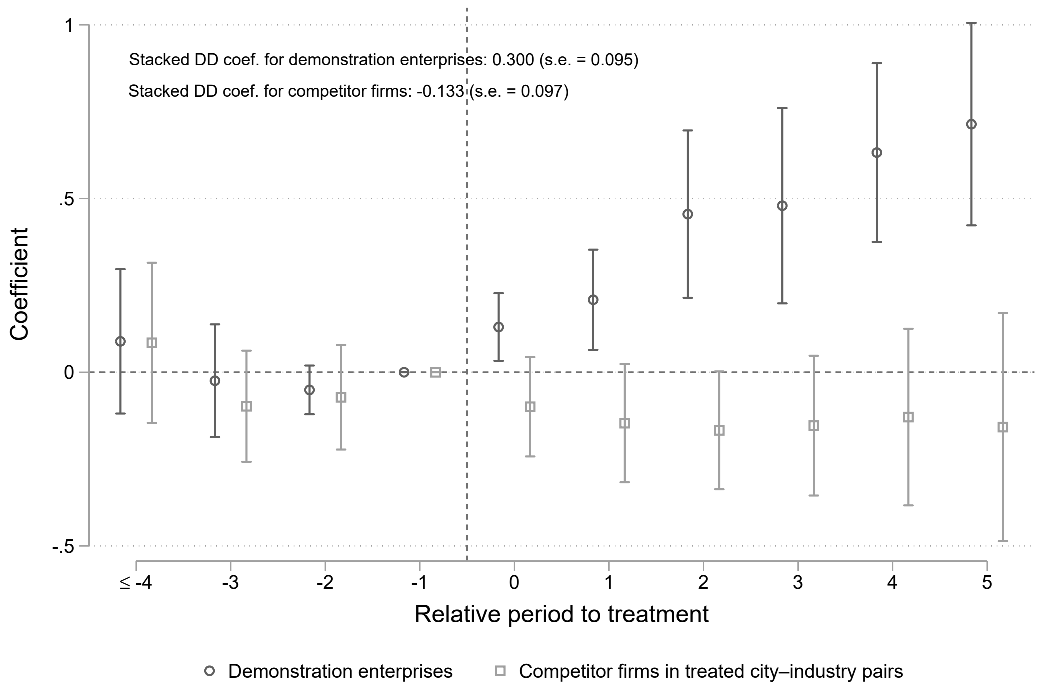

Figure 3: Event study of R&D expenditures

Notes: This figure presents the estimated coefficients obtained from the event study on R&D expenditures of demonstration enterprises and competitor firms located in the same city and industry as the demonstration enterprises. The circles represent the point estimates, and the lines indicate the 95% confidence intervals. The figure also reports the average treatment effects for the two treatment groups, calculated from the estimation of Equation (12). Additional details of the stacked DD estimates are provided in Appendix Table A.4.

frontier within their respective local markets. Using this measure, I categorize competitor firms into two distinct groups: those operating in markets with the top 25% degree of productivity dispersion and those in markets with lower levels of dispersion. Based on this, I conduct event studies for each group to examine the heterogeneity in their responses.

Figure 4 presents the results of the event study. The two groups of competitor firms exhibit divergent trends following the treatment: the R&D expenditures of competitor firms in markets with less dispersed productivity distributions show almost no change, whereas those in markets with greater productivity dispersion experience a significant decline in R&D expenditures by 39.2%. This finding suggests that the reduction in R&D expenditures among competitor firms is primarily driven by firms that are further from the productivity frontier, a result that aligns with the theoretical prediction.[11]

4.2 Policy effects on firm entries

This subsection shifts attention to investigating the effects on potential entrants. In the theoretical model, a reduction in firms' R&D investment implies a lower likelihood of new firms entering the market and competing for the market share of leading firms. Consequently, it is expected that the NTIDE policy will have a negative impact on new firm entry.

To examine the impact on firm entry, firm-level data must be aggregated to a higher level of analysis. To achieve this, I construct a city–industry panel dataset to investigate changes in the number of new firm entries following the emergence of a demonstration enterprise within a specific city–industry pair.

[11] To confirm that this trend is not attributable to changes in government R&D subsidies for the two groups, Appendix Figure A.6 displays the event study graphs for the policy R&D subsidies received by the two groups of competitor firms. The estimation results reveal no significant change in government R&D subsidies for either group.

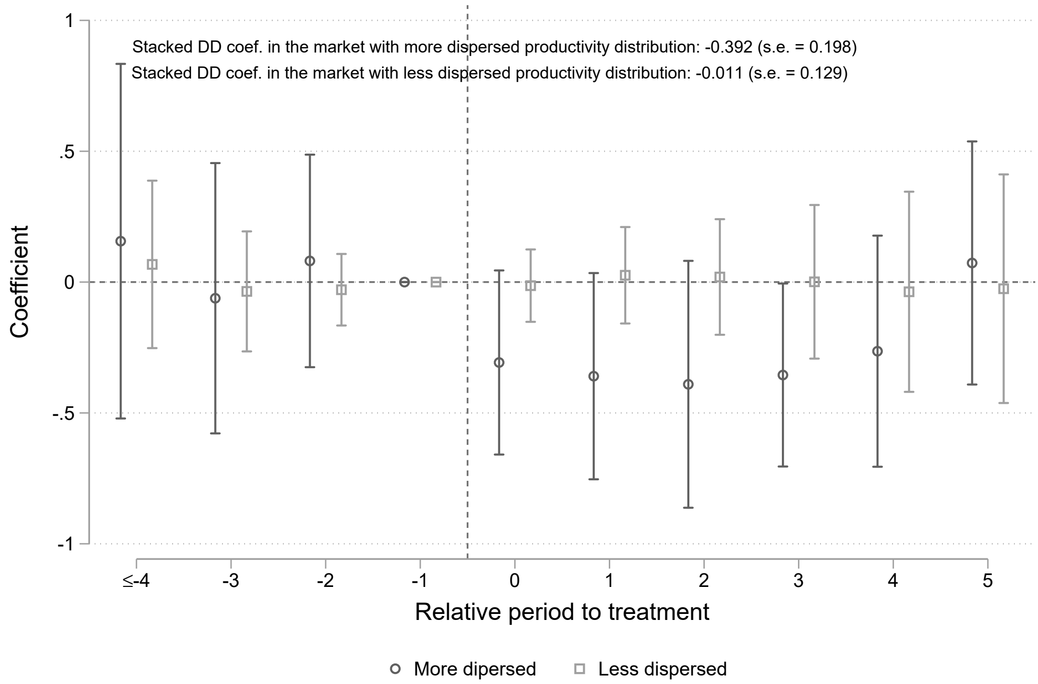

Figure 4: Event study of R&D expenditures by TFP distribution

Notes: This figure presents the estimated coefficients obtained from the event study on R&D expenditures of two groups of competitor firms: those operating in markets with the top 25% degree of productivity dispersion, as measured by the Gini coefficient of the TFP distribution of listed firms, and those in markets with lower levels of dispersion. The circles denote the point estimates, while the lines represent the 95% confidence intervals. Additionally, the figure reports the average treatment effects for the two treatment groups, computed from the estimation of Equation (12). Further details regarding the stacked difference-in-differences (DD) estimates are provided in Appendix Table A.5.

Utilizing the business registration record database provided by "Tianyancha," I identify newly established private firms, foreign firms, and public firms (including state-owned and collectively owned enterprises) in each year based on their establishment dates and firm types. These firms are subsequently aggregated to the city–industry level according to their respective industries and locations.

For identification, I again employ the stacked DD method. Based on the timing of the first demonstration enterprise's emergence in each city–industry pair, the sample is divided into seven treatment cohorts (with treatment years ranging from 2012 to 2018). City–industry pairs that did not have any demonstration enterprises before 2018 serve as the control group. Consistent with the approach used to construct the firm-level dataset, each treatment cohort is matched with all control groups, creating seven stacks. These stacks are then merged into a single dataset. The dataset covers 337 cities and 97 industries, with a sample period spanning from 2008 to 2018. The estimation model is specified as follows:

$$\ln Entry_{c,i,t,s} = \beta \times \mathbb{1}\{Treated\}_{c,i,t} + \eta_{c,i,s} + \rho_{i,t,s} + \gamma_{c,t,s} + \varepsilon_{c,i,t,s}, \tag{14}$$

where the subscripts c, i, t, and s represent city, industry, year, and the stack, respectively. $\ln Entry_{c,i,t,s}$ denotes the logarithm of the number of new firm entries in industry i of city c in year t. The variable $\mathbb{1}\{Treated\}_{c,i,t}$ takes the value of 1 for all years after the first demonstration enterprise emerges in industry i of city c. The term $\eta_{c,i,s}$ represents stack-specific city–industry fixed effects, which control for time-invariant differences between treatment and control groups. $\rho_{i,t,s}$ denotes stack-specific industry–year fixed effects, primarily used to control for industry-level heterogeneity. For example, the wholesale industry has the highest average annual number of firm entries, but firms in this industry are less likely to engage in innovation and thus are less likely to be designated as demonstration enterprises (see Figure A.4 in the Appendix). Additionally, $\gamma_{c,t,s}$ represents stack-specific city–year fixed effects, which are included to account for city-level innovation policies.[12] Finally, $\varepsilon_{c,i,t,s}$ is the error term. To account for spatial and industry correlations, standard errors are two-way clustered at the city and industry levels.

Table 1 reports the estimated results regarding the entry of private and foreign firms. In columns (1) and (3), I first estimate a simplified specification, which excludes stack-specific city–industry fixed effects and year fixed effects. Columns (2) and (4), on the other hand, present the results from the full specification of Equation (14). After controlling for heterogeneity at the city and industry levels, the absolute magnitude of the estimated coefficients decreases significantly, but they remain statistically significant. These results are consistent with theoretical expectations: when a leading firm in a city–industry pair receives subsidies, it discourages the entry of private and foreign firms, leading to an average reduction of 5.1% in the number of private firm entries and 14% in the number of foreign firm entries.

It is evident that the sample sizes in columns (3) and (4) are significantly smaller than those in the first two columns. This discrepancy arises because many city–industry pairs in certain years experienced no foreign firm entry, and these observations are automatically excluded when the dependent variable is logged. In contrast, due to the large number of private firm entries across years, such cases are rare. Since this study focuses on the policy's impact on the intensive margin (i.e., changes in the number of firm entries) rather than the extensive margin (i.e., transitions from no entry to entry or vice versa), dropping samples with a dependent variable of zero is a straightforward approach (Chen and Roth, 2024).

[12] For instance, in the certification process for province-level demonstration enterprises in Jiangsu Province, firms are recommended by city-level governments to the provincial government. According to relevant policy documents in Jiangsu Province, "each city can recommend no more than 5 firms, while innovative cities (such as Suzhou, Nanjing, Wuxi, and Changzhou) can recommend up to 8 firms." As a result, the "innovative city" title, a city-level innovation policy, increases the likelihood of provincial-level demonstration enterprises emerging in these cities. Since provincial-level demonstration enterprises are often a prerequisite for applying for national title, this policy also raises the probability of national-level demonstration enterprises appearing in these cities. At the same time, such city-level innovation policies may influence firm entry, making them a potential confounding factor in identification.

However, given the potential risk of significant sample size reduction, I re-estimate the regression model using Poisson Pseudo Maximum Likelihood (PPML). The results, reported in Appendix Table A.7, provides consistent findings.

Table 1: Policy effects on firm entries

	Logarithm of the number of firm entries			
	Private firm		Foreign firm	
	(1)	(2)	(3)	(4)
Treated	-0.329***	-0.059*	-0.212***	-0.138***
	(0.081)	(0.030)	(0.078)	(0.047)
City FEs × Industry FEs × Stack FEs	Yes	Yes	Yes	Yes
Year FEs × Stack FEs	Yes	No	Yes	No
Industry FEs × Year FEs × Stack FEs	No	Yes	No	Yes
City FEs × Year FEs × Stack FEs	No	Yes	No	Yes
# of clusters: city	337	337	326	301
# of clusters: industry	89	89	87	85
# of observations	1,971,558	1,971,558	241,790	238,064

Notes: This table reports the treatment effects of the NTIDE policy on the logarithm of annual firm entries. Columns (1) and (2) present the effects on private firms, while Columns (3) and (4) show the effects on foreign firms. Standard errors, two-way clustered at the city and industry levels, are reported in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 5 presents the estimation results of the event study. As illustrated in the figure, there is a clear downward trend in the entry of both private and foreign firms following the policy treatment. Prior to the intervention, there are no notable pre-trends for private firms, but a somewhat downward pre-trend is observed for foreign firms. Due to data limitations, it is not feasible to further control for confounding factors at the city–industry level for foreign firm entries. Consequently, it implies that estimates regarding foreign firm entry may be somewhat overstated and should be interpreted with caution.

In summary, the empirical evidence presented in this section corroborates the existence of the discouraging effect posited by the theoretical model: policies that subsidize leading firms in local markets may generate adverse spillover effects on other incumbent firms and potential entrants. First, the R&D incentives of competing incumbent firms in the market are diminished, particularly in markets where a significant number of firms lag behind the productivity frontier. Second, private firms anticipate reduced potential returns from market entry, leading to a notable decline in private firm entry and a suppression of the creative destruction process. These spillover effects collectively indicate a negative impact on aggregate innovation, rendering the overall effects of selective subsidy policies targeting leading firms ambiguous.

5 Overall effects on innovation

In this section, I examine the overall effects of the NTIDE policy on innovation to reflect the relative dominance of the direct and discouraging effects.

5.1 Baseline estimation

I employ the same identification strategy as in Section 4.2 to investigate changes in patent outputs following the emergence of the first demonstration enterprise in a given city and industry. To achieve this, it is first necessary to aggregate patent counts by city and industry. I utilize micro-level patent application data obtained from the China National Intellectual Property Administration, which includes information

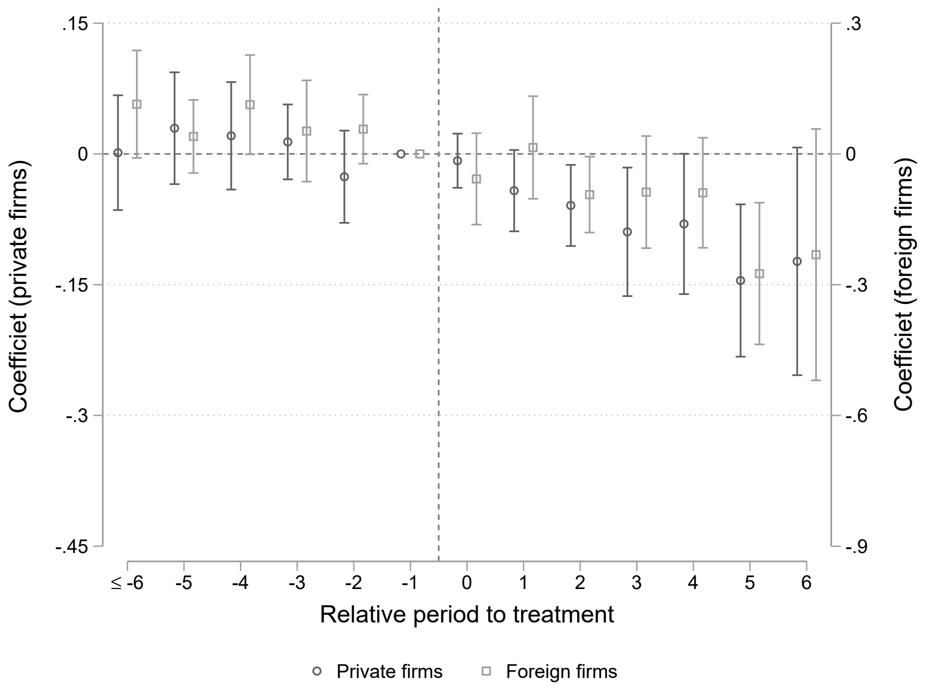

Figure 5: Event study of private and foreign firm entries

Notes: This figure shows the estimated coefficient in the event study for private firm entries and foreign firm entries, respectively. Point estimates and 95% confidential intervals are shown in the graph.

such as each patent's applicant, application date, publication date, primary International Patent Classification (IPC) code, and address. In most of the following analysis, I limit the focus to invention patents, excluding utility model patents and design patents, as these are typically considered to reflect lower levels of innovation.

Two steps are applied to identify each patent's city and industry. First, the address information generally specifies the applicant's location down to the sub-county level, including postal codes. Based on the city names or postal codes in the address text, I identify the city associated with each patent. Second, since the primary IPC code and industry classifications follow different systems, I utilize an official matching table, provided by the China National Intellectual Property Administration, to map IPC codes to industry categories.[13] If a patent's primary IPC code corresponds to multiple industry categories, each relevant industry is counted as having one additional patent.[14]

It should be clarified that IPC codes are typically based on the fields in which patents are utilized. Consequently, the approach adopted in this study assumes that the invention patents generated by firms are primarily applied within their respective industries. Furthermore, out of the 97 industries examined, only 54 can be matched with IPC codes, with these industries predominantly concentrated in manufacturing and supply sectors. The remaining 43 industries are not considered fields of patent application. As a result, only the 54 industries have positive patent counts, while the others are automatically assigned a value of zero. Therefore, in the subsequent empirical analysis, I restrict the sample to these 54 industries.

The 43 excluded industry categories can roughly be divided into two groups. The first group comprises industries in which firms exhibit minimal engagement in research and innovation activities. Examples of

[13]This document is available at `https://www.gov.cn/zhengce/zhengceku/2018-12/31/5443898/files/74249b84a762440fbe0fa195a3c14e93.pdf` (accessed February 2025).

[14]Theoretically, if one could identify the applicant—whether an individual, firm, or institution—for each patent, it would be possible to calculate patent counts based on the industries of the applicants. However, this approach is infeasible in practice due to the lack of standardization in applicant names. This inconsistency results in a very low matching rate when attempting to align applicant names with the business registration records dataset.

such industries include transportation, social organizations, and certain service sectors. Notably, these industries also feature a limited number of firms designated as demonstration enterprises. Consequently, their exclusion from the analysis is justified.

The second group encompasses several industries characterized by a substantial number of firms actively engaged in research and innovation, as well as a significant presence of demonstration enterprises. However, due to their unique nature, these industries cannot be matched with any IPC codes. A prominent example is the "Research and Development" industry category. Among the seven batches of demonstration enterprises certified between 2011 and 2017, 28 firms belonged to this industry. Nevertheless, no patents can be directly attributed to the this industry, as it does not align with any specific IPC codes. Consequently, patents generated by firms in this industry are instead assigned to other relevant industries. If a firm within such an industry in a given city is certified as a demonstration enterprise, it may influence the patent counts of other local industries. However, as long as this influence is proportionally distributed across industries, the issue can be effectively addressed by incorporating city-level time-varying fixed effects.

After matching patents to cities and industries, I aggregate patent counts by city and industry based on the application years of the patents. Utilizing application years, rather than publication years, is a common practice in the literature, as publication dates often exhibit significant delays relative to application dates.[15] Firms typically seek patent protection shortly after completing their R&D activities, making application dates a more accurate indicator of the timing of their innovation efforts (Lerner and Seru, 2022).

Furthermore, to account for patent quality, I construct the citation network based on the citations of each invention patent and subsequently calculate the number of times each invention patent is cited by others within 3 or 5 years following its publication date. Referring to methodologies of Lanjouw and Schankerman (2004) and Johnson et al. (2023), I use the number of citations as weights to calculate the citation-weighted patent count for each city–industry pair, which simultaneously incorporates both the quantity and quality of patents and serves as the core dependent variables in the subsequent analysis.[16]

Initially, I disregard potential inter-regional or inter-industry spillover effects and utilize all city–industry pairs that did not have any demonstration enterprises prior to 2018 as the control group. This approach relies on the assumption that such spillovers are negligible. If this assumption does not hold, the comparison not only introduces biases into the estimation but also fails to accurately capture the overall impact on the economy as a whole. In the subsequent section, I further divide the control group pairs to investigate spatial and inter-industry spillovers in innovation, where the findings reveal that both types of spillovers are small in magnitude and statistically insignificant. As a result, while the analysis in this section primarily pertains to the "local effects" of the policy, it also indicates the direction of the overall influence on innovation at the national level. The estimation equation is specified as follows:

$$\ln Patents_{c,i,t,s} = \beta \times \mathbb{1}\{Treated\}_{c,i,t} + \eta_{c,i,s} + \rho_{i,t,s} + \gamma_{c,t,s} + \varepsilon_{c,i,t,s}, \tag{15}$$

which is identical to Equation (14) except for the substitution of the dependent variable with the logarithm of the number of patents. It is important to clarify that the industry–year fixed effects $\rho_{i,t,s}$ additionally

[15] According to the *Patent Law of the People's Republic of China*, upon receiving an invention patent application, the patent administrative department of the State Council conducts a preliminary examination. If the application is determined to comply with the provisions of the law, it will be published 18 months after the application date. The patent administrative department may, at the request of the applicant, publish the application prior to the 18-month period.

[16] A related issue is that many patents applied for in recent years have not yet been published and are therefore not recorded in the database. This results in a significant underestimation of patent application counts and citations in recent years (Lerner and Seru, 2022). For this reason, I set the sample period cutoff at 2018, ensuring that the database contains invention patents during the sample period as comprehensively as possible.

control for heterogeneity in patent applications across industries. For instance, certain industries exhibit significantly higher patent application volumes, rendering direct comparisons between industries inappropriate. Compared to studies that standardize the dependent variable within industries, this control is more rigorous.

Additionally, I apply a logarithmic transformation to the dependent variable, which inherently excludes city–industry pairs with zero patents (or zero total citations) from the estimation.[17] There are two primary reasons for excluding these samples. First, since the treatment group consists of city–industry pairs with innovation star firms that have received certification, their innovation output is theoretically guaranteed to be positive. Removing non-innovator pairs from the control group is an effective approach to enhancing the comparability between the treatment and control groups. Second, the nature of subsidizing leading firms under this policy implies that its impact on innovation competition primarily influences innovation activities on the intensive margin rather than the extensive margin. In other words, the policy affects the intensity of innovation activities within a city–industry pair rather than converting non-innovator pairs into innovator pairs. Therefore, excluding non-innovators with zero patent output aligns with the focus of this study.

Table 2 presents the estimation results, where the dependent variables are the raw counts of invention patents, the number of invention patents weighted by citations within three years, and the number of invention patents weighted by citations within five years, respectively. Columns (1), (3), and (5) adhere to Equation (15), while Columns (2), (4), and (6) replace the core explanatory variable with the cumulative stock of demonstration enterprises in each city–industry pair over time. This substitution is intended to construct a continuous variable related to the treatment intensity.[18]

The table demonstrates consistent estimation results across different dependent and explanatory variables: the demonstration enterprise policy reduces the innovation output of city–industry pairs where demonstration enterprises are located. This finding suggests that, on average, the negative effects on competitor firms and potential entrants outweigh the positive effects on demonstration enterprises, resulting in negative overall effects.

Moreover, given the observed consistency across various measures of innovation patents, the subsequent analysis primarily employs the 3-year weighted measure as the dependent variable. This approach serves a dual purpose: it mitigates the limitations associated with the raw count measure, which overlooks patent quality, and addresses the concern that longer forward citations rely on patents applied in more recent years, which may be incomplete in the dataset.

The reliability of these estimates still faces the critical challenge of the comparability of the treatment and control groups. Specifically, if a city–industry pair has a demonstration enterprise after 2011, it often indicates that the city–industry pair has a relatively strong foundation for R&D and innovation. Appendix Table A.11 shows that, in the first period of the sample (i.e., 2008), only 2.56% of the treatment group city–industry pairs had zero invention patents, while 40.19% of the control group city–industry pairs had zero invention patents. This raises a potential issue: since the total number of patent applications nationwide generally increases year by year, the control group with few patents in the initial period also experiences

[17] I refrain from employing a commonly adopted method of applying a log-like transformation to the dependent variable, since recent studies emphasize the potential of introducing significant estimation biases, particularly when extensive-margin effects are substantial and cannot be disregarded. With log-like transformations, the estimated coefficients "can be made to take any desired value through the appropriate choice of [the units of the dependent variable]" (Chen and Roth, 2024).

[18] It should be clarified that, for the treatment group, treatment intensity is not necessarily positively correlated with the number of demonstration enterprises. This is because the discouraging effects resulting from the alteration of innovation competition due to the policy do not necessarily increase or decrease with a greater number of subsidized leading firms. In Appendix Table A.8, I preliminarily attempt to incorporate high-order polynomials into the specification, revealing a significant third-order relationship: as the number of demonstration enterprises certified in a city–industry pair increases, the negative effects are initially alleviated but eventually exacerbated. However, as the number of treatment pairs with more than one demonstration enterprise is quite limited (see Appendix Table A.2), I acknowledge that there may be insufficient variation to accurately identify the true relationship.

Table 2: Policy effects on patent output

	Logarithm of the number of invention patents					
	Raw counts		3-year weighted		5-year weighted	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	-0.164***		-0.167***		-0.159***	
	(0.026)		(0.026)		(0.026)	
# of demonstration enterprises		-0.134***		-0.135***		-0.127***
		(0.023)		(0.024)		(0.023)
City FEs × Ind. FEs × Stack FEs	Yes	Yes	Yes	Yes	Yes	Yes
Ind. FEs × Year FEs × Stack FEs	Yes	Yes	Yes	Yes	Yes	Yes
City FEs × Year FEs × Stack FEs	Yes	Yes	Yes	Yes	Yes	Yes
# of clusters: city	336	336	335	335	335	335
# of clusters: industry	54	54	54	54	54	54
# of observations	1,035,694	1,035,694	932,788	932,788	962,735	962,735

Notes: This table reports the treatment effects of the NTIDE policy on the logarithm of annual innovation patent applications. Standard errors, two-way clustered at the city and industry levels, are reported in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

a year-by-year increase in patent applications. When the initial base is small, the patent applications of this control group will exhibit a large percentage growth in subsequent periods, leading to a natural pre-existing trend of narrowing the gap between the treatment and control groups.

To address this issue, I impose increasingly stringent restrictions on the city–industry pairs included in the estimation, requiring that their invention patent applications in 2008 exceed a specific threshold. Figure 6 presents the estimation results under these varying constraints. As expected, the point estimates of the coefficients gradually decline as the constraints become stricter; however, all estimates remain negative and statistically significant. When the constraint reaches 50 or more, the sample size reduces to approximately or less than 10% of the baseline estimation, and the point estimates stabilize, fluctuating around -0.05. Across these estimations, a conservative quantitative conclusion can be drawn: the NTIDE policy reduces the total patent output of the treated city–industry pairs by at least 4%.

The estimation of the event study is presented in Figure 7. In line with the preceding discussion, the sample is restricted to city–industry pairs with invention patent applications in 2008 exceeding 50.[19] Prior to the NTIDE policy intervention, no significant pre-trends are observed; however, following its implementation, the treatment group exhibits increasingly negative effects.

Additionally, I conduct three robustness checks to further validate the reliability of these findings. First, I separately estimate the treatment effects for seven treatment cohorts to examine whether the negative impact identified in the earlier estimates is driven by a specific cohort. Figure A.7 presents the estimation results. With the exception of the 2018 cohort, which was treated in the final period of the sample, the treatment effects for all other cohorts are negative and of comparable magnitude. Second, I analyze city–industry pairs where the first demonstration enterprise was certified in 2019 as a placebo test. Given the sample period cutoff of 2018, this treatment cohort is expected to exhibit no significant treatment effect within the sample period. Table A.9 reports the estimation results of the event study, where all coefficients are statistically insignificant, and fewer of them are negative compared to the treatment cohorts. Third, as presented in Appendix Table A.10, the number of utility model patents is employed as an alternative dependent variable. The estimation results similarly demonstrate a negative aggregate effect of the demonstration enterprise policy, suggesting that the NTIDE policy also discourages innovation with a focus on practical applicability.

[19] Consistent with the preceding discussion, utilizing the full sample in the estimation reveals a significant pre-trend, which gradually diminishes as the constraints imposed on the sample become stricter and the treatment and control groups become more comparable.

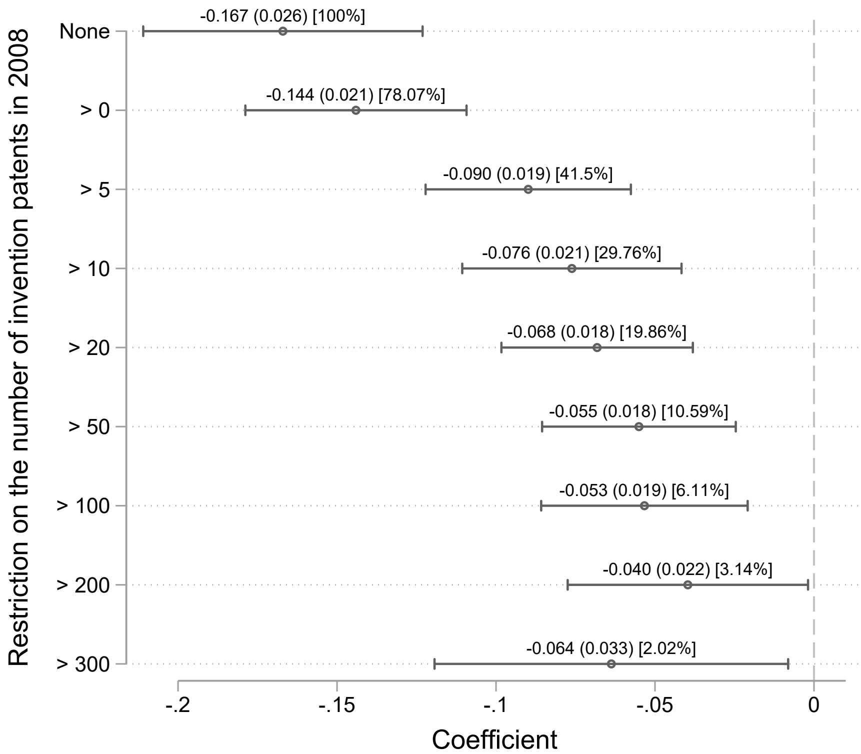

Figure 6: Estimated coefficients with sample restriction on the number of patents in 2008

Notes: This figure presents the estimation results derived by applying varying constraints on the number of invention patent applications in 2008 for each city–industry pair. The first row imposes no constraints, mirroring the results reported in Column (3) of Table 5. The second to ninth rows restrict the estimation to city–industry pairs with invention patent applications in 2008 exceeding 0, 5, 10, 20, 50, 100, 200, and 300, respectively. The circles represent the point estimates of the treatment variable coefficients, while the lines indicate the 90% confidence intervals. The point estimates are displayed alongside the standard errors of the coefficients in parentheses. The square brackets report the ratio of the sample size used in the regression to the sample size under no constraints (i.e., the first row).

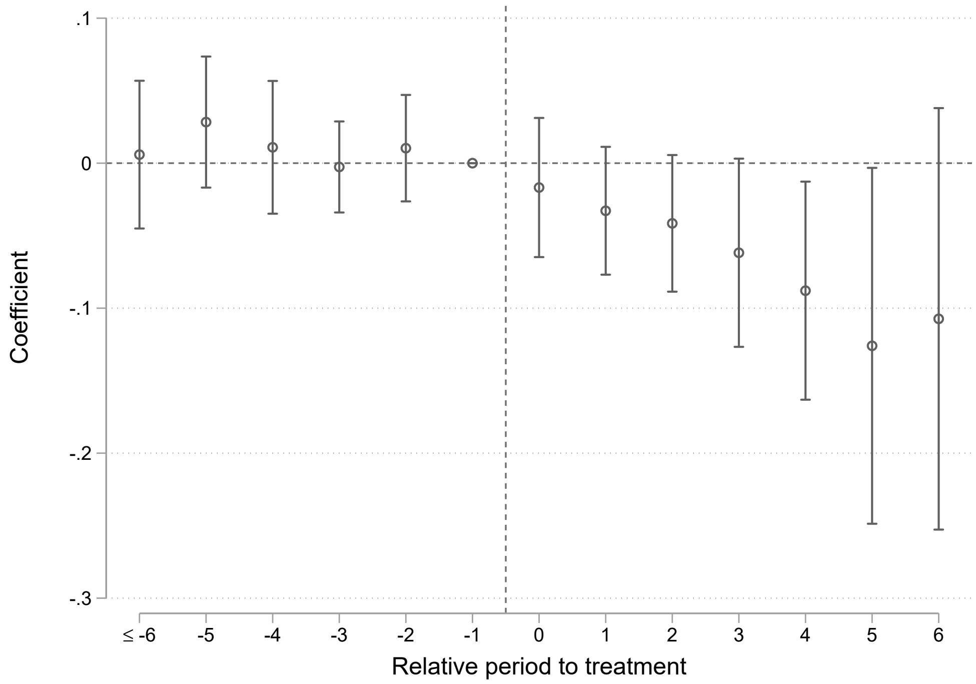

Figure 7: Treatment effects on patent outputs: event study

Notes: This figure presents the estimation of the event study on patent outputs. The sample is restricted to city–industry pairs with invention patent applications in 2008 exceeding 50. The circles represent the point estimates, while the lines indicate the 95% confidence intervals.

5.2 Heterogeneity

In this subsection, I estimate the heterogeneous treatment effects of the NTIDE policy and discuss potential determinants of the heterogeneity. I primarily focus on the heterogeneous average treatment effects by industry, which can be separately estimated with samples corresponding to each industry. For industry i, the estimation equation is as follows:

$$\ln Patent^{i}_{c,t,s} = \beta \times \mathbb{1}\{Treated\}^{i}_{c,t} + \eta^{i}_{c,s} + \gamma^{i}_{p_c,t,s} + \varepsilon^{i}_{c,t,s}. \tag{16}$$

Since each estimation utilizes samples from a single industry, the analysis fundamentally relies on comparisons between cities with demonstration enterprises and those without any. Consequently, I replace the time-varying city fixed effects with time-varying province fixed effects $\gamma^{i}_{p_c,t,s}$.

Figure 8 presents the estimation results. To mitigate estimation biases arising from an insufficient number of treatment pairs, only treatment effects of industries with more than 5 treated pairs are reported.[20] Throughout these estimates, more than two third industries exhibit negative point estimates, consistent with the negative overall effects estimated above.[21]

The overall effects of the policy are an aggregation of the responses of various firms engaged in innovation activities. Consequently, heterogeneity essentially arises from differences in the degree to which various innovation agents respond. Building on the earlier analysis of the divergent impacts on subsi-

[20]The median number of treatment pairs across industries is 5.

[21]An observation worth noting is the absence of a significant correlation between the treatment effects and the number of treatment pairs, as illustrated in Appendix Figure A.8. This finding helps to rule out the possibility that the observed heterogeneity arises from diminishing positive marginal effects as the number of treatment pairs increases. This is indeed understandable, as demonstration enterprises are typically dispersed across cities. Furthermore, it is observed that in industries with more than 20 treatment cities, the treatment effects are predominantly negative. This observation suggests that the NTIDE policy primarily generated unintended negative consequences in the industries on which it placed greater emphasis. Consequently, the overall effects, which represent a weighted average of the heterogeneous treatment effects across industries, are negative.

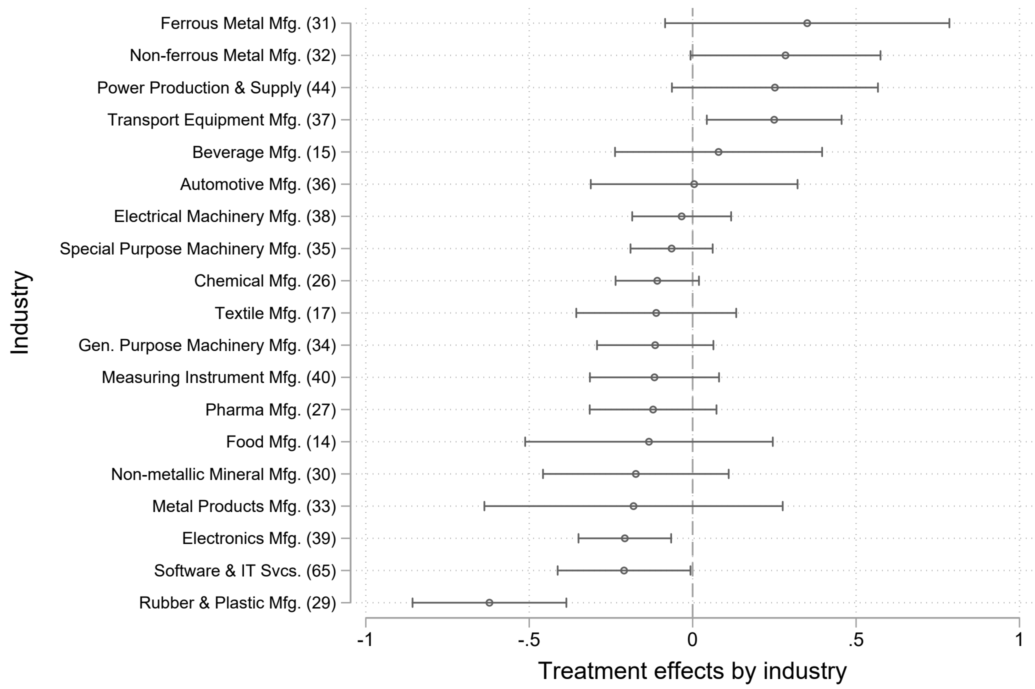

Figure 8: Treatment effects on patent outputs by industry

Notes: This figure illustrates the heterogeneous treatment effects by industry on patent outputs, weighted by 3-year-forward citations. To mitigate significant estimation biases, only industries with more than 5 treatment city–industry pairs are included in the analysis. The circles denote the point estimates, and the lines represent the 90% confidence intervals.

dized leading firms, competitor firms, and new entrants, two potential determinants for the observed heterogeneity emerge: market competition among incumbents and the rate of new firm entry. In markets with higher levels of competition and greater firm entry, follower firms and new entrants are likely to play a more significant role in driving technological advancement. As a result, it is anticipated that more discouraging effects will be observed for these firms when policies subsidize leading firms.

To test the first determinant, I measure the degree of market competition in each industry using the Industrial Enterprise Database, employing the methodology proposed by De Loecker et al. (2020). This approach measures monopoly levels through industry-average markups. The data used to calculate this indicator are sourced from the Industrial Enterprise Database prior to the implementation of the NTIDE policy to mitigate potential reverse causality. Figure 9 depicts the correlation between industry competition levels and the policy treatment effect, revealing a significant negative relationship. Specifically, in industries with higher levels of competition, the negative aggregate effects of subsidizing leading firms are more pronounced.

Another potential determinant is the entry of new firms. The rate of new firm entry reflects the degree of creative destruction, wherein new firms enter the market and compete with incumbents for market share. To explore this, I calculate the average annual number of new firms entering each industry following the implementation of the NTIDE policy and examine its correlation with the policy treatment effect. Figure 10 illustrates this relationship, revealing a significant negative correlation, suggesting that in industries characterized by active new firm entry, subsidies to leading firms generate larger negative spillover effects.

In summary, this section provides evidence that the NTIDE policy generates negative overall effects on innovation in the regions where it is implemented, as well as nationwide, as discussed in the subsequent section. Combined with the divergence between the positive direct effects on subsidized leading firms

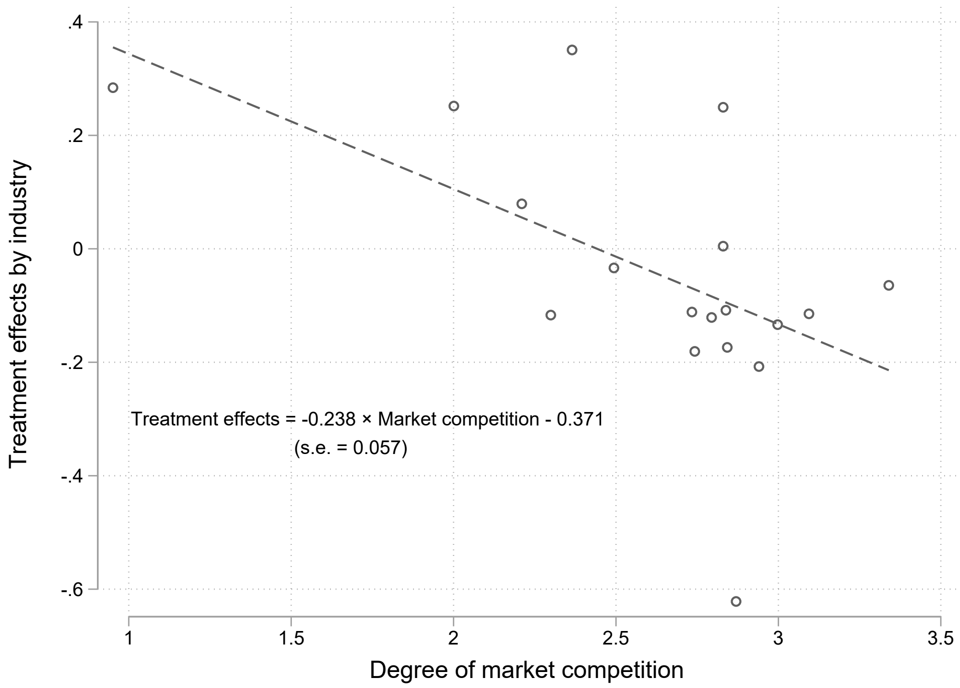

Figure 9: Treatment effects and market competition

Notes: This figure depicts the correlation between treatment effects and the degree of market competition, measured by the average mark-up in each industries before the policy implementation. The darker dashed line represents the fitted line.

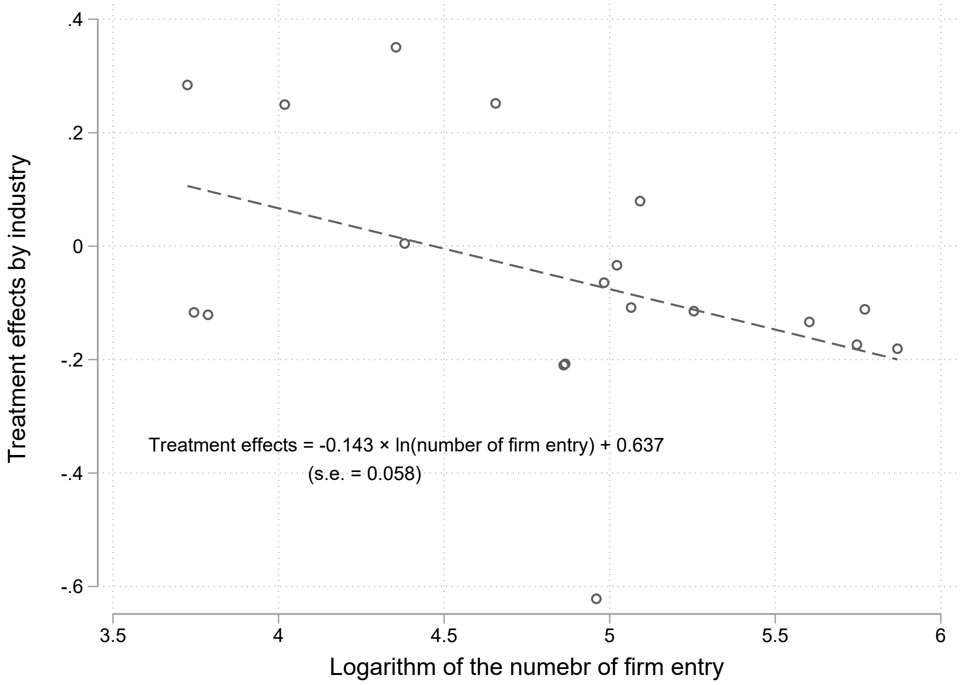

Figure 10: Treatment effects and firm entries

Notes: This figure depicts the correlation between treatment effects and the number of firm entries, measured by the mean of annual new entries in each industries before the policy implementation. The darker dashed line represents the fitted line.

and the negative effects on competitor firms and potential entrants identified in the previous section, the findings in this section are interpreted as evidence that the negative spillover effects outweigh the direct positive effects. This interpretation is further supported by the observed heterogeneity, wherein the negative overall effects are more pronounced in markets characterized by greater competition and creative destruction. These results underscore the unintended consequences of the NTIDE policy, which arise from its failure to account for the indirect effects by altering the innovation competition among firms.

6 Spillover effects

6.1 Inter-industry and spatial spillovers in innovation

Industrial policies frequently generate spillover effects. Specifically, when the innovation output of treatment city–industry pairs is altered due to the NTIDE policy, their productivity and the overall competitiveness of the market may also be impacted. This could potentially lead to two types of spillover effects on other regions or industries, which can

The first type is inter-industry spillovers. Given the input–output linkages and knowledge spillovers across industries, the policy's impact on innovation activities in one industry could induce a negative productivity shock, which in turn influences innovation activities in other local industries through two primary channels. First, the productivity shock may translate into a cost shock for other industries via input–output linkages, thereby reducing their expected returns on R&D expenditures. Second, the adverse effects of the policy on innovation could hinder inter-industry knowledge spillovers. Consequently, the NTIDE policy may lead to negative inter-industry spillover effects.

The second type of spillover effects is spatial spillovers. On one hand, firms in the same industry across different cities compete for the national market. Thus, the decrease in the innovation outputs of the treatment group reduces their competitiveness and could increase the expected returns of R&D investments for competitors in other cities, potentially encouraging firms in those cities to increase their innovation activities. On the other hand, considering knowledge diffusion among regions, the treatment cities could also negatively affect surrounding cities by reducing the intensity of new technology diffusion. Taken together, the NTIDE policy theoretically has the potential to exhibit positive spatial spillover effects.

To identify these spillover effects, I reclassify all control group city–industry pairs into four sub-groups:

1. *Pure control group*: City–industry pairs that differ from the industries and cities of all demonstration enterprises. Based on the analysis above, these control group samples theoretically should not experience any spillover effects.

2. *Inter-industry spillover control group*: City–industry pairs where demonstration enterprises exist in the city but not in the industry. These control groups are not subject to spatial spillover effects but may experience inter-industry spillovers within the city.

3. *Spatial spillover control group*: City–industry pairs where demonstration enterprises exist in the industry but not in the city. These control groups are not subject to intra-city inter-industry spillover effects but may experience spatial spillover effects.

4. *Mixed spillover control group*: City–industry pairs where demonstration enterprises exist in both the industry and the city. Since these control groups may experience both types of spillover effects, they are excluded from the estimation.

Following the classification, I identify the treatment years for each spillover control group pair based on the initial appearance of demonstration enterprises in their corresponding city or industry. This process results in a staggered treatment structure comprising seven treatment cohorts. Consequently, I employ the similar approach to construct stacked samples for estimation.

6.1.1 Inter-industry spillover effects in innovation

I first estimate the inter-industry spillover effects by comparing the inter-industry spillover control group and the pure control group. The estimation equation is as follows:

$$\ln Patent_{c,i,t,s} = \beta^{ind} \times \mathbb{1}\left\{Treated^{city}\right\}_{c,t} + \eta_{c,i,s} + \rho_{i,t,s} + \gamma_{p_c,t,s} + Trend_{c,t} \cdot \delta_s + \varepsilon_{c,i,t,s}, \quad (17)$$

where $\mathbb{1}\{Treated^{city}\}_{c,t}$ takes the value of one after city c occurs the first demonstration enterprises. Different from estimations in earlier sections, this estimations relies on the variation in the city level, essentially comparing cities with demonstration enterprises to cities without any of them. Therefore, it is not longer feasible to control city-level time-varying fixed effects. Instead, I control for the province–year interactive fixed effects $\gamma_{p_c,t,s}$. The event study employs a similar specification, with the exception that the treatment status indicator is replaced by a series of interaction terms between relative time dummies and the treatment group indicator.

To enhance the comparability across cities, I employ two additional strategies. First, I introduce a stack-specific linear time trend term into the estimation, where $Trend_{c,t} \equiv \mathbb{1}\{Same\ city\}_{c,t} \cdot t$ represents the product of a dummy variable indicating the spillover control group and a linear time term. This approach is designed to account for potential linear time trends arising from unobserved confounding factors (Moser and Voena, 2012).[22] Second, I again restrict the estimation sample to city–industry pairs whose number of invention patent applications in 2008 exceeds a specific threshold. However, given that the number of patent applications in 2008 for city–industry pairs in the pure control group is generally low (with a maximum of 58, as detailed in Appendix Table A.12), it is impractical to impose overly stringent restrictions.

Figure 11 presents the results of the event study estimations. I clearly shows that, when the linear time trend is excluded from the specification, a positive pre-trend is observed in the differences between the two groups, resulting in positive point estimates in the stacked DD estimation. However, once the time trend term is incorporated to account for this pre-trend, all coefficients in the event study become small and statistically insignificant, and the average treatment effect estimated by the stacked DD decreases to 0.006. In Appendix Table A.13, I additionally provide estimates under different sample restrictions, where the results remain consistent across all variations. These findings suggest that the inter-industry spillover effects in innovation of the NTIDE policy is negligible in magnitude.

6.1.2 Spatial spillover effects in innovation

In contrast to inter-industry spillovers, spatial spillovers present a significant challenge to the overall effects of the policy. While inter-industry spillovers, which are theoretically negative, may lead to an underestimation of the average treatment effect, such underestimation does not undermine the qualitative conclusions of this study. However, if spatial spillover effects of the policy exist, theoretical expectations suggest they could potentially be positive, which could result in an overestimation of the local effects and

[22] However, if the treatment effect is not immediate but instead manifests gradually over time (an example can be observed in 7), a linear time trend may inadvertently absorb part of the treatment effect, leading to a significant underestimation of the true effect. Consequently, in subsequent analysis, I present results both with and without the inclusion of a linear time trend control. The appropriateness of this control will be evaluated based on the event study.

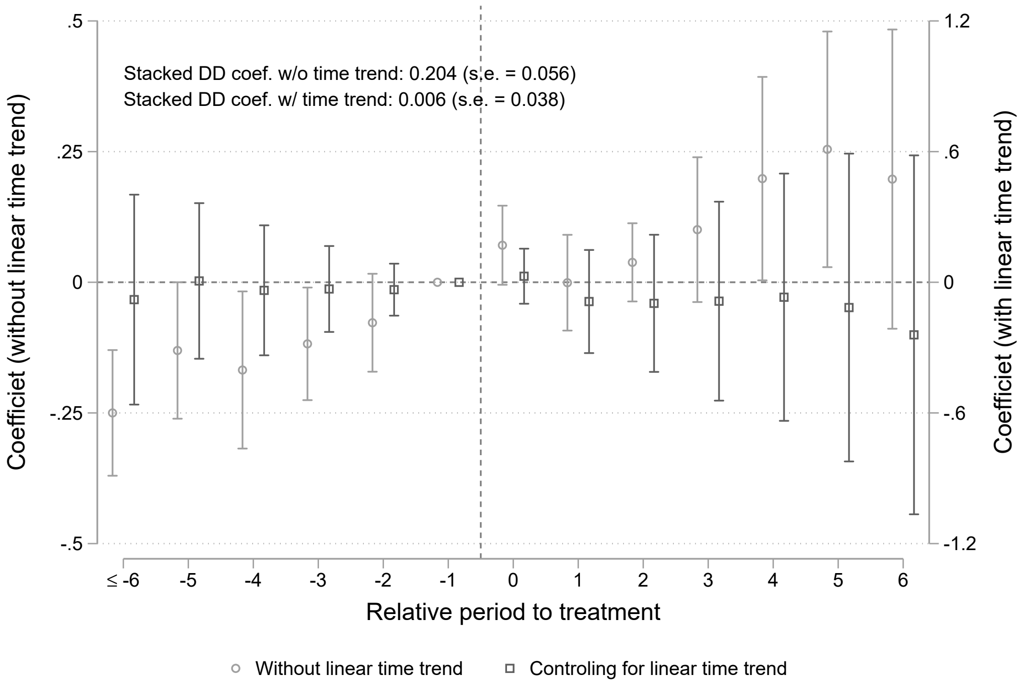

Figure 11: Inter-industry spillover effects

Notes: This figure illustrates the event study results for inter-industry spillover effects, comparing the inter-industry spillover control group with the pure control group. The analysis is restricted to city–industry pairs with at least one invention patent application in 2008. The circles denote the point estimates, while the lines represent the 95% confidence intervals. Lighter circles and lines correspond to estimates without controlling for a linear time trend, whereas darker circles and lines correspond to estimates that include a linear time trend control. Additionally, the figure reports the average treatment effects computed from the estimation of Equation (17). Further details regarding the stacked DD estimates are provided in Appendix Table A.13.

the policy's adverse impact on nationwide innovation. Consequently, identifying spatial spillover effects is essential to ensure the reliability of the findings presented in the previous text.

I first employ the following specification to compare the spatial spillover control group with the pure control group:

$$\ln Patent_{c,i,t,s} = \beta^{spatial} \times \mathbb{1}\left\{Treated^{ind}\right\}_{i,t} + \eta_{c,i,s} + \rho_{I,t,s} + \gamma_{c,t,s} + Trend_{i,t} \cdot \delta_s + \varepsilon_{c,i,t,s}, \tag{18}$$

where $\mathbb{1}\{Treated^{ind}\}_{i,t}$ takes the value of one after the first demonstration enterprise emerges in industry i. This estimation relies on variation across industries. Consequently, similar to Equation (17), I replace the industry-level time-varying fixed effects with sector-level time-varying fixed effects. The linear time trend term, $Trend_{i,t} \equiv \mathbb{1}\{same\ industry\}_{i,t} \cdot t$, is also included in this estimation.

Figure 12 presents the estimation of the event study. Regardless of whether the time linear trend is controlled for, there are no significant treatment effects observed after the implementation of the policy. Furthermore, the estimates derived from the stacked DD approach remain small in magnitude.

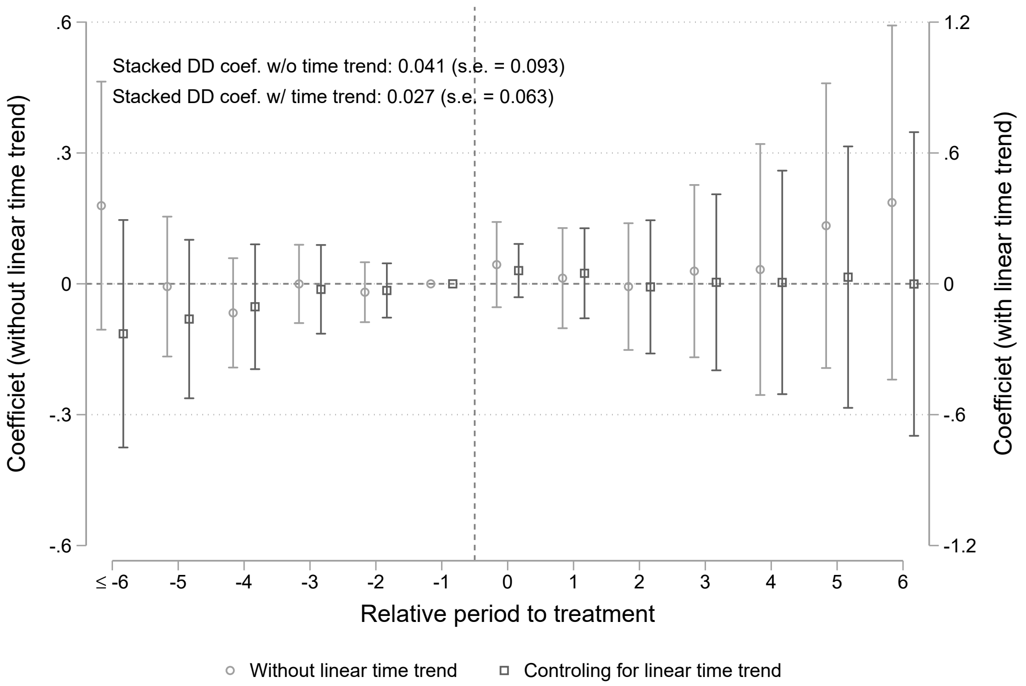

Figure 12: Spatial spillovers: spatial spillover control group versus pure control group

Notes: This figure illustrates the event study results for spatial spillover effects, comparing the spatial spillover control group with the pure control group. The analysis is restricted to city–industry pairs with at least one invention patent application in 2008. The circles denote the point estimates, while the lines represent the 95% confidence intervals. Lighter circles and lines correspond to estimates without controlling for a linear time trend, whereas darker circles and lines correspond to estimates that include a linear time trend control. Additionally, the figure reports the average treatment effects computed from the estimation of Equation (18). Further details regarding the stacked DD estimates are provided in Appendix Table A.14.

The above estimation relies on the implicit assumption that when demonstration enterprises emerge in a specific industry in certain cities, the same industry in other cities potentially experience spatial spillover effects. Therefore, by comparing industries with demonstration enterprises to those without, the magnitude of spatial spillover effects can be estimated. However, a potential concern arises as the spatial spillover effects of the policy may not apply uniformly across all regions. Consequently, conducting comparisons at the industry level might dilute the estimated magnitude of these effects.

To address this concern, specific assumptions about the spatial scope of spillover effects should be made, and the groups can be reconstructed accordingly for estimation. I assume that spatial spillover effects decay with distance and primarily affect control group cities adjacent to the treatment group cities. Under this assumption, the same industry in cities adjacent to treatment group cities is defined as the spillover group, while the remaining city–industry pairs are defined as the control group. By comparing these two groups, the magnitude of spillover effects is estimated. Figure 13 presents the event study results, where insignificant treatment effects are observed again.

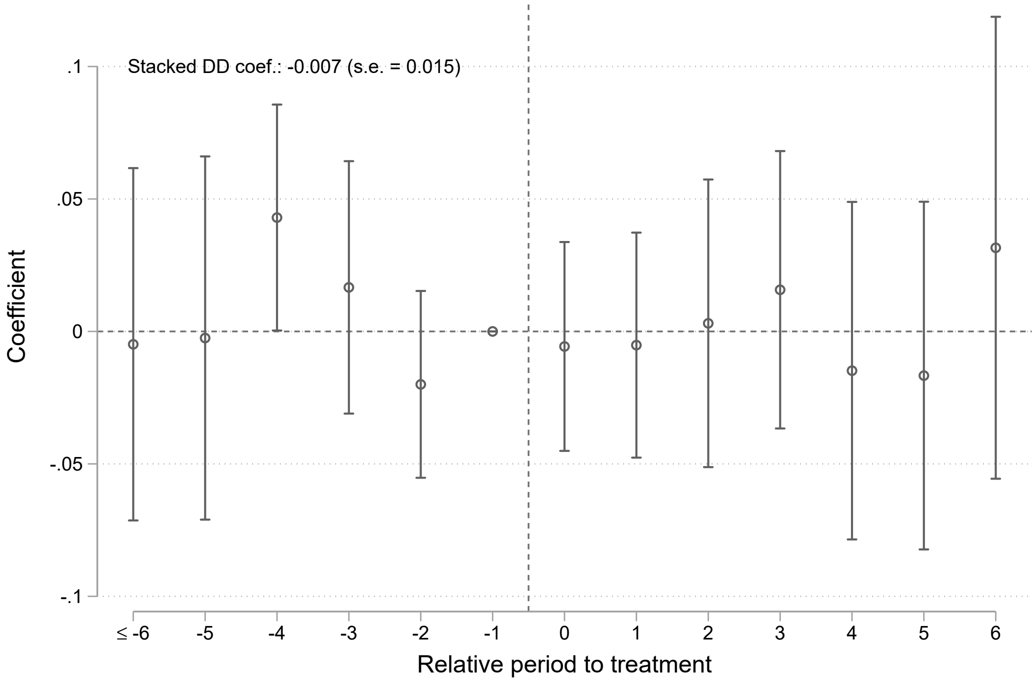

Figure 13: Spatial spillovers: adjacent cities versus other cities

Notes: This figure illustrates the event study results for spatial spillover effects, comparing the cities adjacent to those with demonstration enterprises and other cities. The analysis is restricted to city–industry pairs with at least one invention patent application in 2008. The circles denote the point estimates, while the lines represent the 95% confidence intervals. Details regarding the stacked DD estimates are provided in Appendix Table A.15.

6.2 Local knowledge spillovers

Finally, I examine whether subsidies to leading firms can promote local knowledge spillovers. A substantial body of literature has emphasized the critical role of knowledge spillovers in enhancing the overall productivity of cities or clusters, highlighting the rapid decay of knowledge spillover effects with distance (Moretti, 2021; Atkin et al., 2022). The NTIDE policy incentivizes leading firms to increase their R&D investments, thereby generating more innovations, which may facilitate the diffusion of new technologies from leading firms to other firms. However, as previously documented, the policy suppresses the R&D investments of competitor firms and deters new entrants, potentially hindering knowledge diffusion among other firms. Consequently, the net impact of the policy on local knowledge spillovers remains ambiguous.

Based on the patent citation network, I identify each patent's citations to other patents within the same city–industry pair. This allows me to compute the average number of local citations per patent for each city–industry pair over time, which serves as a measure for local knowledge spillovers. The estimation equation is consistent with Equation (15), with the dependent variable replaced by the logarithm of the average number of local citations per patent. Table 3 reports the estimation results. Across different sample restrictions, the estimated coefficients are statistically insignificant, and the point estimates are small, indicating that the policy did not promote local knowledge spillovers where demonstration enterprises are located.

This finding carries two important implications. First, the local knowledge spillover effects generated by subsidizing leading firms are weak. Demonstration enterprises may be reluctant to actively share their innovations due to self-interest, which may be attributed to the lack of incentives or regulations requiring demonstration enterprises to share their inventions after awarding the policy title. Second, subsidies to leading firms may negatively affect other competitor firms and potential entrants, thereby hindering knowledge spillovers from these firms. Therefore, selective innovation policies aimed at promoting knowledge diffusion must carefully consider the impact of policies on the competitive structure of innovation among firms, rather than focusing solely on the behavioral changes of the direct policy targets.

Table 3: Policy effects on local knowledge spillovers

	Logarithm of local citations per patent			
		Restrictions on # of invention patents in 2008		
		> 0	> 20	> 40
	(1)	(2)	(3)	(4)
Treated	-0.004	-0.005	-0.014	-0.006
	(0.045)	(0.045)	(0.029)	(0.028)
City FEs × Ind. FEs × Stack FEs	Yes	Yes	Yes	Yes
Ind. FEs × Year FEs × Stack FEs	Yes	Yes	Yes	Yes
City FEs × Year FEs × Stack FEs	Yes	Yes	Yes	Yes
# of clusters: city	292	289	175	127
# of clusters: industry	54	54	54	50
# of observations	465,430	422,334	162,932	107,272

Notes: This table uses local patent citations to estimate the local knowledge spillover effects of the NTIDE policy. Columns (2) to (4) estimate the effects using city–industry pairs with more than 0, 20, and 40 patent applications in the sample year (i.e., 2008), respectively. Standard errors, two-way clustered at the city and industry levels, are reported in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

7 Conclusion

This study highlights the negative spillover effects of selective R&D expenditures resulting from changes in innovation competition among firms. At its core, firms' innovation efforts represent a competition for market share, meaning that the R&D investment decisions of individual firms are jointly influenced by the actions of all firms in the market. When governments selectively provide subsidies to specific firms—particularly leading firms close to the productivity frontier—it indirectly alters the competitive landscape, reducing the incentives for other firms to innovate and challenge the leading firms. This economic intuition is formalized using a Schumpeterian model, which demonstrates that while government R&D subsidies to leading firms incentivize them to increase R&D investment and enhance expected productivity, they simultaneously diminish the R&D investment incentives of other firms, especially those relatively lagging in productivity.

The theoretical predictions are corroborated by empirical evidence from the implementation of the "National Technology Innovation Demonstration Enterprise" policy in China, which primarily subsidizes local innovation star firms. The study also evaluates the overall effects of the policy and finds that it leads to a decline in citation-weighted patent applications both in the regions where it is implemented and nationwide. These negative effects are more pronounced in markets characterized by intense competition and active entry of new firms, consistent with the theoretical explanation that competitor firms and new entrants are disproportionately discouraged by the policy in such markets.

This study carries three policy implications. First, governments should be cautious about the potential discouraging effects of subsidizing leading firms. Particularly, in industries characterized by intense market competition and active entries of new firms, such selective R&D subsidy policies may yield adverse outcomes. Second, the negative aggregate effects suggest that new firms and small-to-medium enterprises (SMEs), which are relatively lagging behind the productivity frontier, may play a more significant role in driving aggregate innovation. Consequently, governments should implement measures to promote competition, encourage firm entry, and support the development of SMEs. Third, given the interconnected nature of innovation competition among firms, selective innovation policies are susceptible to unanticipated firm responses and unintended consequences. This aligns with the broader debate on industrial policies and the question of whether governments can effectively identify future winners (Juhász et al., 2024). Therefore, governments may consider adopting non-selective policies, such as investing in education and training or providing universal innovation support, to effectively incentivize aggregate innovation.

References

Acemoglu, D., U. Akcigit, H. Alp, N. Bloom, and W. Kerr (2018, November). Innovation, Reallocation, and Growth. *American Economic Review 108*(11), 3450–3491.

Aghion, P., A. Bergeaud, G. Cette, R. Lecat, and H. Maghin (2019). Coase Lecture - The Inverted-U Relationship Between Credit Access and Productivity Growth. *Economica 86*(341), 1–31. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/ecca.12297.

Aghion, P., N. Bloom, R. Blundell, R. Griffith, and P. Howitt (2005, May). Competition and Innovation: an Inverted-U Relationship. *The Quarterly Journal of Economics 120*(2), 701–728.

Aghion, P., R. Blundell, R. Griffith, P. Howitt, and S. Prantl (2009, February). The Effects of Entry on Incumbent Innovation and Productivity. *The Review of Economics and Statistics 91*(1), 20–32.

Aghion, P. and P. Howitt (1992). A Model of Growth Through Creative Destruction. *Econometrica 60*(2), 323–351.

Akcigit, U., S. Baslandze, and F. Lotti (2023). Connecting to Power: Political Connections, Innovation, and Firm Dynamics. *Econometrica 91*(2), 529–564.

Akcigit, U. and W. R. Kerr (2018, August). Growth through Heterogeneous Innovations. *Journal of Political Economy 126*(4), 1374–1443. Publisher: The University of Chicago Press.

Arora, A., W. Cohen, H. Lee, and D. Sebastian (2023, January). Invention value, inventive capability and the large firm advantage. *Research Policy 52*(1), 104650.

Atkin, D., M. K. Chen, and A. Popov (2022, June). The Returns to Face-to-Face Interactions: Knowledge Spillovers in Silicon Valley.

Autor, D., D. Dorn, G. H. Hanson, G. Pisano, and P. Shu (2020, September). Foreign Competition and Domestic Innovation: Evidence from US Patents. *American Economic Review: Insights 2*(3), 357–374.

Blundell, R., R. Griffith, and J. van Reenen (1999, July). Market Share, Market Value and Innovation in a Panel of British Manufacturing Firms. *The Review of Economic Studies 66*(3), 529–554.

Braguinsky, S., J. Choi, Y. Ding, K. Jo, and S. Kim (2023, July). Mega Firms and Recent Trends in the U.S. Innovation: Empirical Evidence from the U.S. Patent Data. Technical Report w31460, National Bureau of Economic Research.

Chen, J. and J. Roth (2024, May). Logs with Zeros? Some Problems and Solutions. *The Quarterly Journal of Economics 139*(2), 891–936.

Cohen, W. M. (2010, January). Chapter 4 - Fifty Years of Empirical Studies of Innovative Activity and Performance. In B. H. Hall and N. Rosenberg (Eds.), *Handbook of the Economics of Innovation*, Volume 1 of *Handbook of The Economics of Innovation, Vol. 1*, pp. 129–213. North-Holland.

De Loecker, J., J. Eeckhout, and G. Unger (2020, May). The Rise of Market Power and the Macroeconomic Implications. *The Quarterly Journal of Economics 135*(2), 561–644.

Deshpande, M. and Y. Li (2019, November). Who Is Screened Out? Application Costs and the Targeting of Disability Programs. *American Economic Journal: Economic Policy 11*(4), 213–248.

Dong, X., Y. Li, and J. Sun (2024, September). R&D project subsidy V.S. government innovation reward: The effectiveness on corporate innovation. *China Economic Review*, 102288.

Edler, J. and J. Fagerberg (2017, January). Innovation policy: what, why, and how. *Oxford Review of Economic Policy 33*(1), 2–23.

Falk, R. (2007, June). Measuring the effects of public support schemes on firms innovation activities: Survey evidence from Austria. *Research Policy 36*(5), 665–679.

Feldman, M. P. and M. R. Kelley (2006, December). The *ex ante* assessment of knowledge spillovers: Government R&D policy, economic incentives and private firm behavior. *Research Policy 35*(10), 1509–1521.

Garcia-Macia, D., C.-T. Hsieh, and P. J. Klenow (2019). How Destructive Is Innovation? *Econometrica 87*(5), 1507–1541. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA14930.

Gilbert, R. J. (2020, July). *Innovation Matters: Competition Policy for the High-Technology Economy*. The MIT Press.

Giroud, X., E. Liu, and H. Mueller (2024, July). Innovation Spillovers across U.S. Tech Clusters.

Goettler, R. L. and B. R. Gordon (2011, December). Does AMD Spur Intel to Innovate More? *Journal of Political Economy 119*(6), 1141–1200. Publisher: The University of Chicago Press.

Greenstone, M., R. Hornbeck, and E. Moretti (2010, June). Identifying Agglomeration Spillovers: Evidence from Winners and Losers of Large Plant Openings. *Journal of Political Economy 118*(3), 536–598.

Gutiérrez, G. and T. Philippon (2017, July). Declining Competition and Investment in the U.S.

Gutiérrez, G. and T. Philippon (2019, May). Fading Stars. *AEA Papers and Proceedings 109*, 312–316.

Howell, S. T. (2017, April). Financing Innovation: Evidence from R&D Grants. *American Economic Review 107*(4), 1136–1164.

Johnson, M. S., M. Lipsitz, and A. Pei (2023, July). Innovation and the Enforceability of Noncompete Agreements.

Juhász, R., N. Lane, and D. Rodrik (2024, May). The New Economics of Industrial Policy. *Annual Review of Economics*. Publisher: Annual Reviews.

König, M., K. Storesletten, Z. Song, and F. Zilibotti (2022). From Imitation to Innovation: Where Is All That Chinese R&D Going? *Econometrica 90*(4), 1615–1654.

Lanjouw, J. O. and M. Schankerman (2004, April). Patent Quality and Research Productivity: Measuring Innovation with Multiple Indicators. *The Economic Journal 114*(495), 441–465.

Lerner, J. and A. Seru (2022, June). The Use and Misuse of Patent Data: Issues for Finance and Beyond. *The Review of Financial Studies 35*(6), 2667–2704.

Liu, Q. and H. Ma (2020, November). Trade policy uncertainty and innovation: Firm level evidence from Chinas WTO accession. *Journal of International Economics 127*, 103387.

Lu, Y., J. Wang, and L. Zhu (2019, August). Place-Based Policies, Creation, and Agglomeration Economies: Evidence from Chinas Economic Zone Program. *American Economic Journal: Economic Policy 11*(3), 325–360.

Mamuneas, T. P. and M. Ishaq Nadiri (1996, December). Public R&D policies and cost behavior of the US manufacturing industries. *Journal of Public Economics 63*(1), 57–81.

Moretti, E. (2021, October). The Effect of High-Tech Clusters on the Productivity of Top Inventors. *American Economic Review 111*(10), 3328–3375.

Moretti, E., C. Steinwender, and J. Van Reenen (2023, February). The Intellectual Spoils of War? Defense R&D, Productivity, and International Spillovers. *The Review of Economics and Statistics*, 1–46.

Moser, P. and A. Voena (2012, February). Compulsory Licensing: Evidence from the Trading with the Enemy Act. *American Economic Review 102*(1), 396–427.

Olley, G. S. and A. Pakes (1996, November). The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica 64*(6), 1263.

Pallante, G., E. Russo, and A. Roventini (2023, October). Does public R&D funding crowd-in private R&D investment? Evidence from military R&D expenditures for US states. *Research Policy 52*(8), 104807.

Romer, P. M. (1990, October). Endogenous Technological Change. *Journal of Political Economy 98*(5, Part 2), S71–S102.

Schumpeter, J. A. (1934). *The Theory of Economic Development: An Inquiry into Profits, Capital, Credits, Interest, and the Business Cycle*. Harvard University Press.

Xu, C. (2022, November). Reshaping Global Trade: The Immediate and Long-Run Effects of Bank Failures. *The Quarterly Journal of Economics 137*(4), 2107–2161.

For Online Publication

A Additional policy background

This appendix provides additional background on the National Technological Innovation Demonstration Enterprise (NTIDE) policy.

A.1 Submitted materials and criteria prioritized in certification

I begin by providing a more comprehensive summary of the materials that applicant enterprises are required to submit to the government. This is significant because these materials reflect the criteria prioritized by the government during the certification process. As stipulated in the policy document, enterprises must submit a declaration, the *Table of Enterprise Basic Information*, and the *Table of Evaluation Indicators for Enterprise Technological Innovation*. The latter two tables encompass critical indicators of the enterprise's financial performance as well as its innovation achievements. A translation of these tables is provided in Table A.1 and A.2. [1]

After enterprises submit their application materials, the provincial departments of industry and information technology, in coordination with their respective finance departments, conduct a review of the submitted documents and determine the list of recommended enterprises. The application materials of the recommended enterprises, accompanied by the review comments, are forwarded to the Ministry of Industry and Information Technology (MIIT) within the designated time frame. Furthermore, provincial governments are required to submit the *Summary Table of Recommended Enterprises for National Technology Innovation Demonstration Enterprises* to the MIIT.

Figure A.3 presents the summary table submitted by local governments to the MIIT during the 2012 certification process. In addition to listing the names of the recommended enterprises, the table includes detailed information on each enterprise's type, industry, R&D investment, main business revenue, new product sales revenue, number of patent applications from the previous year, and any prior policy-related titles awarded to the enterprises. These variables, contingent on data availability, are utilized as covariates in the empirical analysis when matching the control group for the treated firms.

A.2 Detailed summary of annual certification and re-evaluation

Appendix Table A.1 presents the number of certified demonstration enterprises, the number of re-evaluated enterprises, the number of enterprises failing in the re-evaluation, the passing rate, and the cumulative number of demonstration enterprises at the end of the year from 2011 to 2017. On average, 71 demonstration enterprises were certified annually between 2011 and 2017. Demonstration enterprises are subject to a re-evaluation process every three years. For instance, the 55 demonstration enterprises certified in 2011 underwent two re-evaluations in 2014 and 2017, respectively. From 2014 to 2017, an average of 84.5 demonstration enterprises underwent re-evaluation annually, with an average approval rate of 99.2%.

The table indicates that, during the sample period of this study, nearly no enterprises in the treatment group lost the policy title. Consequently, in the main text, when estimating treatment effects, once an enterprise is certified as a demonstration enterprise or a city–industry pair experiences its first demonstration enterprise, it is reasonably assumed to remain treated for the entire sample period. This approach allows me to circumvent the complexities associated with addressing the issue of exiting treatment status, which is particularly challenging when treatment effects vary over time.

[1] The original tables in Chinese are available at `https://www.miit.gov.cn/gyhxxhb/jgsj/kjs/wzpz/ztzl/gjjscxsfqy/tzgg/art/2020/art_c89910df1c7b42c5a6807d5eafaaf38c.html` (accessed February 2025).

A.3 The industry distribution of demonstration enterprises

Figure A.4 illustrates the industry distribution of demonstration enterprises. The left panel presents the distribution of the 494 demonstration enterprises existing after the certification in 2017 (i.e., all treatment cohorts from 2012 to 2018) across industries, while the right panel displays the proportion of invention patent applications classified into each industry from 2008 to 2018.

Broadly speaking, demonstration enterprises are predominantly concentrated in heavy manufacturing industries, which also account for a significant share of patents. This aligns with the policy objectives aimed at promoting overall innovation. The left panel reveals that the four industries with the highest concentration of demonstration enterprises are "Pharmaceutical Manufacturing," "Electronics Manufacturing," "Electrical Machinery Manufacturing," and "Chemical Manufacturing."

It is important to note that, in this study, patents are assigned to industries based on the matching between International Patent Classification (IPC) codes and major industry categories. This approach essentially examines the industries in which patents are exploited, under the assumption that patents invented by enterprises are primarily utilized within their respective industries. However, this assumption does not hold for certain industries. For instance, there is no IPC code corresponding to the "R&D" industry. Consequently, although this category includes 28 demonstration enterprises, its patent share is zero. For this reason, all empirical analyses regarding patents in the main text are restricted to the 54 industries that correspond to IPC codes.

A.4 The spatial distribution of demonstration enterprises

Appendix Table A.2 presents the distribution of the cumulative number of demonstration enterprises, specifically examining whether multiple demonstration enterprises exist within the same city–industry pair. For example, as shown in the first row, among the 52 city–industry pairs treated in 2012 (where the first demonstration enterprise was certified in 2011), 50 had only one demonstration enterprise, accounting for 96.15% of the sample. Only 2 treated city–industry pairs had two demonstration enterprises, representing 3.85% of the sample.

Although the proportion of treated city–industry pairs with only one demonstration enterprise decreased over time, as of the 2017 certification, 85.29% of treated city–industry pairs still had only one demonstration enterprise. This observation provides two key insights. First, the use of a binary treatment variable in this study is reasonable. While it is possible to construct a continuous variable representing treatment intensity based on the number of demonstration enterprises, switching to a continuous treatment variable would only alter the variable values for a very small proportion of the sample. Second, the policy objective of the demonstration enterprise program is unlikely to be signaling policy incentives by subsidizing "star enterprises" to attract innovation from other local firms. This is because city–industry pairs with an existing demonstration enterprise rarely have a second enterprise certified.

A.5 The market standing of demonstration enterprises

Finally, I examine the market standing of demonstration enterprises to support the conclusion in the main text that demonstration enterprises are typically leading firms within their local markets. Specifically, I calculate the percentile rankings of listed demonstration enterprises in their respective provinces and industries across four variables: the number of invention patent applications, the number of utility model patents, R&D expenditure, and asset size. These rankings are based on data of listed firms from the year prior to certification.

Figure A.5 presents the results. On average, demonstration enterprises rank between the 70th and 80th percentiles across the four variables. To better reflect the market standing of early-certified demonstration enterprises, I further restrict the sample to industries with no more than three listed demonstration enterprises nationwide. In these industries, the average ranking of demonstration enterprises in terms of invention patent applications approaches the 85th percentile, and their average ranking in R&D investment reaches the 87th percentile, indicating more pronounced leading positions.

Given that listed firms generally have larger production scales, higher R&D expenditures, and greater productivity levels compared to the overall population of firms, these findings support the conclusion that demonstration enterprises hold a significantly leading position within their respective industries and provinces. Additionally, the results suggest that, when certifying demonstration enterprises, the government may place greater emphasis on R&D expenditure and the number of invention patents—which reflect higher levels and quality of innovation—than on firm size or the number of utility model patents. This again aligns with the policy's underlying objectives.

B Additional proofs

B.1 Proof of Equation (2)

On the demand side, the utility of the representative household is the consumption of final goods, which is represented by the following utility function:

$$U_t = Y_t = \left(\sum_{i \in \mathscr{I}} Y_{i,t}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}. \tag{A.1}$$

The representative household maximizes its utility by choosing the optimal consumption of goods from each industry $Y_{i,t}$. The utility maximization problem is formulated as:

$$\begin{aligned} \max_{\{Y_{i,t}\}_{i \in \mathscr{I}}} \ & U_t = \left(\sum_{i \in \mathscr{I}} Y_{i,t}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}} \\ \text{s.t.} \quad & \sum_{i \in \mathscr{I}} P_{i,t} Y_{i,t} \le S_t, \end{aligned} \tag{A.2}$$

where S_t represents the budget constraint. Given that the marginal utility of each good is always positive and approaches infinity as its quantity approaches zero, utility maximization implies that all goods are consumed, and the representative household exhausts its entire budget on consumption. Therefore, the Lagrangian is

$$\mathscr{L} = \left(\sum_{i \in \mathscr{I}} Y_{i,t}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}} - \lambda \left(\sum_{i \in \mathscr{I}} P_{i,t} Y_{i,t} - S_t \right). \tag{A.3}$$

Considering the consumption of goods from industry i and another industry i', the first-order conditions require that their optimal consumption satisfy

$$Y_{i',t} = \left(\frac{P_{i,t}}{P_{i',t}} \right)^{\eta} Y_{i,t}. \tag{A.4}$$

Using this relationship, the optimal consumption of any good can be expressed in terms of the consumption of good i. Substituting these expressions into the utility function yields:

$$Y_{i,t} = \left(\frac{P_{i,t}}{P_t} \right)^{-\eta} Y_t, \tag{A.5}$$

where $P_t \equiv \left(\sum_{i \in \mathscr{I}} P_{i,t}^{1-\eta} \right)^{1/(1-\eta)}$. ■

B.2 Proof of Equation (4)

Given a production level $Y_{i,t}$, firm i selects the optimal combination of labor and capital inputs to minimize its cost. Formally, the optimization problem is expressed as

$$\begin{aligned} \min_{\{K_{i,t}, L_{i,t}\}} \ & c_{i,t} = w_t L_{i,t} + r_t K_{i,t} \\ \text{s.t.} \quad & Y_{i,t} = A_{i,t} K_{i,t}^{\alpha} L_{i,t}^{1-\alpha}. \end{aligned} \tag{A.6}$$

From the first-order conditions, the optimal capital input can be expressed in terms of the optimal labor input as:

$$K_{i,t}^* = \frac{\alpha}{1-\alpha} \frac{w_t}{r_t} L_{i,t}^*. \tag{A.7}$$

Substituting this expression into the production function yields the optimal labor input required to produce $Y_{i,t}$ units of output:

$$L_{i,t}^{*} = \frac{Y_{i,t}}{A_{i,t}} \left(\frac{r_t}{w_t}\right)^{\alpha} \left(\frac{1-\alpha}{\alpha}\right)^{\alpha}. \tag{A.8}$$

The corresponding optimal capital input is then derived as

$$K_{i,t}^{*} = \frac{Y_{i,t}}{A_{i,t}} \left(\frac{r_t}{w_t}\right)^{\alpha-1} \left(\frac{1-\alpha}{\alpha}\right)^{\alpha-1}. \tag{A.9}$$

Combining these two results, the minimum cost of producing $Y_{i,t}$ units of output is given by

$$\begin{aligned} c_{i,t}^{*} &= w_t L_{i,t}^{*} + r_t K_{i,t}^{*} \\ &= \frac{\alpha^{-\alpha} (1-\alpha)^{1-\alpha} r_t^{\alpha} w_t^{1-\alpha}}{A_{i,t}} Y_{i,t}. \end{aligned} \tag{A.10}$$

Thus, the minimum cost is a linear function of production, and the unit cost is

$$C_{i,t} = \frac{\alpha^{-\alpha} (1-\alpha)^{1-\alpha} r_t^{\alpha} w_t^{1-\alpha}}{A_{i,t}}. \tag{A.11}$$

■

B.3 Proof of Equation (6)

The profit maximization problem of monopolistic firm i in period t is

$$\max_{P_{i,t}} \pi_{i,t} = P_{i,t} Y_{i,t} - C_{i,t} Y_{i,t}, \tag{A.12}$$

where $Y_{i,t} = \left(P_{i,t}/P_t\right)^{-\eta} Y_t$ represents the demand for the firm's product. Substituting the demand function into the profit equation and solving the first-order condition yields the optimal price set by the monopolistic firm:

$$P_{i,t} = \frac{\eta}{\eta-1} C_{i,t}, \tag{A.13}$$

which reflects a markup over the unit (marginal) cost. Substituting the optimal price back into the profit function, the optimal profit is derived as

$$\begin{aligned} \pi_{i,t}^{*} &= \eta^{-\eta} \left(\eta-1\right)^{\eta-1} Y_t P_t^{\eta} C_{i,t}^{1-\eta} \\ &= \eta^{-\eta} \left(\eta-1\right)^{\eta-1} Y_t P_t^{\eta} C_t^{1-\eta} A_{i,t}^{\eta-1}, \end{aligned} \tag{A.14}$$

where $C_t \equiv \alpha^{-\alpha} (1-\alpha)^{\alpha-1} r_t^{\alpha} w_t^{1-\alpha}$ is an exogenous term that is constant across industries/firms. ■

B.4 Proof of Proposition 1

Proposition 1. *As government-provided innovation subsidies to the leading firm increase, the direction of the change in its private R&D investments depends on the degree of substitutability between private R&D investments and subsidies σ.*

Proof. I start with discussing a more general assumption for the specification of $\mathbb{E}\left[(1+\lambda)^{\eta-1} \mid I_{i,t}\right]$. Suppose that $\mathbb{E}\left[(1+\lambda)^{\eta-1} \mid I_{i,t}\right] = \mu\left(I_{i,t}\right)$, with $\mu' > 0$ and $\mu'' < 0$ to depict two well-acknowledged properties: positive gains and diminishing marginal effects. Accordingly, the inter-temporal profits maximization problem is given by

$$\max_{R_{i,t}} \Pi_i = \tilde{\Pi}_t A_{i,t}^{\eta-1} - R_{i,t} + \frac{1}{1+\beta}\tilde{\Pi}_{t+1} A_{i,t}^{\eta-1} \mu\left(I_{i,t}\right),$$
$$\text{with} \quad I_{i,t} = \left(R_{i,t}^{\frac{\sigma-1}{\sigma}} + S_{i,t}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \tag{A.15}$$

the first-order condition of which is

$$\begin{aligned}\frac{\partial \Pi_i}{\partial R_{i,t}} &= -1 + \frac{1}{1+\beta}\tilde{\Pi}_{t+1} A_{i,t}^{\eta-1} \mu' \frac{\partial I_{i,t}}{\partial R_{i,t}} \\ &= -1 + \frac{1}{1+\beta}\tilde{\Pi}_{t+1} A_{i,t}^{\eta-1} \mu' \left(R_{i,t}^{\frac{\sigma-1}{\sigma}} + S_{i,t}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{1}{\sigma-1}} R_{i,t}^{-\frac{1}{\sigma}} = 0,\end{aligned} \tag{A.16}$$

and the second-order condition is

$$\frac{\partial^2 \Pi_i}{\partial R_{i,t}^2} = \frac{1}{1+\beta}\tilde{\Pi}_{t+1} A_{i,t}^{\eta-1} \left[\mu'' \left(\frac{\partial I_{i,t}}{\partial R_{i,t}}\right)^2 + \mu' \frac{\partial^2 I_{i,t}}{\partial R_{i,t}^2}\right]. \tag{A.17}$$

The CES aggregation implies that $\partial^2 I_{i,t}/\partial R_{i,t}^2 \leq 0$. Specifically,

$$\frac{\partial^2 I_{i,t}}{\partial R_{i,t}^2} = -\frac{1}{\sigma}\left(R_{i,t}^{\frac{\sigma-1}{\sigma}} + S_{i,t}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{2-\sigma}{\sigma-1}} R_{i,t}^{-\frac{\sigma+1}{\sigma}} S_{i,t}^{\frac{\sigma-1}{\sigma}} \leq 0. \tag{A.18}$$

With $\mu' > 0$ and $\mu'' < 0$, I prove that the second-order condition is always negative (i.e., $\partial^2 \Pi_i/\partial R_{i,t}^2 < 0$). Therefore, the second-order condition ensures the uniqueness of the optimal private R&D investments as long as the solution of the first-order condition exists.

I first assume that the solution exists and discuss its property with respect to the innovation subsidies $S_{i,t}$. Denoting the optimal private R&D investments that solves the first-order condition as $R_{i,t}^*$ and defining $\mathscr{F} \equiv \partial \Pi_i/\partial R_{i,t}$, applying the implicit function theorem to Equation (A.16) yields

$$\frac{\mathrm{d}R_{i,t}^*}{\mathrm{d}S_{i,t}} = -\frac{\partial \mathscr{F}/\partial S_{i,t}}{\partial \mathscr{F}/\partial R_{i,t}}, \tag{A.19}$$

where the denominator is negative due to the second-order condition. Therefore, the direction of the change in the optimal private R&D investments with respect to the innovation subsidies $S_{i,t}$ is determined by the sign of $\partial \mathscr{F}/\partial S_{i,t}$. Further,

$$\frac{\partial \mathscr{F}}{\partial S_{i,t}} = \frac{1}{1+\beta}\tilde{\Pi}_{t+1} A_{i,t}^{\eta-1} \left(R_{i,t}^{\frac{\sigma-1}{\sigma}} + S_{i,t}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{2-\sigma}{\sigma-1}} R_{i,t}^{-\frac{1}{\sigma}} S_{i,t}^{-\frac{1}{\sigma}} \left(\mu'' I_{i,t} + \frac{1}{\sigma}\mu'\right), \tag{A.20}$$

and the sign of this equation is determined by $\mu'' I_{i,t} + \frac{1}{\sigma}\mu'$. This equation indicates that, given $\mu(\cdot)$ and $I_{i,t}$, if private R&D investments and government-provided innovation subsidies are better complementary (i.e., σ is smaller), $\partial \mathscr{F}/\partial S_{i,t}$ will be larger, suggesting that public innovation funds will less crowd out private R&D investments. However, unless allowing more assumptions on the specification of $\mu(\cdot)$, it is still unable to determine the direction of the change in the optimal private investments as well as the total R&D expenditure.

With the assumption in the main text, $\mu\left(I_{i,t}\right) = \tau \ln I_{i,t}$, where $\tau > 0$ controls for the measurement units, I derive

$$\mu'' I_{i,t} + \frac{1}{\sigma}\mu' = \frac{\tau}{I_{i,t,}}\left(\frac{1}{\sigma} - 1\right). \tag{A.21}$$

Therefore, if $\sigma > 1$ (more substitute), then $\mu'' I_{i,t} + \frac{1}{\sigma}\mu' < 0$ and, consequently, $\mathrm{d}R_{i,t}^*/\mathrm{d}S_{i,t} < 0$, suggesting the increase on innovation subsidies crowds out private R&D investment. On the contrary, if $0 < \sigma < 1$ (more complementary), the increase on innovation subsidies can encourage private R&D investments.

Finally, I back to prove the existence of the solution of the first-order condition. Substituting $\mu\left(I_{i,t}\right) = \tau \ln I_{i,t}$ into Equation (A.16) yields

$$\frac{R_{i,t}^{-\frac{1}{\sigma}}}{R_{i,t}^{\frac{\sigma-1}{\sigma}} + S_{i,t}^{\frac{\sigma-1}{\sigma}}} = \frac{1+\beta}{\tau \tilde{\Pi}_{t+1} A_{i,t}^{\eta-1}}, \tag{A.22}$$

where the right-hand side of this equation is a positive constant. Notice that the second-order condition ensures that the left-hand side decreases as $R_{i,t}$ increases, thus it is convenient to investigate the existence of the solution by discussing the values at the endpoints of the domain. Since $R_{i,t}^{-1/\sigma} \to 0$ and $R_{i,t}^{(\sigma-1)/\sigma} + S_{i,t}^{(\sigma-1)/\sigma} > 0$ when $R_{i,t} \to \infty$, the value of the left-hand side approaches zero when $R_{i,t} \to \infty$. Additionally, $R_{i,t}^{-1/\sigma} \to \infty$ when $R_{i,t} \to 0$. If $\sigma \geq 1$, then $R_{i,t}^{(\sigma-1)/\sigma} + S_{i,t}^{(\sigma-1)/\sigma} \to 2$ $(\sigma = 1)$ or $S_{i,t}^{(\sigma-1)/\sigma}$ $(\sigma > 1)$. Therefore, the value of the left-hand side approaches infinity when $R_{i,t} \to 0$. If $0 < \sigma < 1$, when $R_{i,t} \to 0$, $R_{i,t}^{-1/\sigma} / \left(R_{i,t}^{(\sigma-1)/\sigma} + S_{i,t}^{(\sigma-1)/\sigma}\right) \sim R_{i,t}^{-1/\sigma} / R_{i,t}^{(\sigma-1)/\sigma} = R_{i,t}^{-1} \to \infty$. Taken together, when $R_{i,t} \to 0$, the left-hand side of the first-order condition approaches infinity, while it approaches zero when $R_{i,t} \to \infty$. As the right-hand size is a positive constant, the continuity and monotonicity of the left-hand side ensure the existence of the solution. ■

B.5 Proof of Proposition 2

Proposition 2. *As government-provided innovation subsidies to the leading firm increase, its total R&D expenditure rises, regardless of the value of σ.*

Proof. I begin with discussing a special case with $\sigma = 1$. Based on Equation (A.21), $\mathrm{d}R_{i,t}^{*}/\mathrm{d}S_{i,t} = 0$ when $\sigma = 1$, suggesting private R&D investment will be neither crowded out nor encouraged when government-provided innovation subsidies increase. Therefore, the total R&D expenditure will increase as subsidies increases.

When $\sigma \neq 1$, I can transform the first-order condition in Equation (A.22) into

$$\begin{aligned} \frac{R_{i,t}^{-\frac{1}{\sigma}\times\frac{\sigma}{\sigma-1}}}{\left(R_{i,t}^{\frac{\sigma-1}{\sigma}} + S_{i,t}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}} &= \left(\frac{1+\beta}{\tau \tilde{\Pi}_{t+1} A_{i,t}^{\eta-1}}\right)^{\frac{\sigma}{\sigma-1}} \\ \Leftrightarrow \; I_{i,t} &= \left(\frac{1+\beta}{\tau \tilde{\Pi}_{t+1} A_{i,t}^{\eta-1}}\right)^{\frac{\sigma-1}{\sigma}} R_{i,t}^{-\frac{1}{\sigma-1}}. \end{aligned} \tag{A.23}$$

Accordingly, discussing the direction of the change in the total R&D expenditure under optimization is equivalent to discuss the right-hand size of this equation with $R_{i,t}$ being the optimal private investment (i.e., $R_{i,t}^{*}$).

If $\sigma > 1$, Equation (A.21) suggests that $\mathrm{d}R_{i,t}^{*}/\mathrm{d}S_{i,t} < 0$. As $-1/(\sigma-1) < 0$, the increase of $S_{i,t}$ decreases $R_{i,t}^{*}$ and increases ${R_{i,t}^{*}}^{-1/(\sigma-1)}$, thus $I_{i,t}$ under optimization increases as subsidies $S_{i,t}$ increase. Additionally, if $\sigma < 1$, Equation (A.21) suggests that $\mathrm{d}R_{i,t}^{*}/\mathrm{d}S_{i,t} > 0$. As $-1/(\sigma-1) > 0$, the increase of $S_{i,t}$ increases both $R_{i,t}^{*}$ and ${R_{i,t}^{*}}^{-1/(\sigma-1)}$, thus $I_{i,t}$ under optimization again increases as subsidies $S_{i,t}$ increase. Taken together, I prove that as government-provided innovation subsidies to the leading firm increase, the total R&D expenditure of the leading firm rises, regardless of the value of σ. ■

B.6 Proof of Proposition 3

Proposition 3. *As government-provided innovation subsidies to the leading firm increase, firms exhibiting larger productivity lag relative to the leading firm will decrease their total R&D expenditure, thereby leading to a decline in their probability of firm entry.*

Proof. The expected profits maximization problem for other firms is given by

$$\max_{R_{o,t}} \Pi_o = -R_{o,t} + \frac{1}{1+\beta}\int_0^\infty F_\lambda\left(\frac{x}{A_{i,t}} - 1 \mid I_{i,t}\right)\tilde{\Pi}_{t+1}x^{\eta-1}\mathrm{d}F_A\left(x \mid R_{o,t}\right). \tag{A.24}$$

The first-order condition is

$$\frac{\partial \Pi_o}{\partial R_{o,t}} = -1 + \frac{\partial}{\partial R_{o,t}}\left[\frac{1}{1+\beta}\int_0^\infty F_\lambda\left(\frac{x}{A_{i,t}} - 1 \mid I_{i,t}\right)\tilde{\Pi}_{t+1}x^{\eta-1}\mathrm{d}F_A\left(x \mid R_{o,t}\right)\right] = 0, \tag{A.25}$$

and the Inada conditions on $\delta\left(R_{o,t}, I_{i,t}\right)$ ensures that the second-order condition is negative and the solution to the first-order condition exists and is unique.

Define $\mathscr{G} \equiv \partial\Pi_o/\partial R_{o,t}$. Using the implicit function theorem, the direction of the change in the optimal $R_{o,t}$ (denoted as $R^*_{o,t}$) with respect to $I_{i,t}$ is

$$\frac{\mathrm{d}R^*_{o,t}}{\mathrm{d}I_{i,t}} = -\frac{\partial\mathscr{G}/\partial I_{i,t}}{\partial\mathscr{G}/\partial R_{o,t}}, \tag{A.26}$$

where the denominator is negative due to the second-order condition. The numerator is

$$\frac{\partial\mathscr{G}}{\partial I_{i,t}} = \frac{1}{1+\beta}\cdot\frac{\partial^2}{\partial R_{o,t}\partial I_{i,t}}\left[\int_0^\infty F_\lambda\left(\frac{x}{A_{i,t}} - 1 \mid I_{i,t}\right)\tilde{\Pi}_{t+1}x^{\eta-1}\mathrm{d}F_A\left(x \mid R_{o,t}\right)\right]. \tag{A.27}$$

Using the Leibniz integral rule, I put the derivative inside the integral and obtain

$$\begin{aligned}\frac{\partial\mathscr{G}}{\partial I_{i,t}} &= \frac{1}{1+\beta}\int_0^\infty \tilde{\Pi}_{t+1}x^{\eta-1}\frac{\partial F_\lambda\left(\frac{x}{A_{i,t}} - 1 \mid I_{i,t}\right)}{\partial I_{i,t}}\frac{\partial f_A\left(x \mid R_{o,t}\right)}{\partial R_{o,t}}\mathrm{d}x\\ &= \frac{1}{1+\beta}\int_{A_{i,t}}^\infty \tilde{\Pi}_{t+1}x^{\eta-1}\frac{\partial F_\lambda\left(\frac{x}{A_{i,t}} - 1 \mid I_{i,t}\right)}{\partial I_{i,t}}\frac{\partial f_A\left(x \mid R_{o,t}\right)}{\partial R_{o,t}}\mathrm{d}x.\end{aligned} \tag{A.28}$$

Since $\lambda > 0$ by definition, the derivative $\partial F_\lambda\left(x/A_{i,t} - 1 \mid I_{i,t}\right)/\partial I_{i,t}$ can only be non-zero when $x > A_{i,t}$. As a result, the integral can be equivalently computed over the interval $\left(A_{i,t}, \infty\right)$.

The partial derivative $\partial F_\lambda\left(x/A_{i,t} - 1 \mid I_{i,t}\right)/\partial I_{i,t}$ is non-positive and has at least one interval over which its value is strictly negative, which is guaranteed by the condition of first-order stochastic dominance. Consequently, the sign of the integral is determined by $\partial f_A\left(x \mid R_{o,t}\right)/\partial R_{o,t}$. The rightward shift of $F_A\left(x \mid R_{o,t}\right)$ as $R_{o,t}$ increases implies that $\partial f_A\left(x \mid R_{o,t}\right)/\partial R_{o,t}$ is negative for some smaller values of x and positive for larger values of x. As a result, further analysis of this derivative is required.

I first demonstrate the existence of a critical value of x, denoted by $\hat{x}$, such that for $x < \hat{x}$, the partial derivative $\partial f_A\left(x \mid R_{o,t}\right)/\partial R_{o,t} < 0$, and for $x > \hat{x}$, $\partial f_A\left(x \mid R_{o,t}\right)/\partial R_{o,t} > 0$. This property holds given two assumptions outlined in the main text. The first assumption is that $R_{o,t}$ influences the first-order moment of the distribution but does not affect higher-order moments. Consequently, as $R_{o,t}$ increases, the density function shifts rightward while preserving its shape. To formalize this, let $f^0_A(x)$ denote the baseline density function, which represents the density conditional on $R_{o,t} = 0$. Then, other conditional density functions can be expressed as

$$f_A\left(x \mid R_{o,t}\right) = f^0_A\left(x - \mu\left(R_{o,t}\right)\right), \tag{A.29}$$

where $\mu\left(R_{o,t}\right)$ governs the shift of the density function and satisfies $\mu'\left(R_{o,t}\right) > 0$.

The second assumption is that the density function is unimodal. Let m^0 denote the mode of the baseline density function $f_A^0(x)$. It follows that the derivative $f_A^{0\prime}(x) > 0$ when $x < m^0$ and $f_A^{0\prime}(x) < 0$ when $x > m^0$. Consequently, the mode of the conditional density function $f_A\left(x \mid R_{o,t}\right)$ is given by $m^0 + \mu\left(R_{o,t}\right)$.

Using the relationship expressed in Equation (A.29), the partial derivative of the conditional density function with respect to $R_{o,t}$ can be derived as:

$$\frac{\partial f_A\left(x \mid R_{o,t}\right)}{\partial R_{o,t}} = -f_A^{0\prime}\left(x - \mu\left(R_{o,t}\right)\right)\mu'\left(R_{o,t}\right). \tag{A.30}$$

From this, it is evident that $\hat{x} = m^0 + \mu\left(R_{o,t}\right)$. This critical point delineates the regions where the partial derivative changes sign.

This property enables the distinction between two cases. The first case arises when the productivity distribution of the competitor firm is sufficiently close to that of the leading firm, such that $m^0 + \mu\left(R_{o,t}\right) > A_{i,t}$. In this scenario, Equation (A.28) can be reformulated as follows:

$$\begin{aligned}\frac{\partial \mathcal{G}}{\partial I_{i,t}} = &\underbrace{\frac{1}{1+\beta}\int_{A_{i,t}}^{m^0+\mu(R_{o,t})} \tilde{\Pi}_{t+1} x^{\eta-1} \frac{\partial F_\lambda\left(\frac{x}{A_{i,t}} - 1 \mid I_{i,t}\right)}{\partial I_{i,t}} \frac{\partial f_A\left(x \mid R_{o,t}\right)}{\partial R_{o,t}} \mathrm{d}x}_{\text{non-negative}} \\ &+ \underbrace{\frac{1}{1+\beta}\int_{m^0+\mu(R_{o,t})}^{\infty} \tilde{\Pi}_{t+1} x^{\eta-1} \frac{\partial F_\lambda\left(\frac{x}{A_{i,t}} - 1 \mid I_{i,t}\right)}{\partial I_{i,t}} \frac{\partial f_A\left(x \mid R_{o,t}\right)}{\partial R_{o,t}} \mathrm{d}x}_{\text{non-positive}}.\end{aligned} \tag{A.31}$$

Therefore, the sign of $\partial\mathcal{G}/\partial I_{i,t}$ hinges on the relative dominance of the two integrals. However, this relationship remains indeterminate, which implies that the direction of the change in the total R&D expenditure of the competitor firm, in response to an increase in subsidies to the leading firm, cannot be conclusively determined.

In the alternative case, where the competitor firm exhibits a larger productivity lag relative to the leading firm—formally, $m^0 + \mu\left(R_{o,t}\right) \leq A_{i,t}$—it follows that $\partial\mathcal{G}/\partial I_{i,t} < 0$ and, consequently, $\mathrm{d}R_{o,t}^*/\mathrm{d}I_{i,t} < 0$. This result suggests that an increase in the leading firm's R&D expenditure, driven by government-provided subsidies, exerts a discouraging effect on the R&D expenditure of the competitor firm. ■

C Additional figures and tables

Basic Information Form of the Enterprise

<table>
<tr><td>Name</td><td colspan="5"></td></tr>
<tr><td>Address</td><td colspan="3"></td><td>Postal Code</td><td></td></tr>
<tr><td>Legal Representative</td><td></td><td>Phone</td><td></td><td>Mobile</td><td></td></tr>
<tr><td>Contact Person</td><td></td><td>Phone</td><td></td><td>Mobile</td><td></td></tr>
<tr><td>Fax</td><td></td><td>E-mail</td><td colspan="3"></td></tr>
<tr><td>Enterprise Type</td><td colspan="5">1. State-Owned 2. Joint Venture 3. Private 4. Others</td></tr>
<tr><td>Number of Employees</td><td></td><td>Number of Employees with a Bachelor's Degree or Above</td><td></td><td>Number of Employees with a Senior Professional Title or Above</td><td></td></tr>
<tr><td rowspan="5">Economic Performance in 2011</td><td colspan="2">Total Assets</td><td></td><td>Total Liabilities</td><td></td></tr>
<tr><td colspan="2">Main Business Revenue</td><td colspan="3">, increase of ___% compared to 2010</td></tr>
<tr><td colspan="2">Revenue from New Product Sales</td><td></td><td>Taxes Paid</td><td></td></tr>
<tr><td colspan="2">Total Profit</td><td colspan="3">, increase of ___% compared to 2010
Continuous Profitability for the Past Three Years: Yes/No</td></tr>
<tr><td colspan="2">Market Share of Main Products</td><td></td><td>Total Export Revenue</td><td></td></tr>
<tr><td colspan="3">Total R&D Investment in the Last Three Years</td><td></td><td>R&D Investment in 2011</td><td></td></tr>
<tr><td rowspan="3">Number of Patent Applications</td><td colspan="2" rowspan="3"></td><td>Inventions</td><td colspan="2"></td></tr>
<tr><td>Utility Models</td><td colspan="2"></td></tr>
<tr><td>Designs</td><td colspan="2"></td></tr>
<tr><td>Have a Provincial or National-Level Technology Center?</td><td colspan="2">1. Provincial
2. National</td><td>Relevant Certification Authority</td><td colspan="2"></td></tr>
<tr><td>Bank Credit Rating</td><td colspan="5"></td></tr>
</table>

Note: The above indicators should be based on data as of the end of 2011.

Figure A.1: The *Table of Enterprise Basic Information* (2012)

Enterprise Technological Innovation Evaluation Indicators

Primary Indicators	Secondary indicators	Tertiary Indicators	Unit	Value
Innovation Mechanism	Innovation Investment	1. Proportion of enterprise R&D expenditure to product sales revenue	%	
		2. Increase in R&D expenditure ratio compared to the previous year	Percentage points	
	Talent Incentives	3. Ratio of annual per capita income of R&D personnel to the enterprise's annual per capita income		
		4. Proportion of R&D personnel training expenses to total income of technical center staff	%	
	Innovation Cooperation	5. Number of external experts engaged in technology development	Person-months	
		6. Proportion of external cooperation projects to total development projects	%	
Technology and Talent	Innovation Team Development	7. Proportion of R&D personnel to total employees	%	
		8. Number of senior experts and PhD holders in enterprise R&D institutions	Person	
	Innovation Infrastructure	9. Original value of enterprise technology development instruments and equipment	10,000 CNY	
		10. Number of laboratories certified by national and international organizations		
	Technology Accumulation and Reserves	11. Proportion of projects with an R&D cycle of three years or more	%	
		12. Total number of valid invention patents owned by the enterprise		
		13. Number of Chinese well-known brands or famous trademarks owned by the enterprise		
Output and Benefits	Technological Innovation Output	14. Number of new product, technology, and process development projects completed during the year		
		15. Number of patent applications filed during the year Of which, number of invention patent applications filed during the year		
		16. Number of international, national, and industry standards formulated or participated in		
	Technological Innovation Benefits	17. Proportion of new product sales revenue to total product sales revenue	%	
		18. Proportion of new product sales profit to total product sales profit	%	
		19. Export earnings from proprietary brand products and technologies	10,000 USD	
Others		20. Number of projects awarded by National Natural Science, Technological Invention, or Science and Technology Progress Awards		
		21. Difference between year-end net cash flow and distributable profit	10,000 CNY	

Figure A.2: The *Table of Evaluation Indicators for Enterprise Technological Innovation* (2012)

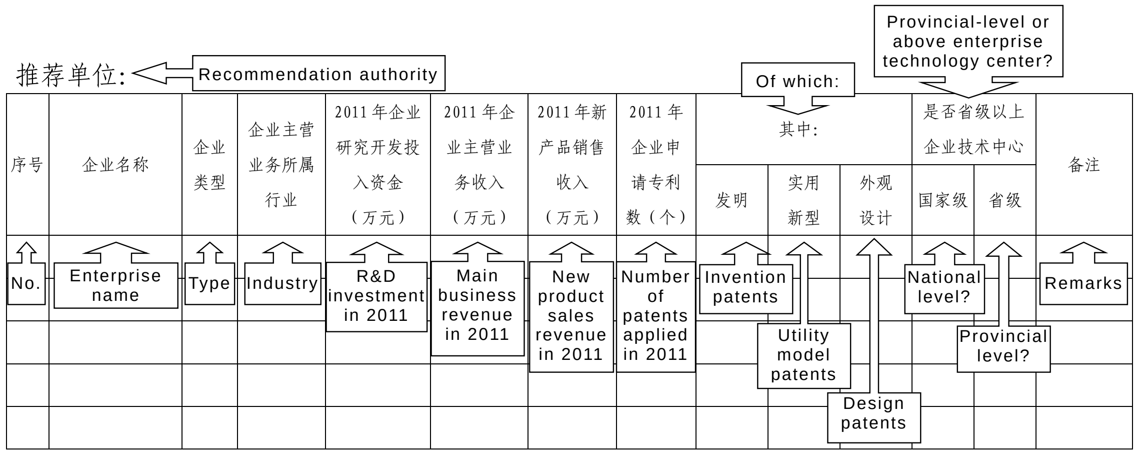

Figure A.3: The *Summary Table of Recommended Enterprises for National Technological Innovation Demonstration Enterprises* (2012)

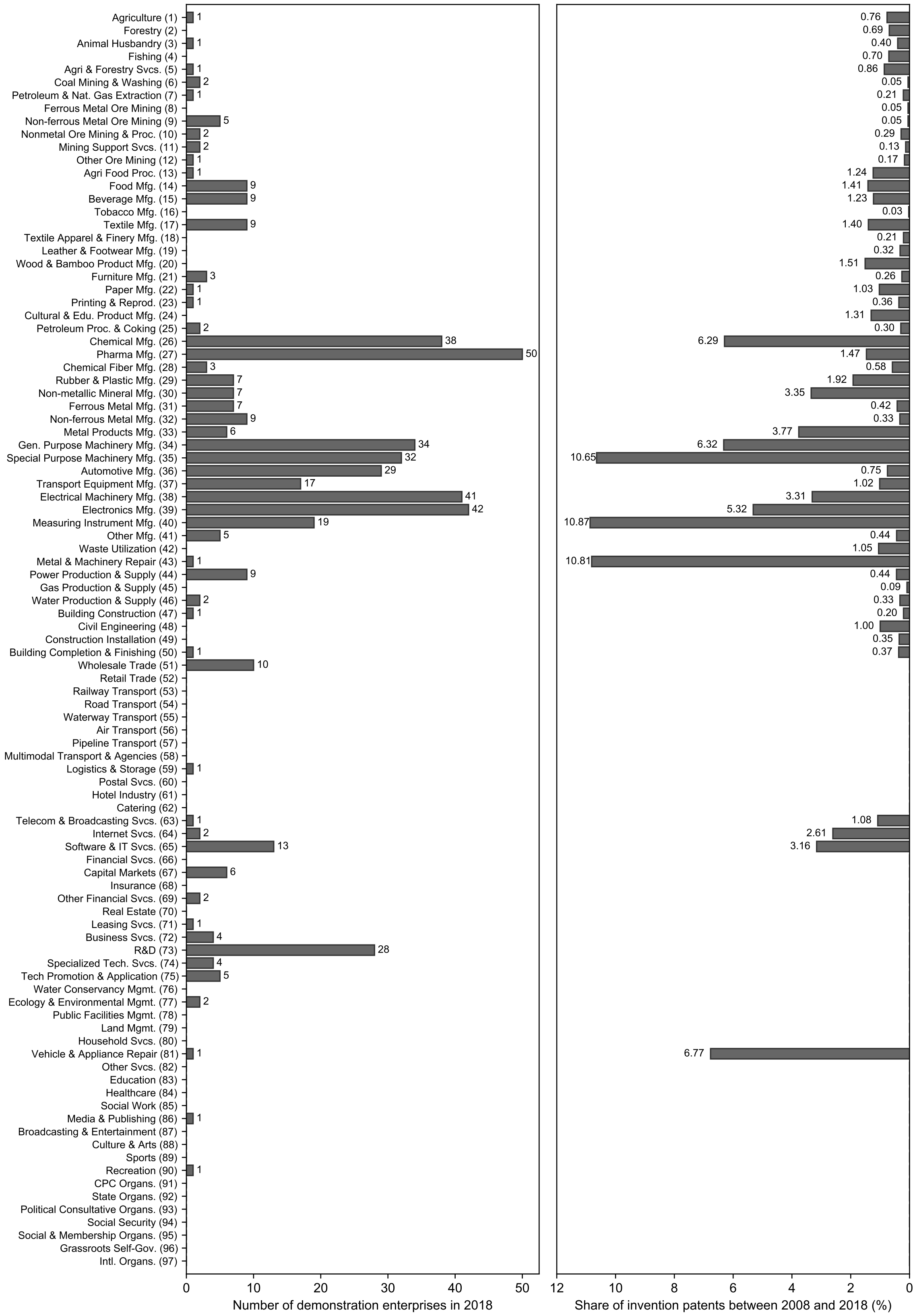

Figure A.4: Number of demonstration enterprises and share of invention patents by industry

Notes: This figure summarizes the industry distribution of demonstration enterprises and the share of invention patents by industry. The left panel displays the accumulated number of demonstration enterprises by industry after the certification in 2017, encompassing all treatment cohorts from 2012 to 2018. The right panel presents the share of invention patent applications from 2008 to 2018 by industry, calculated by matching each patent's IPC code with its corresponding industry. Industries are classified according to the National Bureau of Statistics of China (GB/T 4754-2017), with industry codes indicated in parentheses.

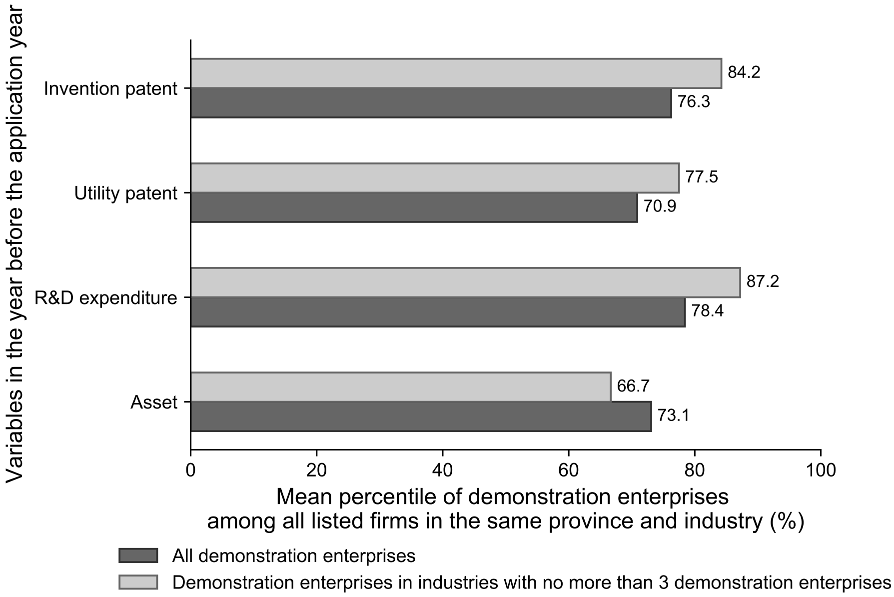

Figure A.5: The percentile of demonstrations firms in the local market

Notes: This figure presents the mean percentile of four variables—the number of invention patent applications, the number of utility model patent applications, R&D expenditure, and asset size—for demonstration enterprises relative to all listed firms in the corresponding industry and province at the end of the year prior to their application year. The darker bar represents the mean for all demonstration enterprises, while the lighter bar represents the mean for demonstration enterprises in industries with no more than three listed demonstration enterprises.

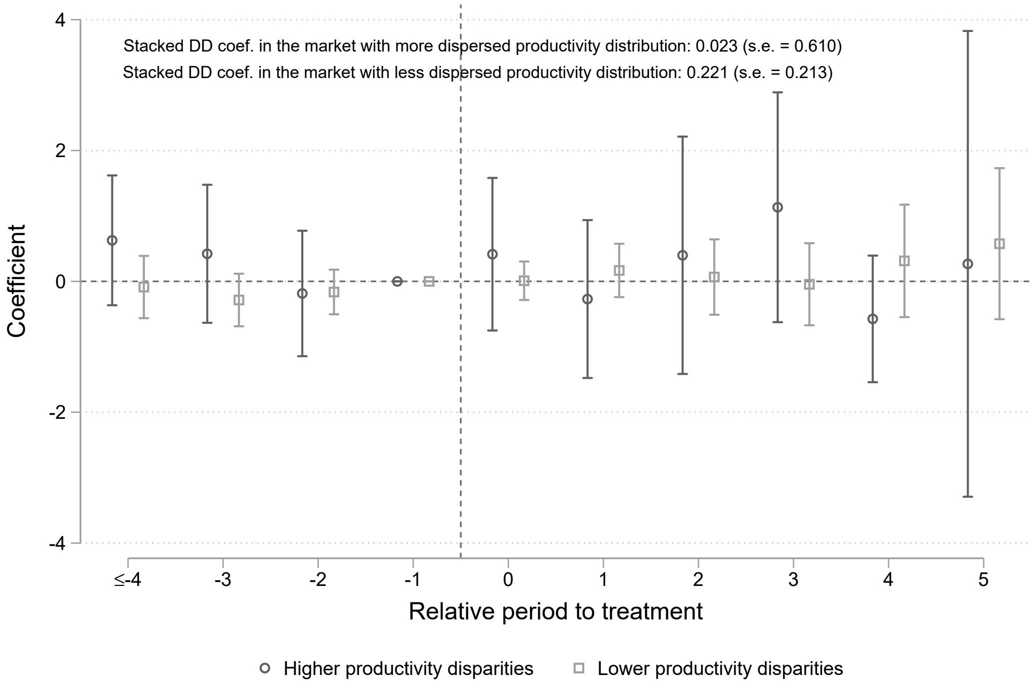

Figure A.6: Event study of government-provided R&D subsidies by TFP distribution

Notes: This figure presents the estimated coefficients obtained from the event study on government-provided R&D subsidies of two groups of competitor firms: those operating in markets with the top 25% degree of productivity dispersion, as measured by the Gini coefficient of the TFP distribution of listed firms, and those in markets with lower levels of dispersion. The circles represent the point estimates, and the lines indicate the 95% confidence intervals. The figure also reports the average treatment effects for the two treatment groups, calculated from the estimation of Equation (12).

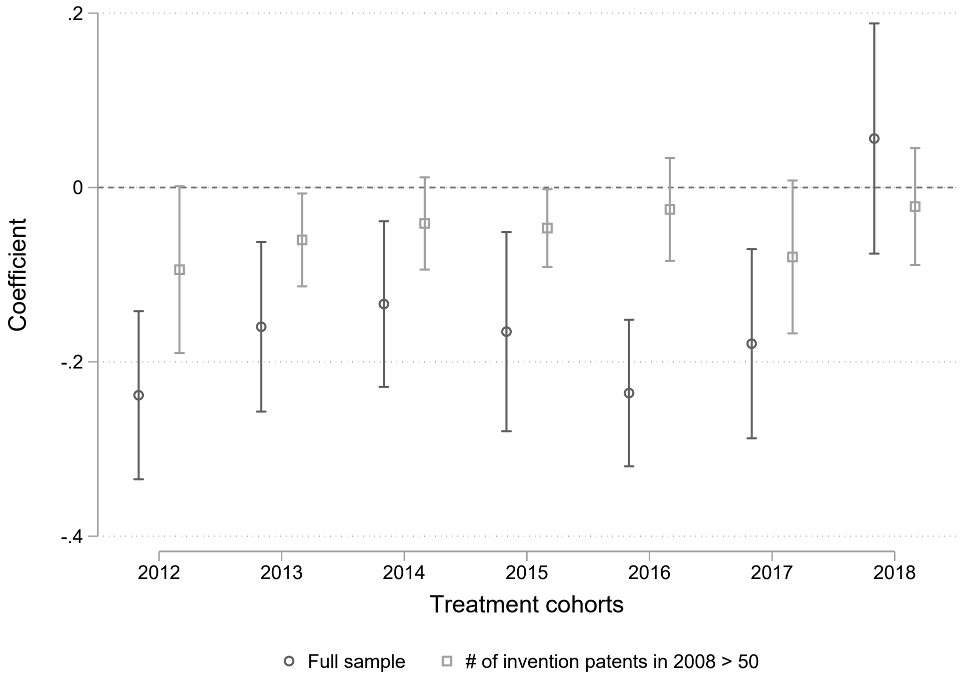

Figure A.7: Treatment effects on patent outputs by cohort

Notes: This figure presents the estimations of treatment effects on seven treatment cohorts from 2012 to 2018. The estimation model is consistent with Column (3) of Table 2, with the only difference being that the estimation is conducted separately for each stack. The dark-colored results are obtained using all city–industry pairs, while the light-colored results are obtained using city–industry pairs with more than 50 invention patent applications in 2008. The circles represent the point estimates of the coefficients, while the lines represent the 90% confidence intervals.

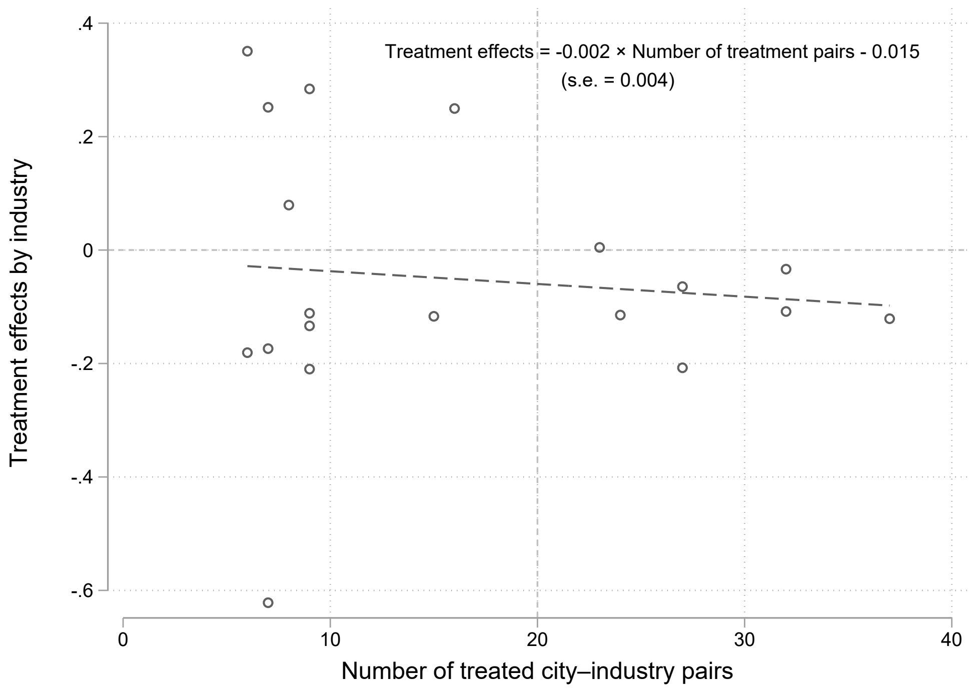

Figure A.8: Treatment effects and number of treatment pairs

Notes: This figure depicts the correlation between treatment effects and the number of treatment pairs across industries. The darker dashed line represents the fitted line.

Table A.1: Summary of demonstration enterprises and re-evaluated enterprises by year

Year	# of new certified	Re-evaluated enterprises			Accumulation
		Total	# of failed	Passing rate (%)	
2011	55				55
2012	76				131
2013	80				211
2014	72	55	0	100	283
2015	75	76	1	98.68	357
2016	69	80	1	98.75	425
2017	70	127	1	99.21	494
Mean	71	84.5	0.75	99.16	

Notes: This table presents statistics on the number of certified demonstration enterprises, the number of re-evaluated enterprises, the number of enterprises failing in the re-evaluation, the passing rate, and the cumulative number of demonstration enterprises at the end of the year from 2011 to 2017. Since demonstration enterprises undergo re-evaluation three years after their initial certification, the first round of re-evaluation occurred in 2014.

Table A.2: Distribution of accumulated demonstration enterprises

	Fraction of city–industry pairs for whose # of demonstration enterprises ≥ 1 (%)					
Year	# of DEs = 1	# of DEs = 2	# of DEs = 3	# of DEs = 4	# of DEs = 5	# of DEs = 6
2011	96.15	3.85	0	0	0	0
2012	95.90	2.46	1.64	0	0	0
2013	93.78	5.18	0.52	0.52	0	0
2014	91.24	7.17	1.20	0	0.40	0
2015	88.93	7.82	2.61	0.33	0.33	0
2016	86.20	10.70	1.97	0.85	0	0.28
2017	85.29	10.78	2.70	0.98	0	0.25

Notes: This table presents the distribution of the accumulated number of demonstration enterprises across city–industry pairs. The second to seventh columns present the fraction of treatment city–industry pairs for which the number of demonstration enterprises equals 1, 2, 3, 4, 5, and 6, respectively, during the period from 2011 to 2017.

Table A.3: Policy effects on government-provided R&D subsidies

	Logarithm of R&D subsidies	
	(1)	(2)
Panel A. Demonstration enterprises		
Treated	0.322*	0.474***
	(0.198)	(0.176)
# of clusters	204	204
# of observations	2,464	2,464
Panel B. Competitor enterprises		
Treated	0.042	0.034
	(0.145)	(0.156)
# of clusters	383	383
# of observations	7,564	7,564
Enterprise FEs × Stack FEs	Yes	Yes
Year FEs × Stack FEs	Yes	Yes
Controls^{2008} × Year FEs × Stack FEs	No	Yes
Industry FEs × Year FEs × Stack FEs	No	Yes

Notes: This table presents the estimated effects of the NTIDE policy on the subsidies received by listed demonstration enterprises (Panel A) and their competitor firms operating in the same city and industry (Panel B). Standard errors, clustered at the firm level, are reported in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.

Table A.4: Policy effects on R&D expenditures

	Logarithm of R&D expenditure	
	(1)	(2)
Panel A. Demonstration enterprises		
Treated	0.249**	0.300***
	(0.115)	(0.095)
# of clusters	199	199
# of observations	2,541	2,541
Panel B. Competitor enterprises		
Treated	-0.196**	-0.133
	(0.089)	(0.097)
# of clusters	386	386
# of observations	8,450	8,450
Enterprise FEs × Stack FEs	Yes	Yes
Year FEs × Stack FEs	Yes	Yes
Controls^{2008} × Year FEs × Stack FEs	No	Yes
Industry FEs × Year FEs × Stack FEs	No	Yes

Notes: This table presents the estimated effects of the NTIDE policy on the R&D expenditures of listed demonstration enterprises (Panel A) and their competitor firms operating in the same city and industry (Panel B). Standard errors, clustered at the firm level, are reported in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.

Table A.5: Policy effects on R&D expenditures by TFP distribution

	Logarithm of R&D expenditure	
	(1)	(2)
Panel A. Larger productivity dispersion		
Treated	-0.602***	-0.392*
	(0.147)	(0.198)
# of clusters	71	71
# of observations	774	774
Panel B. Less productivity dispersion		
Treated	-0.070	-0.011
	(0.110)	(0.129)
# of clusters	222	222
# of observations	4,125	4,125
Enterprise FEs × Stack FEs	Yes	Yes
Year FEs × Stack FEs	Yes	Yes
Controls^{2008} × Year FEs × Stack FEs	No	Yes
Industry FEs × Year FEs × Stack FEs	No	Yes

Notes: This table presents the estimated effects of the NTIDE policy on the R&D expenditures of two groups of competitor firms: those operating in markets with the top 25% degree of productivity dispersion, as measured by the Gini coefficient of the TFP distribution of listed firms, and those in markets with lower levels of dispersion. Standard errors, clustered at the firm level, are reported in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.

Table A.6: Policy effects on public firm entries

	Logarithm of the number of public firm entries	
	(1)	(2)
Treated	-0.060	0.048
	(0.120)	(0.065)
City FEs × Industry FEs × Stack FEs	Yes	Yes
Year FEs × Stack FEs	Yes	No
Industry FEs × Year FEs × Stack FEs	No	Yes
City FEs × Year FEs × Stack FEs	No	Yes
# of clusters: city	336	335
# of clusters: industry	87	85
# of observations	308,962	308,204

Notes: This table reports the treatment effects of the NTIDE policy on the logarithm of annual public firm entries, which includes state-owned and collectively owned firms. Given that the entry of public firms in China is often driven by public objectives, it is anticipated that changes in innovation competition will have a less significant impact on public firm entries. Consequently, the estimation in this table serves as a placebo test. Standard errors, two-way clustered at the city and industry levels, are reported in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.

Table A.7: Using PPML to estimate the policy effects on firm entries

	Number of firm entries			
	Private firm		Foreign firm	
	(1)	(2)	(3)	(4)
Treated	-0.192***	-0.072*	-0.321***	-0.147***
	(0.066)	(0.044)	(0.102)	(0.047)
City FEs × Industry FEs × Stack FEs	Yes	Yes	Yes	Yes
Year FEs × Stack FEs	Yes	No	Yes	No
Industry FEs × Year FEs × Stack FEs	No	Yes	No	Yes
City FEs × Year FEs × Stack FEs	No	Yes	No	Yes
# of clusters: city	337	337	335	333
# of clusters: industry	93	93	89	88
# of observations	1,996,910	1,996,175	800,210	788,598

Notes: This table reports the re-estimation results of the treatment effects of the NTIDE policy on the logarithm of annual firm entries using the Poisson Pseudo Maximum Likelihood (PPML) estimator. The PPML estimator is used to estimate the non-linear specification of the form $Y = \exp(X\beta + \varepsilon)$, thereby simultaneously accounting for the effects on both the extensive and intensive margins of the dependent variable. Columns (1) and (2) present the effects on private firms, while Columns (3) and (4) show the effects on foreign firms. Standard errors, two-way clustered at the city and industry levels, are reported in parentheses.
*** p < 0.01, ** p < 0.05, * p < 0.1.

Table A.8: Estimating local effects with the continuous treatment variable

	Logarithm of the number of 3-year weighted invention patents			
	(1)	(2)	(3)	(4)
# of demonstration enterprises	-0.135***	-0.151***	-0.262***	-0.244***
	(0.024)	(0.027)	(0.033)	(0.068)
(# of demonstration enterprises)^2		0.009	0.120***	0.093
		(0.015)	(0.023)	(0.084)
(# of demonstration enterprises)^3			-0.019***	-0.009
			(0.003)	(0.029)
(# of demonstration enterprises)^4				-0.001
				(0.003)
City FEs × Ind. FEs × Stack FEs	Yes	Yes	Yes	Yes
Ind. FEs × Year FEs × Stack FEs	Yes	Yes	Yes	Yes
City FEs × Year FEs × Stack FEs	Yes	Yes	Yes	Yes
# of clusters: city	335	335	335	335
# of clusters: industry	54	54	54	54
# of observations	932,788	932,788	932,788	932,788

Notes: This table presents the estimation results using the number of demonstration enterprises as the core explanatory variable. Column (1) replicates the results from Column (4) of Table 2, while Columns (2)–(4) progressively incorporate second-, third-, and fourth-order polynomials into the specification.
***p < 0.01, **p < 0.05, *p < 0.1.

Table A.9: Event study on the cohort with the first demonstration enterprise certified in 2019

	Logarithm of the number of 3-year-citation weighted invention patents	
	All samples	# of patents in 2008 > 50
$\mathbb{1}\{t=2009\} \times \mathbb{1}\{\text{Treatment group}\}$	0.115	0.074
	(0.120)	(0.164)
$\mathbb{1}\{t=2010\} \times \mathbb{1}\{\text{Treatment group}\}$	0.103	0.028
	(0.163)	(0.097)
$\mathbb{1}\{t=2011\} \times \mathbb{1}\{\text{Treatment group}\}$	-0.030	0.040
	(0.178)	(0.119)
$\mathbb{1}\{t=2012\} \times \mathbb{1}\{\text{Treatment group}\}$	0.234	0.003
	(0.182)	(0.094)
$\mathbb{1}\{t=2013\} \times \mathbb{1}\{\text{Treatment group}\}$	0.218	0.071
	(0.169)	(0.097)
$\mathbb{1}\{t=2014\} \times \mathbb{1}\{\text{Treatment group}\}$	0.079	0.031
	(0.197)	(0.132)
$\mathbb{1}\{t=2015\} \times \mathbb{1}\{\text{Treatment group}\}$	0.189	0.077
	(0.215)	(0.110)
$\mathbb{1}\{t=2016\} \times \mathbb{1}\{\text{Treatment group}\}$	-0.030	0.058
	(0.237)	(0.140)
$\mathbb{1}\{t=2017\} \times \mathbb{1}\{\text{Treatment group}\}$	0.060	0.087
	(0.219)	(0.162)
$\mathbb{1}\{t=2018\} \times \mathbb{1}\{\text{Treatment group}\}$	-0.008	0.070
	(0.239)	(0.157)
City FEs × Industry FEs	Yes	Yes
Industry FEs × Year FEs	Yes	Yes
City FEs × Year FEs	Yes	Yes
# of clusters: city	335	107
# of clusters: industry	54	49
# of observations	133,046	13,948

Notes: This table reports the result of the event study on city–industry pairs with the first demonstration enterprises certified in 2019. Standard errors, two-way clustered at the city and industry levels, are reported in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table A.10: Policy effects on the annual number of utility patent applications

	Logarithm of the number of utility patents			
	All samples		# of patents in 2008 > 50	
	(1)	(2)	(3)	(4)
Treated	-0.108***		-0.049**	
	(0.032)		(0.023)	
# of demonstration enterprises		-0.087***		-0.038**
		(0.027)		(0.016)
City FEs × Industry FEs × Stack FEs	Yes	Yes	Yes	Yes
Industry FEs × Year FEs × Stack FEs	Yes	Yes	Yes	Yes
City FEs × Year FEs × Stack FEs	Yes	Yes	Yes	Yes
# of clusters: city	336	336	110	110
# of clusters: industry	54	54	48	48
# of observations	1,092,447	1,092,447	98,705	98,705

Notes: This table reports the treatment effects of the NTIDE policy on the logarithm of annual utility patent applications. Standard errors, two-way clustered at the city and industry levels, are reported in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.11: The distribution of the number of invention patent applications in treatment and control city–industry pairs

	Fraction of samples (%)	
# of invention patents in 2008	Treatment city–industry pairs	control city–industry pairs
0	2.56 (2.56)	40.19 (40.19)
1–10	20.52 (23.08)	39.65 (79.84)
11–20	5.13 (28.21)	6.7 (86.54)
21–30	6.55 (34.76)	3.14 (89.68)
31–40	5.13 (39.89)	1.91 (91.59)
41–50	2.85 (42.74)	1.24 (92.83)
51–100	12.53 (55.27)	3.06 (95.89)
101–200	12.25 (67.52)	1.98 (97.87)
201–500	12.54 (80.06)	1.42 (99.29)
501–1000	9.68 (89.74)	0.43 (99.72)
> 1000	10.26 (100)	0.28 (100)

Notes: This table presents the distribution of the number of invention patent applications for treatment and control city–industry pairs in the initial sample year (i.e., 2008). The values outside the parentheses denote the sample proportions for each group, and the values inside the parentheses represent the cumulative proportions.

Table A.12: Summary of the number of patent applications in different control groups

	Observations	Mean	Std. Dev.	Minimum	Maximum
Panel A. The first sample year (2008)					
Pure control group	2,268	1.484	3.780	0	58
Spatial-spillover control group	7,938	3.930	3.930	0	444
Inter-industry-spillover control group	1,776	21.018	65.538	0	1,119
Panel B. All sample years					
Pure control group	24,948	10.437	40.203	0	1,454
Spatial-spillover control group	87,318	25.437	122.719	0	6,863
Inter-industry-spillover control group	19,536	91.470	266.263	0	5,544

Notes: This table presents descriptive statistics on the number of invention patent applications for different types of control groups, categorized based on spillover effects. Panel A reports the statistics for the year 2008, while Panel B covers the full sample period from 2008 to 2018. The pure control group consists of city–industry pairs that differ from both the industries and cities of all demonstration enterprises. The inter-industry-spillover control group consists of city–industry pairs where demonstration enterprises are present in the city but not in the industry. The spatial-spillover control group consists of city–industry pairs where demonstration enterprises are present in the industry but not in the city.

Table A.13: Stacked DD estimations for inter-industry spillover effects

	Logarithm of the number of 3-year-citation weighted invention patents			
		Restrictions on # of invention patents in 2008		
		> 0	> 1	> 5
	(1)	(2)	(3)	(4)
Panel A. Without linear time trend				
Treated	0.196***	0.204***	0.215**	0.158**
	(0.052)	(0.056)	(0.071)	(0.063)
Linear time trend	No	No	No	No
Panel B. Controlling for linear time trend				
Treated	-0.017	0.006	0.039	-0.003
	(0.041)	(0.038)	(0.042)	(0.040)
Linear time trend	Yes	Yes	Yes	Yes
City FEs × Ind. FEs × Stack FEs	Yes	Yes	Yes	Yes
Ind. FEs × Year FEs × Stack FEs	Yes	Yes	Yes	Yes
City FEs × Year FEs × Stack FEs	Yes	Yes	Yes	Yes
# of clusters: city	332	310	263	171
# of clusters: industry	12	12	12	12
# of observations	99,421	64,476	44,754	19,996

Notes: This table presents the estimation results for inter-industry spillover effects by comparing the inter-industry spillover control group with the pure control group. Panel A reports estimates without controlling for the linear time trend, while Panel B reports estimates with the inclusion of the linear time trend control. Columns (2) to (4) present the estimated effects using city–industry pairs with more than 0, 1, and 5 patent applications in the sample year (i.e., 2008), respectively. Standard errors, clustered two-way at the city and industry levels, are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.14: Stacked DD estimations for spatial spillover effects

	Logarithm of the number of 3-year-citation weighted invention patents			
		Restrictions on # of invention patents in 2008		
		> 0	> 1	> 5
	(1)	(2)	(3)	(4)
Panel A. Without linear time trend				
Treated	0.052	0.041	0.028	0.007
	(0.095)	(0.093)	(0.099)	(0.071)
Linear time trend	No	No	No	No
Panel B. Controlling for linear time trend				
Treated	0.022	0.027	0.016	0.054
	(0.053)	(0.063)	(0.069)	(0.064)
Linear time trend	Yes	Yes	Yes	Yes
City FEs × Ind. FEs × Stack FEs	Yes	Yes	Yes	Yes
Ind. FEs × Year FEs × Stack FEs	Yes	Yes	Yes	Yes
City FEs × Year FEs × Stack FEs	Yes	Yes	Yes	Yes
# of clusters: city	187	174	167	127
# of clusters: industry	54	54	54	48
# of observations	135,386	86,802	59,845	24,867

Notes: This table presents the estimation results for spatial spillover effects by comparing the spatial spillover control group with the pure control group. Panel A reports estimates without controlling for the linear time trend, while Panel B reports estimates with the inclusion of the linear time trend control. Columns (2) to (4) present the estimated effects using city–industry pairs with more than 0, 1, and 5 patent applications in the sample year (i.e., 2008), respectively. Standard errors, clustered two-way at the city and industry levels, are reported in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.15: Stacked DD estimations for spatial spillover effects using adjacent cities as the treatment group

	Logarithm of the number of 3-year-citation weighted invention patents			
		Restrictions on # of invention patents in 2008		
		> 0	> 20	> 40
	(1)	(2)	(3)	(4)
Treated	0.000	-0.007	-0.029	-0.015
	(0.015)	(0.015)	(0.022)	(0.018)
City FEs × Ind. FEs × Stack FEs	Yes	Yes	Yes	Yes
Ind. FEs × Year FEs × Stack FEs	Yes	Yes	Yes	Yes
City FEs × Year FEs × Stack FEs	Yes	Yes	Yes	Yes
# of clusters: city	335	320	176	124
# of clusters: industry	54	54	54	50
# of observations	849,005	653,703	156,170	95,381

Notes: This table reports the estimation results for spatial spillover effects by comparing cities adjacent to those with demonstration enterprises and other cities. Columns (2) to (4) present the estimated effects using city–industry pairs with more than 0, 20, and 40 patent applications in the sample year (i.e., 2008), respectively. Standard errors, clustered two-way at the city and industry levels, are reported in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.