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

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Abstract

This paper examines the unintended consequences of selective R&D subsidy policies that target leading firms, focusing on the innovation activities of non-subsidized competitors and new entrants. Although such subsidies are typically intended to stimulate innovation, the paper utilizes a Schumpeterian model to demonstrate that they may, in fact, discourage innovation among competitor firms and deter the entry of new firms, thereby undermining aggregate innovation. Empirical analysis of China’s “National Technological Innovation Demonstration Firm (NTIDF)” policy supports these predictions: R&D expenditures increase by 21.7% for subsidized firms, but fall by 30% for lagging competitors and private firm entry declines by 7.6%. On average, quality-weighted patent output drops by 8.3% within affected city–industry pairs. Incorporating these findings and potential spatial spillovers into a quantitative trade model, counterfactual analysis reveals that the policy leads to a 0.049% reduction in national real GDP, despite covering only 3.3% of city–industry pairs before 2018. Therefore, this paper highlights the necessity of accounting for competitive dynamics in the design of innovation policies.

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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.

Policy practices in China provide a suitable case study to examine this theoretical prediction. Since 2011, the Chinese government has implemented the "National Technological Innovation Demonstration Firm (NTIDF)" policy, which annually designates local "superstar firms" as "demonstration firms" and subsidizes their innovation activities, without reducing subsidies to competitor firms operating in the same city and industry. Empirical evidence indicates that the policy incentivizes listed demonstration firms to increase their R&D expenditures by 21.7%. However, the policy exerts a negative effect on the R&D expenditures of listed competitor firms that lag behind the productivity frontier. In particular, R&D expenditures of the top 25% of competitor firms with the largest productivity gaps decrease by approximately 30%. These divergent effects on R&D expenditures also translate into a divergence in patent outputs between demonstration firms and competitor firms. Furthermore, I find the policy has resulted in a significant reduction in the entry of private firms by 7.6%.

The divergent effects on demonstration firms and other firms imply an ambiguous overall impact on aggregate innovation. To address this, I conduct an estimation at the city–industry level to examine changes in the citation-weighted number of invention patents following the introduction of subsidized demonstration firms within an industry in a given city. The results indicate a progressively worsening negative effect over time, with patent outputs declining by approximately 8.3% on average. Furthermore, I find that the negative impact of the policy is more pronounced on the quantity of innovation than on the average quality. To further substantiate my theoretical interpretation, I analyze heterogeneous policy effects across industries. The evidence suggests that industries characterized by more active firm entry experience more severe negative policy effects. Additionally, I observe an "inverted-U" relationship between market concentration and the policy effects.

Furthermore, to evaluate the nationwide implications, I analyze three types of potential spillover effects associated with the NTIDF policy: inter-industry spillovers, spatial spillovers, and local knowledge spillovers. The results of my analysis indicate that inter-industry spillover effects are negligible, while there is evidence of negative spatial spillovers. These spatial spillovers are likely driven by the policy-induced reduction in innovation outcomes, which subsequently diminishes the transmission of knowledge to neighboring cities. Additionally, my findings suggest that the policy does not promote local knowledge spillovers. To quantify the equilibrium effects on national real GDP, I incorporate the causal estimates as TFP shocks into a quantitative trade model. The counterfactual analysis reveals that the certification of fewer than 500 demonstration firms, representing only 3.3% of all city–industry pairs, leads to a 0.049% decrease in national real GDP, underscoring the potential impact should these superstar-oriented subsidies be extended nationwide.

Taken together, this study sheds light on the potential pitfalls of superstar-oriented 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 NTIDF policy exhibits greater selectivity by targeting "superstar" firms. By modeling and estimating its effects on both 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. Earlier 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 NTIDF policy on aggregate innovation suggest that new firms and small-to-medium firms, 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 NTIDF policy. Section 3 develops a theoretical framework to formulate the propositions. Section 4 conducts an firm-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 NTIDF policy, encompassing inter-industry, spatial, and local knowledge spillovers. Section 7 develops a quantitative trade model to assess policy effects on national real GDP. Section 8 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 Firm (NTIDF)" policy.[1] The document emphasizes that the NTIDF policy is designed to encourage the innovation activities of industrial firms, thereby facilitating the national transition to innovation-driven growth. Specifically, the policy seeks to support "firms with strong technological innovation capabilities, significant innovation performance, and an important role in demonstrating and guiding key industrial sectors."

Demonstration firms 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 firms 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 firms from 2011 to 2017, with an average of 71 firms being awarded the title nationwide each year. Demonstration firms 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 firms 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

[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 firms governed by the central government submit their application materials directly to the MIIT.

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

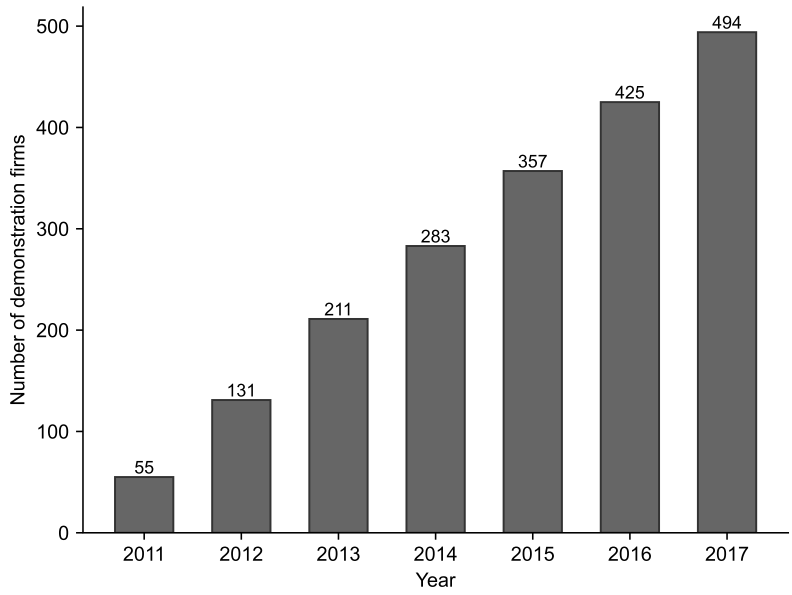

Figure 1: Accumulated number of demonstration firms by year

Notes: This figure presents the accumulated number of demonstration firms by year from 2011 to 2017. From 2011 to 2013, the accumulated number is the sum of newly certified firms in all preceding years. In 2014, demonstration firms 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 firms in all preceding years, adjusted by subtracting the number of firms that failed the re-evaluation and consequently lost the policy title.

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 firms, 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 firms 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 firms possess innovation-related titles at the provincial level or above when submitting their applications. As a result, the policy prevents small and medium-sized firms, as well as startups, from qualifying for the demonstration firm 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. Firms 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 firms. In addition to the firm name, the summary table includes information on the type and industry of the firm, as well as details on R&D investment, main business revenue, new product sales revenue, and the number of patent applications for each recommended firm. Given that the number of firms awarded the demonstration firm title is small each year, it is typically "superstar firms" with outstanding business performance and significant patent output that are granted the policy title.[5]

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

[5] In Appendix Figure A.7, I analyze the number of patents, R&D expenditures, and total assets of the listed demonstration firms 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

Third, once firms are granted the policy title, both central and local governments commit to providing innovation support to the demonstration firms. The policy document stipulates that "the MIIT shall provide guidance and support to the demonstration firms 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 Information Commission and the Municipal Bureau of Finance shall prioritize support for the technological innovation of demonstration firms, offering preferential funding for innovation projects of these firms through municipal industrial revitalization special funds."[6] Additionally, the title of demonstration firm, as an intangible asset, provides firms with enhanced access to financing facilities.[7]

Accordingly, I conceptualize the NTIDF policy as a targeted instrument for identifying and supporting "innovation star firms" through certification and subsidies.

3 Theoretical framework

In this section, I develop a theoretical framework to analyze the impact of the NTIDF 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:

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

there are no more than two listed demonstration firms nationwide, the average ranking in terms of utility patent and invention patent applications rises to approximately the 98th and 88th percentiles, respectively, and their average ranking in R&D investment even reaches the 100th percentile. Given that listed companies generally have larger production scales, R&D expenditures, and productivity levels compared to the broader firms population, this observation supports the conclusion that demonstration firms are clear innovation leaders in their respective local markets.

[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 firms 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 firms, 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 firms. In later sections, I formally test whether the policy indeed results in increased government-provided R&D-related subsidies to demonstration firms.

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 firm—the one with the highest productivity—pays 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 $F_\lambda(x \mid I_{i,t})$, 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 NTIDF 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 lognormal 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 NTIDF 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 firms react

This section examines the propositions derived from the theoretical framework by investigating a range of firm-level dynamics. These empirical explorations help shed light on the underlying mechanisms through which the NTIDF policy operates and provide the basis for understanding the aggregate policy effects analyzed in subsequent sections.

To this end, I first collect the official announcements of certified demonstration firms from the website of the Ministry of Industry and Information Technology (MIIT), which reports the name and province of each selected firm. I then match these names with a comprehensive business registration database provided by the commercial platform Tianyancha (`https://www.tianyancha.com`) to identify the corresponding city and industry of each demonstration firm.[8] Since certification is typically announced in November or December, I treat demonstration firms as receiving their first policy exposure in the calendar year following certification. Accordingly, given that my sample spans from 2008 to 2018, I include seven cohorts of demonstration firms certified between 2011 and 2017 and treated from 2012 to 2018.

Based on these certification lists, I categorize firms into three mutually exclusive groups: (i) demonstration firms explicitly named in the policy documents, (ii) competitor firms operating in the same city and industry as any demonstration firm, and (iii) other firms, which serve as the control group. My main focus is to examine how the policy affects the allocation of government-provided R&D-related subsidies and the R&D investment behavior of demonstration and competitor firms, respectively.

In addition, I analyze the behavior of new entrants to explore broader market dynamics. Specifically, I aggregate firm entry data at the city–industry level and investigate whether the NTIDF policy discourages new firm entry—a commonly used proxy for the intensity of creative destruction.

[8] 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 of 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*).

4.1 Demonstration firms

I begin by examining the impact of the NTIDF policy on demonstration firms. This analysis serves to verify the effective implementation of the policy and the responsiveness of demonstration firms—an essential starting point for the empirical story that follows.

A key challenge in this analysis is identifying an appropriate control group for demonstration firms. To address this, I implement a matching strategy based on financial and innovation indicators that are explicitly emphasized in the NTIDF certification process. This approach aims to construct a control group consisting of firms that were similarly competitive in pursuing the designation, thereby enabling a more credible counterfactual comparison.[9] Due to data availability, the analysis is restricted to 195 listed firms, representing approximately 40% of all certified demonstration firms. An additional 20 firms are excluded because they were not yet listed in the year preceding certification, rendering pre-treatment data unavailable. While these limitations preclude estimation of the ATT for the full treatment group, the results still provide qualitatively meaningful evidence that informs the broader implications of the policy.

I obtain financial and innovation indicators of listed firms from two primary data sources. The first source is the China Stock Market & Accounting Research Database (CSMAR; `https://data.csmar.com`), which provides financial variables including total assets, operating revenues, and profits. CSMAR also compiles data on government subsidies disclosed in the notes to financial statements of listed firms. These disclosures include both the monetary amount and a brief textual description of each subsidy. To identify R&D-related subsidies, I construct a list of ten innovation-related Chinese keywords and classify a subsidy as R&D-related if its description contains any of these terms.[10] A key advantage of the keyword-based method is its transparency and reproducibility.[11] Using this approach, I identify 33.4% of all subsidy records as R&D-related, which account for 10.4% of the total subsidy amount. These records are then aggregated to compute firm-level annual R&D subsidies. The second data source is the Chinese Research Data Services Platform (CNRDS; `https://www.cnrds.com`), which provides information on R&D expenditures and patent applications of listed firms.

Using these data, I implement a propensity score matching (PSM) strategy within each "stack" (as described in the next paragraph) to identify the two nearest control firms for each treated firm based on observations in the year prior to certification, with a caliper of 0.05 to avoid poor-quality matches. Robustness to a variety of alternative matching strategies is examined in subsequent analyses. The covariates used for matching include: (i) the number of invention patent applications, (ii) the number of utility model patent applications,[12] (iii) the logarithm of prime operating revenues, (iv) the logarithm of R&D expenditures, (v) industry fixed effects, and (vi) government-provided R&D subsidies. The first five variables are explicitly highlighted in the summary reports submitted by local governments to the central

[9] Ideally, the control group would comprise firms that were recommended by local governments but ultimately not certified by the central government (similar to the comparison between "winning" and "losing" counties in Greenstone et al. (2010).) Another potential strategy would use province-level demonstration firms as controls, since this title is typically a prerequisite for national-level recommendation. However, these alternatives are infeasible in practice due to the unavailability of local recommendation lists and province-level certification data.

[10] The ten keywords are: "innovation" (*chuangxin*), "research" (*yanjiu*), "R&D" (*yanfa*), "scientific research" (*keyan*), "patent" (*zhuanli*), "talent" (*rencai*), "technology" (*keji*), "technical" (*jishu*), "Industry–University–Research" (*chanxueyan*), and "intellectual property" (*zhishichanquan*).

[11] To evaluate the classification accuracy, I randomly select 3,000 subsidy records (approximately 1% of the full sample) and use five large language models (LLMs) to independently assess whether each should be categorized as R&D-related. The keyword-based method shows over 85% consistency with each LLM. I also use one of these models to classify all subsidy records and re-estimate my regressions using the resulting data; the findings remain broadly consistent. See Appendix C for details.

[12] In China, patents are categorized into three types: invention patents, utility model patents, and design patents. Invention patents pertain to novel technical solutions and are subject to substantive examination. Utility model patents, by contrast, are granted more quickly and without substantive examination, and are generally regarded as reflecting lower technological quality. Design patents protect aesthetic aspects of products and are not indicative of technological innovation. Notably, an invention patent application must pass examination before being formally granted. Unless otherwise stated, all patent counts in this study refer to applications rather than granted patents.

government during the certification process (see Appendix Table A.3). The sixth variable is included as a proxy for potential political connections. Appendix Table A.5 shows that there are no remaining systematic differences between treated and matched control firms across these covariates. The overlap in the distribution of propensity scores between the two groups, as shown in Appendix Figure A.8, further indicates a good quality of match.

To address the staggered adoption of treatment across cohorts, I employ a stacked difference-in-differences (stacked DD) estimator, which has been used in a number of recent applied settings (Cengiz et al., 2019; Deshpande and Li, 2019; Johnson et al., 2025). This approach constructs a separate quasi-experimental design (referred to as a "stack") for each treatment cohort by pooling treated firms in that cohort with all never-treated firms. I form seven such stacks—one for each cohort—and subsequently combine them into a unified dataset for estimation. The empirical specification is given by:

$$y_{f,i,t,s} = \beta \times \mathbb{1}\{Treated\}_{f,t} + \eta_{f,s} + \rho_{i,t,s} + \varepsilon_{f,i,t,s}, \tag{12}$$

where subscripts f, i, t, and s denote firm, industry, year, and stack, respectively. The key treatment indicator $\mathbb{1}\{Treated\}_{f,t}$ equals 1 if firm f is treated in year t. The term $\eta_{f,s}$ captures stack-specific firm fixed effects, while $\rho_{i,t,s}$ denotes stack-specific industry-by-year fixed effects, which absorb confounding macroeconomic shocks at the industry level. $\varepsilon_{f,i,t,s}$ is the error term. Under this framework, the coefficient β can be interpreted as a weighted average of the average treatment effects estimated across the seven stacks. Standard errors are clustered at the firm level.

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

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

where $\mathbb{1}\left\{T^R = m\right\}_{t,s}$ 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 fifth year prior to the treatment and all earlier periods are aggregated into a single period. The reference period is the year immediately preceding the treatment year within each stack.

Table 1 reports the estimation results. Columns (1) and (3) present estimates from a two-way fixed effects specification for each stack, while Columns (2) and (4) report those based on Equation (12), which incorporates stack-specific time-varying industry fixed effects at the cost of a minor sample loss. The results suggest that the NTIDF policy leads to a 43.2% increase in government-provided R&D-related subsidies, which in turn results in a 21.7% increase in firms' R&D expenditures. Appendix Table A.6 presents robustness checks using six alternative matching strategies—varying the number of neighbors, the caliper width, and the kernel method—all of which yield consistent patterns.[13]

The corresponding event study estimates are presented in Appendix Figures A.9 and A.10. For R&D-related subsidies, a noticeable increase is observed in the year preceding the treatment. Given that the treatment year is defined as the year immediately following certification, this pattern is plausible and suggests that local governments may begin allocating subsidies once firms are certified. Following the treatment, the point estimates indicate a continued increase in annual subsidies during the first three

[13] In Appendix Table A.6, Panels A and B use 1-nearest-neighbor and 4-nearest-neighbor PSM, respectively, both with a caliper of 0.05, to test the sensitivity of the results to the number of neighbors. Panels C and D employ 2-nearest-neighbor PSM with a smaller caliper and without any caliper restriction, respectively, to examine whether the findings are driven by specific caliper choices. Panels E and F use kernel matching instead of nearest-neighbor matching, with Triangle and Epanechnikov kernel functions, respectively. Across all specifications, the results remain consistent.

Table 1: Policy effects on demonstration firms

	Logarithm of R&D-related subsidies		Logarithm of R&D expenditures	
	(1)	(2)	(3)	(4)
Treated	0.335*	0.432**	0.199**	0.217**
	(0.175)	(0.184)	(0.086)	(0.089)
Firm 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
# of treated firms	124	120	125	121
# of clusters	303	297	305	299
# of observations	2,790	2,634	3,045	2,906

Notes: This table reports estimation results of Equation (12) using the matched sample constructed via 2-nearest-neighbor propensity score matching with a caliper of 0.05. The regressions are weighted by the matching weights derived from the matching procedure. Standard errors, clustered at the firm level, are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

years. After that, the difference between treated and control firms becomes statistically insignificant.

In contrast, I observe a persistent and growing divergence in R&D expenditures between treated and control firms. This pattern may indicate that early-stage subsidies generate lasting positive effects on firms' innovation investment. Alternatively, it may also reflect the influence of other policy benefits associated with the NTIDF policy—maybe tax incentives or administrative support—that are not captured in the observed subsidy data.

4.2 Competitor firms

Subsequently, I shift my focus to the effects of the NTIDF policy on competitor firms of the demonstration firms. Competitor firms are defined as those operating in the same city and industry as at least one demonstration firm, where demonstration firms include both listed and unlisted companies. For each competitor firm, I assign a "treatment year" corresponding to the earliest treatment year of any demonstration firm within the same city–industry pair. This setup generates seven treatment cohorts.

Based on this definition, I construct a stacked dataset comprising competitor firms and other untreated firms, and apply a stacked DD strategy analogous to that used in the previous analysis. The estimation equation remains the same as Equation (12), except for a modification in the treatment indicator. Specifically, $\mathbb{1}\{Treated\}_{f,t}$ takes the value of 1 if there exists at least one treated demonstration firm in the same city and industry as firm f in year t. To avoid distortions due to the sudden entry of newly listed competitor firms, I restrict the sample to a balanced panel structure.

It is crucial to emphasize that the theoretical model predicts heterogeneous responses among competitor firms. In particular, competitor firms with a larger productivity gap relative to the frontier are expected to be discouraged from investing in R&D to a larger extend when they anticipate continued productivity gains by the leading firm. By contrast, the responses of firms with a smaller productivity gap are theoretically ambiguous. To explore this heterogeneity, I estimate the annual total factor productivity (TFP) for each listed firm using the approach developed by Olley and Pakes (1996). I then calculate the gap between each firm's TFP and the highest TFP within the same city and industry, which is referred to as the "TFP gap." For each firm, I compute the average TFP gap during the pre-treatment years (within each stack) to avoid introducing "bad controls" that could be endogenously affected by the treatment. This average TFP gap is then interacted with the treatment indicator in some specifications.

I begin by examining the policy's impact on R&D-related subsidies received by competitor firms. If the policy increases R&D subsidies for demonstration firms, analyzing its effects on competitor firms allows me to test a competing explanation: the government may reallocate subsidies by reducing support for other local firms, thereby crowding out their innovation investment. This reallocation channel represents a distinct confounding effect, separate from the mechanisms emphasized in the theoretical model.

As shown in Columns (1) and (2) of Table 2, however, the estimated effects on competitor firms are statistically insignificant and substantially smaller in magnitude than those observed for demonstration firms. Moreover, Column (3) reveals limited heterogeneity across competitor firms with different distances to the local TFP frontier.

In contrast, when I shift the focus to competitor firms' R&D expenditures, the anticipated heterogeneity becomes evident. While Columns (4) and (5) indicate no significant average effect across the entire competitor population, the interaction term in Column (6) is significant, suggesting that competitor firms further from the TFP frontier exhibit greater reductions in R&D expenditures.

Table 2: Policy effects on competitor firms

	Logarithm of R&D-related subsidies			Logarithm of R&D expenditures		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	0.069	-0.035	-0.016	0.077	0.009	0.121
	(0.109)	(0.145)	(0.159)	(0.077)	(0.093)	(0.106)
Treated × Avg. TFP gap			-0.011			-0.069*
			(0.060)			(0.039)
Firm FEs × Stack FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs × Stack FEs	Yes	No	No	Yes	No	No
Industry FEs × Year FEs × Stack FEs	No	Yes	Yes	No	Yes	Yes
# of clusters	800	778	778	854	833	833
# of observations	31,949	30,769	30,769	40,713	39,420	39,420

Notes: This table reports estimation results of Equation (12), where the treatment indicator takes the value of 1 when there exists at least one treated demonstration firm in the corresponding city and industry. Standard errors, clustered at the firm level, are reported in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

This heterogeneity is more clearly illustrated in Figure 2, where I divide competitor firms into two groups based on their pre-treatment average TFP gap: the top 25% of firms with the largest gaps to the local frontier, and the remaining 75%. Each group is compared to the same control group to estimate separate event study specifications. The figure reveals a striking divergence in trajectories between the two groups. While competitor firms closer to the frontier show little change in R&D expenditures—if anything, a modest increase—the expenditures of those with larger gaps exhibit an immediate decline, which continues to worsen over time.

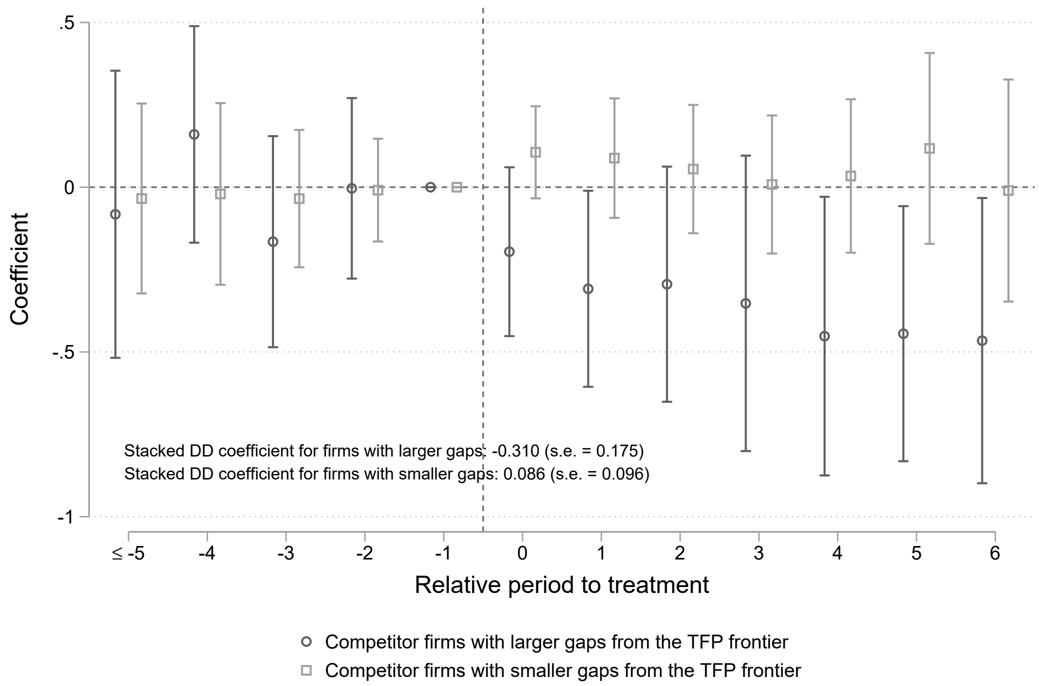

Figure 2: Event study on R&D expenditures of competitor firms

Notes: This figure presents event study estimates of R&D expenditures for competitor firms, divided into two groups based on their pre-treatment average TFP gap: the top 25% with the largest gaps to the local frontier, and the remaining 75%. Each group is compared to the full set of control firms. Circles indicate point estimates, and lines represent 95% confidence intervals. For comparison, the corresponding stacked DD estimates from Equation (12) are also included in the figure.

Finally, I provide suggestive evidence on the policy's impact on innovation outputs by comparing demonstration and competitor firms in terms of their annual invention patent applications. It is important to emphasize that, due to the lack of a comprehensive system for accurately matching patent applicants to registered firms, the patent counts reported by the CNRDS database serve only as rough approximations, likely underestimating the true figures. As a result, the estimates presented in this figure should be interpreted with caution, and I refrain from drawing quantitative conclusions based on them.

Despite this limitation, clear qualitative patterns emerge: following the policy intervention, invention patent applications by demonstration firms exhibit a steadily increasing trend, whereas those of competitor firms show a gradual decline.

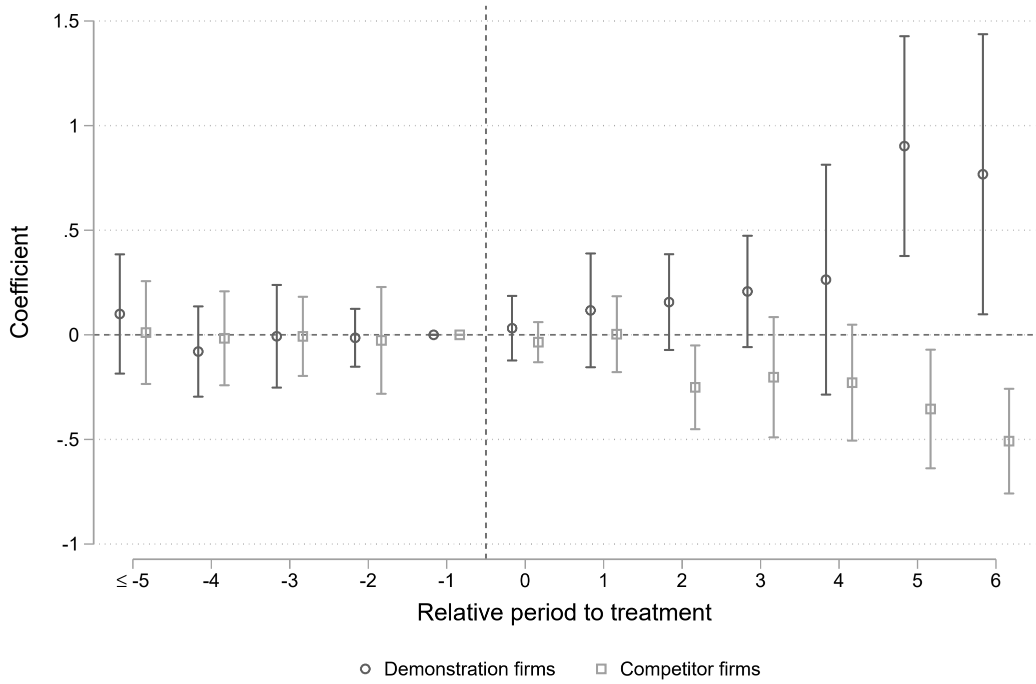

Figure 3: Event study on invention patents of demonstration firms and competitor firms

Notes: This figure presents event study estimates of annual invention patent applications for demonstration firms and competitor firms, respectively. For demonstration firms, the analysis is based on a matched sample constructed using 2-nearest-neighbor propensity score matching with a caliper of 0.05. The regression is then weighted by the matching weights obtained from this procedure. Circles indicate point estimates, and lines represent 95% confidence intervals.

4.3 Firm entries

This subsection moves on 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 NTIDF 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 firm within a specific city–industry pair. 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 firms) 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 firm'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 firms 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 firm 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 firms (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.[14] 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 3 focuses the estimation on the entry of private firms, which is typically characterized as profit-driven. In columns (1), I first estimate a simplified specification, which excludes stack-specific city–industry fixed effects and year fixed effects. Columns (2), 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 while remaining statistically significant, implying that controlling for these fixed effects helps alleviate biases. 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 7.6% in the number

[14] For instance, in the certification process for province-level demonstration firms 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 firms emerging in these cities. Since provincial-level demonstration firms are often a prerequisite for applying for national title, this policy also raises the probability of national-level demonstration firms 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.

of private firm entries.

As a logarithmic transformation is applied to the firm entry variable, city–industry pairs with zero private firm entry are automatically excluded from the estimation, resulting in a certain degree of sample loss. However, since my primary interest here lies in the intensive margin—that is, the policy's effect on the intensity of firm entry rather than on whether entry occurs at all—excluding zero-entry observations is arguably appropriate. To assess the robustness, I also employ the Poisson Pseudo Maximum Likelihood (PPML) estimator, as reported in Columns (3) and (4). It is important to note that the PPML estimator is based on a different multiplicative functional form and relies on different identifying assumptions from OLS, which may result in distinct estimates (Silva and Tenreyro, 2006). In this case, however, the PPML estimates also indicate a consistently negative effect, suggesting a 9% reduction in firm entry, which is closely aligned with the OLS results.

Table 3: Policy effects on firm entries

	(Logarithm of) the number of private firm entries			
	OLS estimator		PPML estimator	
	(1)	(2)	(3)	(4)
Treated	-0.347***	-0.076**	-0.116*	-0.090***
	(0.075)	(0.030)	(0.060)	(0.029)
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	337	337
# of clusters: industry	89	89	93	93
# of observations	1,972,243	1,972,243	2,198,735	2,197,881

Notes: This table reports the estimated effects of the NTIDF policy on the annual private firm entries. Columns (1) and (2) report OLS estimates. Columns (3) and (4) present estimates obtained using the Poisson Pseudo Maximum Likelihood (PPML) estimator, which is specifically designed to estimate the following exponential functional form:

$$Entry_{c,i,t,s} = \exp\left(\beta \times \mathbb{1}\{Treated\}_{c,i,t} + \eta_{c,i,s} + \rho_{i,t,s} + \gamma_{c,t,s}\right) + u_{c,i,t,s}.$$

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 4 presents the results of the event study analysis based on both the OLS and PPML estimators. The two sets of estimates exhibit a similar pattern, further reinforcing the robustness across estimation strategies. Specifically, there is no evidence of significant pre-trends prior to the policy intervention, lending support to the validity of the parallel trends assumption. In contrast, a clear and persistent decline in private firm entry is observed following the NTIDF policy implementation, suggesting cumulative negative effects of the policy over time.

Additionally, in markets with infrequent private firm entries—possibly due to low profit expectations arising from intense competition or strongly monopolistic dominance—the policy's impact on firm entries is likely smaller. To examine this hypothesis, I include an interaction term between the treatment indicator and the number of private firm entries in the initial year of the sample period (i.e., 2008), capturing the moderating effect of baseline entry intensity. Appendix Table A.7 reports the results. To mitigate concerns that this moderating variable may directly influence the outcome or introduce dynamic endogeneity, the sample is restricted to observations starting from 2009, 2010, and 2011 in different columns. Across all specifications, a negative moderating effect is consistently observed: a one-unit (1,000 firms) increase in baseline entry is associated with an approximately 2% larger reduction in private firm entry due to the NTIDF policy.

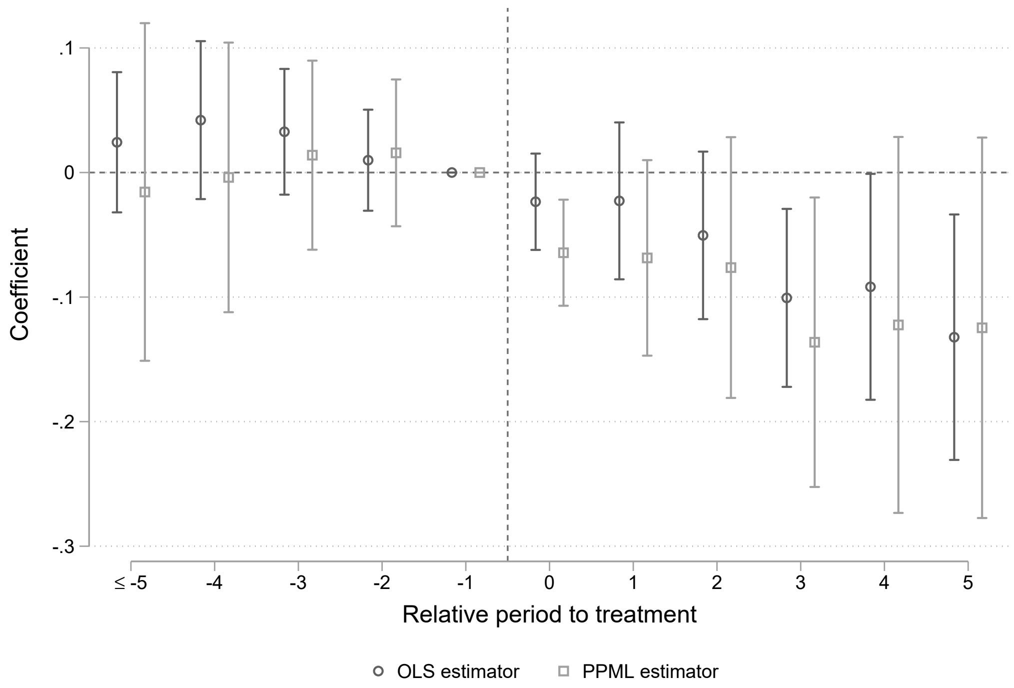

Figure 4: Event study of entry of private firms

Notes: This figure presents the estimated coefficients from the event study analysis of private firm entry. Results based on both the OLS and PPML estimators are displayed. The figure shows point estimates along with 95% confidence intervals.

To further examine the effects on firm entry, I extend the analysis to two additional types of firms—foreign and public firms. However, since annual entries of these firms are much fewer compared to private firms, the variation along the intensive margin appears somewhat limited. Similar to private firms, the entry of foreign firms is typically driven by expectations of profitability. Columns (1) and (2) of Table A.8 report significantly negative effects on foreign firm entry, based on specifications analogous to those used for private firms. The corresponding event study estimates are shown in Figure A.12, which reveal a somewhat downward pre-trend. Due to data limitations, it is not feasible to control for additional confounding factors at the city–industry level in the foreign firm analysis. As a result, the estimates may be upward biased, potentially explaining the relatively large ATT point estimates. Despite this caveat, the results still provide suggestive evidence consistent with the underlying hypothesis.

Additional evidence is provided by a placebo test using the entry of public firms as the dependent variable. In recent decades, public firm entry in China has become increasingly influenced by non-market objectives—such as the provision of public goods and the promotion of technological innovation to enhance national competitiveness—rather than market-driven incentives (Li and Cheong, 2019). This shift is reflected in their growing concentration in strategic sectors, natural monopolies, and public service industries. Accordingly, their entry is not expected to be significantly affected by the policy. As reported in Columns (3) and (4) of Table A.8, the estimated coefficients are statistically insignificant, consistent with. The event study results presented in Figure A.13 further support this conclusion.

In summary, the empirical evidence presented in this section supports the existence of the discouraging effects predicted by the theoretical model: policies that selectively subsidize leading firms in local markets may generate adverse consequences for other incumbent firms and potential entrants. First, the R&D incentives of competitor firms are weakened, especially for those further from the local TFP frontier. Second, private firms anticipate lower potential returns from market entry, resulting in a significant decline in private firm formation and a dampening of the creative destruction process. Taken together, these discouraging effects suggest a negative impact on aggregate innovation, rendering the overall implications of such selective subsidy policies ambiguous.

5 Overall effects on innovation

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

5.1 Baseline estimation

I adopt the same identification strategy as in Section 4.3 to examine the average change in innovation outcomes following the certification of the first demonstration firm within a given city–industry pair. To facilitate this analysis, I first aggregate patent counts at the city–industry level. The patent data are drawn from the micro-level application records of the China National Intellectual Property Administration (CNIPA), which contain detailed information on each patent's applicant, application date, publication date, primary International Patent Classification (IPC) code, and applicant address. In most of the analyses that follow, I restrict the sample to invention patents, excluding utility model and design patents, as the latter are generally considered to reflect lower-quality innovations.

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.[15] Second, since the primary IPC code and industry classifications follow different systems, I utilize an official matching table, provided by CNIPA, to map IPC codes to industry categories.[16] I first match each patent based on its "main group" classification. If the corresponding industries for the group are not found in the table, I then match it based on its "subclass." This two-stage matching strategy ensures that more than 99.9% of invention patents applied between 2008 and 2018 are successfully matched to at least one industry category.[17] For patents corresponding to multiple industries, each relevant industry is credited with one additional patent count.[18]

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 used 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 utilization. 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.

[15] Among all invention patents applied during the sample period (i.e., 2008 to 2018), 99.5% of them are exactly matched to one city.

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

[17] In the IPC system, a "subclass" denotes the 4-character alphanumeric code that identifies a specific technical field within broader hierarchical categories. Each "subclass" can be further divided into "main groups" that represent more specialized technological functions or applications. For instance, consider the IPC code B65G47/64: its subclass B65G corresponds to industry categories 34, 40, and 43, while its main group B65G47 specifically maps to industry category 34. Across invention patent data used in this study, using only the more precise "main group"-level matching successfully links 68.5% of patents to industry classifications, thus a two-stage matching procedure is necessary. On average, 2.18 distinct industries match per patent.

[18] Theoretically, if one could identify the applicant 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.

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 such industries include transportation, social organizations, and certain service sectors. Notably, these industries also feature a limited number of firms designated as demonstration firms. 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 firms. 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 firms certified between 2011 and 2017, 12 firms belonged to this industry (see Appendix Figure A.4). Nevertheless, no patents can be directly attributed to this industry, as none are directly utilized in this industry. 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 firm, 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.[19] 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.[20]

The baseline estimation equation is specified as

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

which is identical to Equation (14), except that the dependent variable is replaced with the logarithm of the 3-year citation-weighted number of patents by default. The industry–year fixed effects $\rho_{i,t,s}$ additionally control for heterogeneity in patent applications across industries. For instance, certain industries exhibit significantly higher patent application volumes, rendering direct comparisons between industries inappropriate. Again, controlling for city–year fixed effects $\gamma_{c,t,s}$ primarily aims to absorb the influences of city-level innovation policies that simultaneously affect policy title certification and innovation outcomes.

Initially, I employ all city–industry pairs without any demonstration firms prior to 2018 as the control group to estimate the ATT. This strategy ensures sufficient variation in the data while controlling for

[19]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.

[20]A methodological consideration arises from the fact that many recently filed patent applications have not yet been published and are consequently absent from the database. Following Lerner and Seru (2022), this leads to systematic underestimation of both patent counts and citations in more recent years. To address this issue, I use 2018 as the cutoff year for the sample period. This choice represents a trade-off between two competing considerations: (1) maintaining sufficient treatment cohorts for robust identification, and (2) ensuring adequate representation of true innovation outcomes in the patent data.

industry–year and city–year fixed effects. However, it should highlight that this approach relies on the assumption that spatial or inter-industry spillover effects are negligible. If this assumption fails, the violation of the SUTVA inherent in DD designs not only introduces bias but also obscures the true direction of the policy's nationwide impact. To validate this approach, in the next section, I further disaggregate the control group to examine spatial and inter-industry spillovers on innovation. Reassuringly, the empirical results indicate that both types of spillovers are statistically insignificant, and any resulting bias is likely negligible.

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.[21] 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 influence on innovation competition primarily operates along the intensive margin rather than the extensive margin. In other words, the policy is more likely to affect the intensity of innovation activity within a city–industry pair, rather than fundamentally changing the innovation status of a city–industry pair—from non-innovating to innovating, or the reverse. Therefore, excluding pairs with zero patent output aligns with the focus of this study.

Furthermore, it is important to acknowledge a key challenge to the credibility of the estimation: the presence of a demonstration firm in a city–industry pair after 2011 often reflects a stronger pre-existing foundation in R&D and innovation. Appendix Table A.9 shows that in the year prior to treatment (corresponding to each stack), only 1.1% of treatment group pairs recorded zero invention patents,[22] compared to 41.56% in the control group. This discrepancy raises a concern: because the total number of patent applications has generally increased over time, city–industry pairs with low initial patent counts may naturally experience faster percentage growth in subsequent years. Consequently, even in the absence of any policy effect, the patenting gap between treatment and control groups may narrow over time, potentially generating a downward pre-trend and confounding the estimation of the policy's true impact.

To address concerns about comparability, a relatively direct and transparent strategy is to restrict the sample to city–industry pairs with at least a certain number of invention patent applications prior to policy intervention. Figure 5 presents estimates of β from Equation (15) under increasingly stringent thresholds on the number of patents in the year preceding treatment, with cutoffs ranging from 0 to 60 patents. As expected, the magnitude of the estimated effects declines as the threshold becomes more restrictive. Nevertheless, the coefficients remain negative and statistically significant across all samples. When the threshold is set at 10 or more patent applications, the sample size falls to approximately 50% (or less) of the unrestricted sample, while the point estimates appear to stabilize around -0.075. Based on this trade-off between sample size and comparability, I adopt the threshold of 10 in the following analyses.

Table 4 presents the estimation results with a threshold of 10. In Panel A, the 3-year and 5-year citation-weighted patent counts are used as the dependent variables, respectively. Column (1) mirrors the estimate in the fifth row of Figure 5, suggesting an 8.3% reduction in innovation outcomes. It is important to note that the 5-year citation-weighted measure tends to systematically underestimate the citation counts for patents filed in recent years, as some of the patents citing them may not have been filed yet. Possibly as a result, Column (3) yields a relatively smaller point estimate of -0.073. In Columns (2) and (4), I re-

[21] 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).

[22] In theory, such cases should not occur. This small share is likely due to imperfect IPC–industry matching, as discussed previously.

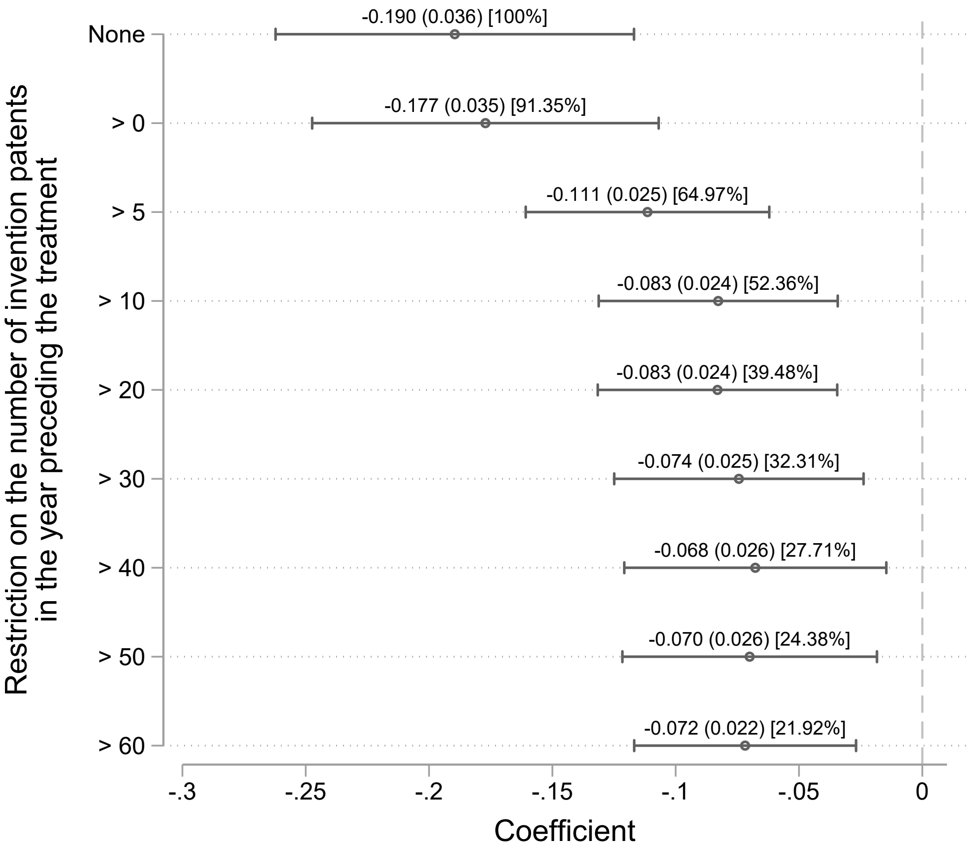

Figure 5: Estimated coefficients with sample restriction on the number of invention patents in the year preceding the treatment

Notes: This figure presents the estimation results obtained by applying different restrictions on the number of invention patent applications in the year preceding treatment, with the preceding year varying by cohort. The first row imposes no restrictions, while the second to ninth rows restrict the estimation to city–industry pairs with more than 0, 5, 10, 20, 30, 40, 50, and 60 patent applications, respectively. The circles represent the point estimates of the treatment variable coefficients, and the lines denote the 95% confidence intervals. 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).

place the explanatory variable with the cumulative stock of demonstration firms in each city–industry pair over time, aiming to construct a continuous variable that reflects treatment intensity. However, as most treated city–industry pairs only have one demonstration firm throughout the sample period (see Appendix Table A.2), the estimates are relatively close to those obtained using the 0–1 indicator. [23]

In Panels B and C, I replace the dependent variable with unweighted invention patent counts and the average number of 3- or 5-year citations received by each invention patent, respectively.[24] This approach aims to decompose the total effects into those on quantity and quality. The results indicate that the NTIDF policy leads to a 5.9% decline in the number of invention patents and a 2.4% decrease in average patent quality, although the latter estimate is less statistically significant. These findings suggest that the negative effect of the policy is more pronounced on the quantity than on the average quality of innovation.

In conclusion, the table demonstrates consistent findings: the NTIDF policy reduces the innovation output of city–industry pairs where demonstration firms are located. This finding suggests that, on average, the negative effects on competitor firms and potential entrants outweigh the positive effects on demonstration firms, resulting in negative overall effects.

Table 4: Policy effects on patent output

	3-year citation-weighted		5-year citation-weighted	
	(1)	(2)	(3)	(4)
Panel A. Effects on citation-weighted patent numbers				
Treated	-0.083***		-0.073**	
	(0.024)		(0.027)	
# of demonstration firms		-0.065***		-0.059**
		(0.020)		(0.023)
Panel B. Effect decomposition: Patent quantity				
Treated	-0.059**		-0.059**	
	(0.024)		(0.024)	
# of demonstration firms		-0.056***		-0.056***
		(0.020)		(0.020)
Panel C. Effect decomposition: Quality per patent				
Treated	-0.024*		-0.014	
	(0.013)		(0.015)	
# of demonstration firms		-0.009		-0.003
		(0.008)		(0.010)
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	319	319	320	320
# of clusters: industry	53	53	53	53
# of observations	391,081	391,081	395,900	395,900

Notes: This table reports the treatment effects of the NTIDF policy on the logarithm of annual innovation patent applications. The sample is restricted to city–industry pairs with invention patent applications in the year preceding the treatment exceeding 10 in each stack. Standard errors, two-way clustered at the city and industry levels, are reported in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

[23] Additionally, it should be noted that for the treatment group, treatment intensity is not necessarily positively correlated with the number of demonstration firms. This is because the negative effects arising from changes in innovation competition due to the policy do not necessarily increase or decrease with a higher number of subsidized leading firms. In Appendix Table A.10, I attempt to incorporate higher-order polynomials into the specification, revealing a significant third-order relationship: as the number of demonstration firms increases in a city–industry pair, the negative effects are initially mitigated but eventually exacerbated. However, since the number of treatment pairs with more than one demonstration firm is quite limited, I acknowledge that there may be insufficient variation to accurately identify the true higher-order relationship.

[24] To ensure exact decomposition, I use the same set of observations for the estimations in Panels B and C as those used in the corresponding columns of Panel A. This approach leads to minor differences in the sample sizes in Panel B, despite the dependent variables—raw counts of invention patents—being constructed in the same way.

The estimation of the event study is presented in Figure 6. Prior to the NTIDF policy intervention, no significant pre-trends are observed. After the implementation of the NTIDF policy, the treatment group exhibits progressively more negative coefficients, suggesting a persistent and worsening negative impact on innovation outcomes. This pattern is consistent with the findings on firm entry. Moreover, the figure again indicates that the adverse effects on average patent quality are much smaller than those on patent quantity.

To illustrate how imposing restrictions on pre-treatment invention patent counts improves the comparability between treatment and control groups, Appendix Figure A.14 presents event study estimates under increasingly stringent thresholds. As shown in the figure, a clear downward pre-trend emerges when no restriction is imposed, consistent with the earlier concern about convergence due to different baseline levels. However, this pre-trend gradually attenuates as the threshold increases, indicating improved balance between treatment and control groups. Meanwhile, the pattern of gradually deteriorating post-treatment effects remains robust across panels, with smaller magnitudes.

Additionally, I conduct five robustness checks to further assess the reliability of the baseline findings. First, I estimate the treatment effects separately for each of the seven treatment cohorts. As previously discussed, the stacked DD estimator can be interpreted as a weighted average of cohort-specific treatment effects derived from their respective 2×2 DD estimations. However, the implicit weights are not transparent, raising concerns that the overall negative effect may be disproportionately influenced by certain cohorts with larger weights. Estimating the treatment effects by cohort helps to directly address this concern. Appendix Figure A.15 presents the results, where all cohorts exhibit negative effects of comparable magnitudes. Cohort-specific event study estimates are presented in Appendix Figure A.16, and the resulting patterns are broadly consistent with the main findings. Interestingly, a few cohorts exhibit some pre-trends, but in different directions. These opposing trends tend to offset each other, thereby illustrating how combining multiple cohorts can improve identification by mitigating cohort-specific biases.

Second, I re-estimate the results using the PPML estimator to incorporate city–industry pairs with zero patent counts into the analysis. Again, since the PPML estimator accounts for both the intensive and extensive margins and relies on different identification assumptions, it may produce different estimates. Nonetheless, the patterns displayed in Appendix Figure A.17 closely mirror those from the OLS specification, exhibiting no significant pre-trend and a clear, progressive decline in innovation outcomes following the policy intervention.

Third, I use the number of utility model patents and the number of eventually granted invention patents as dependent variables, respectively. The results are reported in Appendix Table A.11. Utility model patents, which generally reflect relatively lower technological quality, are employed here to capture a broader spectrum of innovation activities. The findings indicate that the NTIDF policy leads to a 5.9% reduction in utility model patent applications. In contrast, when focusing on invention patent applications that were eventually granted—thus narrowing the scope to higher-quality, officially recognized innovations—the sample size decreases substantially, as more city–industry pairs report zero granted patents. However, the estimated effect is even larger, at -0.105, though the estimate in Column (3) loses statistical insignificance, likely due to increased standard errors resulting from the smaller sample size.

Fourth, I adopt a matching strategy as an alternative to imposing restrictions on pre-treatment patent counts. Unlike firm-level datasets where rich covariates (e.g., financial indicators) are typically available, city–industry level data contain limited observable characteristics. As a fallback, I match treated city–industry pairs to one or more control pairs based on pre-treatment invention patent counts. I implement multiple matching designs and re-estimate the baseline specification using the matched samples. The results are presented in Appendix Table A.12. As indicated by the t-statistics, the matching strategy substantially reduces systematic differences between the treatment and control groups. Throughout all columns,

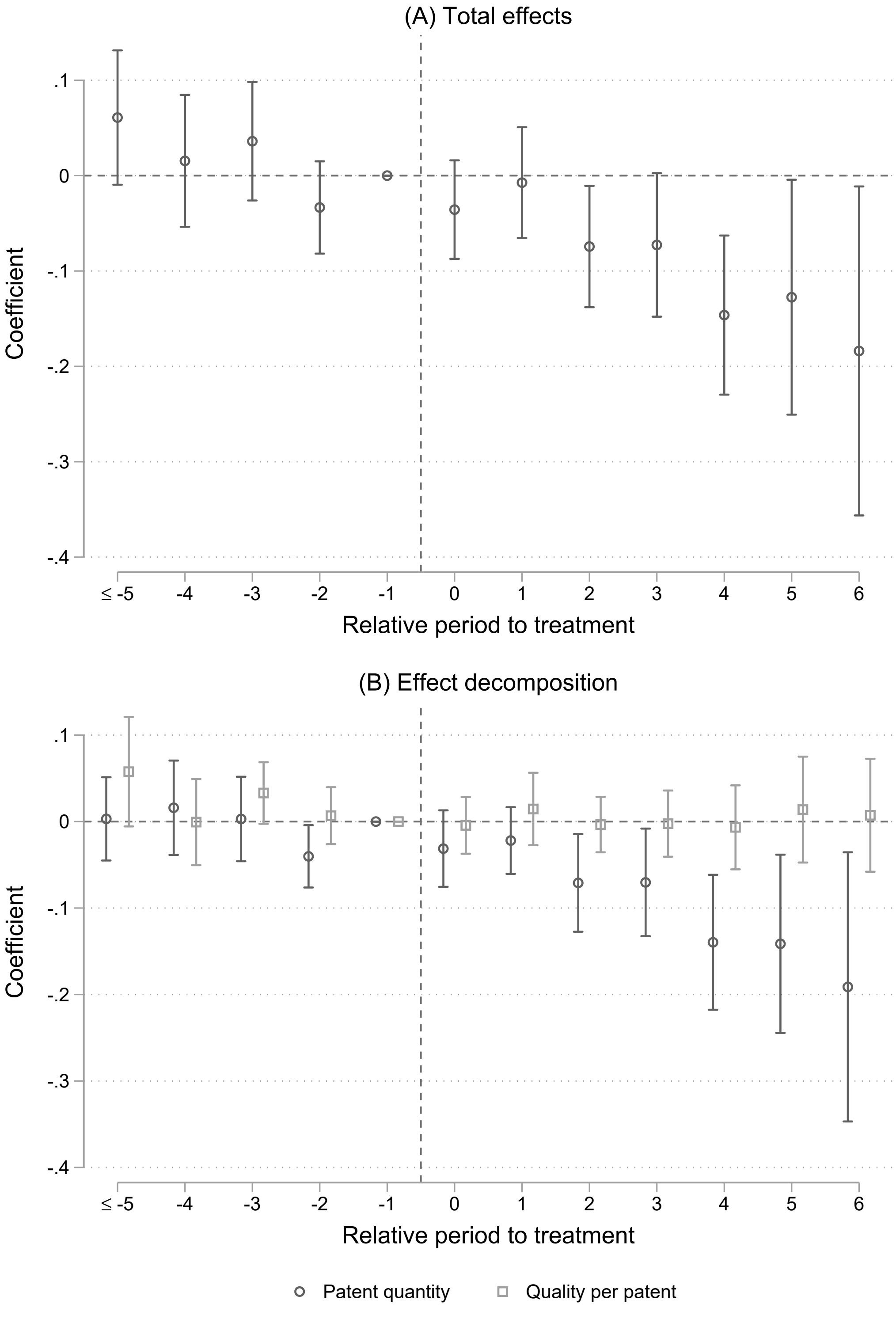

Figure 6: Treatment effects on patent outputs: event study

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 the year preceding the treatment exceeding 10 in each stack. The circles represent the point estimates, while the lines indicate the 95% confidence intervals.

the findings are consistent with those from the baseline estimation.

Finally, I conduct a placebo test on city–industry pairs whose first demonstration firms were certified in 2018 and 2019. Since the sample period ends in 2018, these cohorts are not expected to exhibit significant treatment effects within the observed timeframe. In Table A.13, I construct the stacked sample for these two cohorts and estimate their average treatment effects. Column (1) reports the estimation of Equation (15) where the treatment indicator is set to 1 after 2012, mirroring the treatment timing of the 2012 cohort. The resulting point estimate is statistically insignificant and small in magnitude. Column (2) presents the event study estimates, where all coefficients are insignificant and no notable trend is observed.

5.2 Heterogeneity

In this subsection, I examine the heterogeneous treatment effects of the NTIDF policy and explore potential sources of this heterogeneity. Since treatment is assigned at the city–industry level, heterogeneity could, in principle, arise along this dimension. However, estimating separate effects at the city–industry level would entail using only one treatment pair per estimation, making it difficult to average out noise. As an alternative, I focus on heterogeneity across industries, which provides relatively more variation and enables a tentative exploration of how industry-specific characteristics may shape the policy's effects.

The treatment effect for each industry is estimated separately using the following specification for industry i:

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

Since each estimation is confined to a single industry, identification relies solely on cross-city variation—that is, comparing cities with demonstration firms to those without. As a result, time-varying city fixed effects can no longer be included and are instead replaced by time-varying province fixed effects, $\gamma^{i}_{p_c,t,s}$, to capture broader regional trends. Moreover, to ensure comparability across observations, I again impose a threshold of 10 invention patent counts in the pre-treatment year. Finally, the number of treatment groups per estimation also becomes substantially smaller, which may pose challenges for statistical inference. Following the recommendations of Hansen (2025), I employ the jackknife method for inference, rather than relying on conventional cluster-robust standard errors (CRVE_1).[25]

Figure 7 presents the estimated treatment effects by industry. To reduce potential estimation bias stemming from limited treatment pairs, I report results only for industries with more than four treatment city–industry pairs—the median number across all industries—so that idiosyncratic noise is more likely to average out. A full set of point estimates for all industries is shown in Appendix Figure A.19. It is evident that when the number of treated pairs is small—especially four or fewer—the variance of the estimated effects increases substantially, which motivates the chosen threshold.[26] Across reported industries in Figure 7, over two-thirds exhibit negative point estimates, in line with the overall effects.

Note that the estimated policy effects reflect an aggregation of responses from different types of firms

[25]As an alternative, MacKinnon et al. (2023) recommend using the restricted wild cluster (WCR) bootstrap method for inference. Hansen (2025) further suggest that the WCR method may perform better in cases with mild treatment effect heterogeneity; however, when heterogeneity is substantial, jackknife confidence intervals generally exhibit better coverage. Appendix Figure A.18 reports the re-estimation for Figure 7 confidence intervals obtained via the WCR bootstrap, which closely resemble those produced by the jackknife method.

[26]As shown in Appendix Figure A.19, there is no significant correlation between the estimated treatment effects and the number of treated city–industry pairs. This rules out the explanation that the observed heterogeneity is primarily driven by diminishing marginal effects from additional demonstration firms. This lack of correlation is plausible, as demonstration firms in a given industry are typically dispersed across different cities (see Appendix Table A.2). Moreover, in industries with a relatively large number of treated cities (e.g., more than 20), the estimated effects are predominantly negative. This suggests that the NTIDF policy may have had particularly adverse impacts in industries where it was implemented more extensively. Consequently, the overall treatment effect—essentially a weighted average across industries—is also negative.

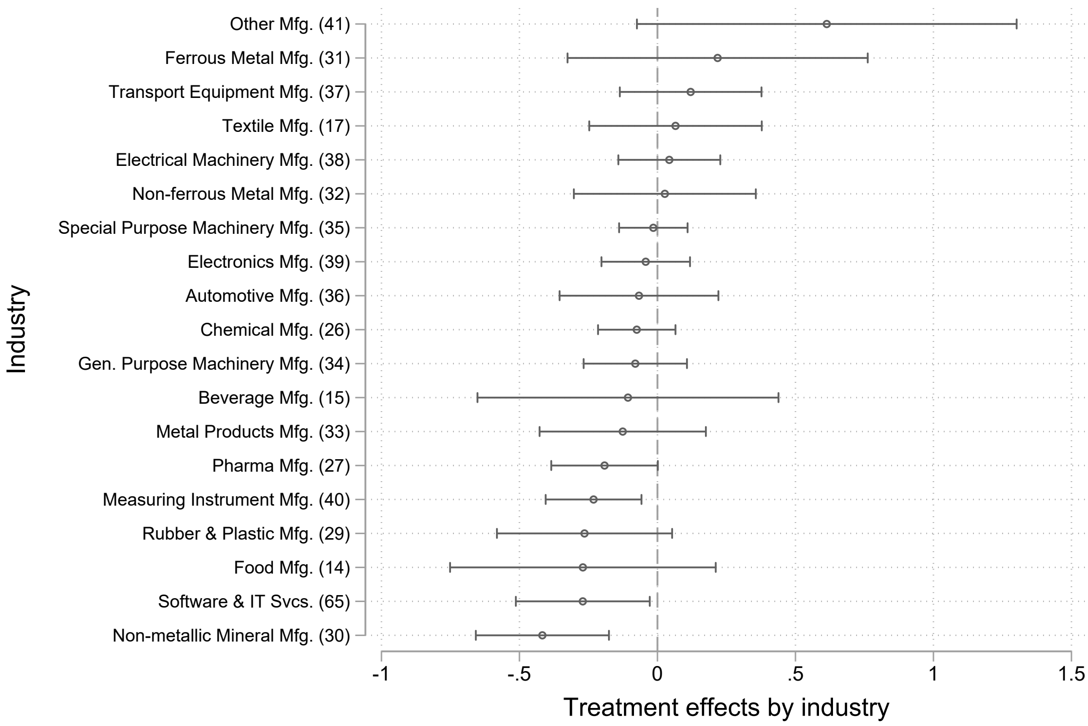

Figure 7: Treatment effects on innovation outcomes by industry

Notes: This figure illustrates the heterogeneous treatment effects of the NTIDF policy on patent outputs, weighted by 3-year-forward citations. To mitigate potential estimation bias, only industries with more than five treated city–industry pairs are included. Circles indicate point estimates, and lines represent 90% confidence intervals, calculated using the jackknife method clustered at the city level.

engaged in innovation. Therefore, explaining the observed heterogeneity essentially hinges on understanding the extent to which various innovation agents respond to the policy. Building on the earlier findings that the NTIDF policy affects subsidized leading firms, incumbent competitors, and potential entrants in divergent ways, two potential sources of heterogeneity naturally arise: the rate of new firm entry and the intensity of competition among incumbents. Intuitively, in industries characterized by higher entry rates and fiercer competition, follower firms and new entrants tend to play a larger role in innovation. In such settings, the discouraging effects of the policy may be more pronounced in shaping the overall outcome.

I begin by examining the first potential determinant—firm entry. The rate of new firm entry serves as a proxy for the degree of creative destruction, whereby new firms enter the market and challenge leading firms. To operationalize this, I compute the number of private firm entries in my first sample year (i.e., 2008) for each industry. I then examine how this variable correlates with the estimated treatment effects across industries. As shown in Figure 8, a negative correlation emerges as expected, suggesting that in industries with more active firm entry, the NTIDF policy may have generated more substantial negative spillovers. However, it is important to acknowledge that, due to the small sample size, this correlation is only significant at the 10% level.

Next, I investigate the relationship between the degree of market competition and the observed treatment effects. In line with standard practice, I employ the Herfindahl–Hirschman Index (HHI) as a measure of market concentration. Specifically, I use data on the primary operating revenues of all listed firms in 2008 to determine each firm's market share within its respective industry. These market shares are subse-

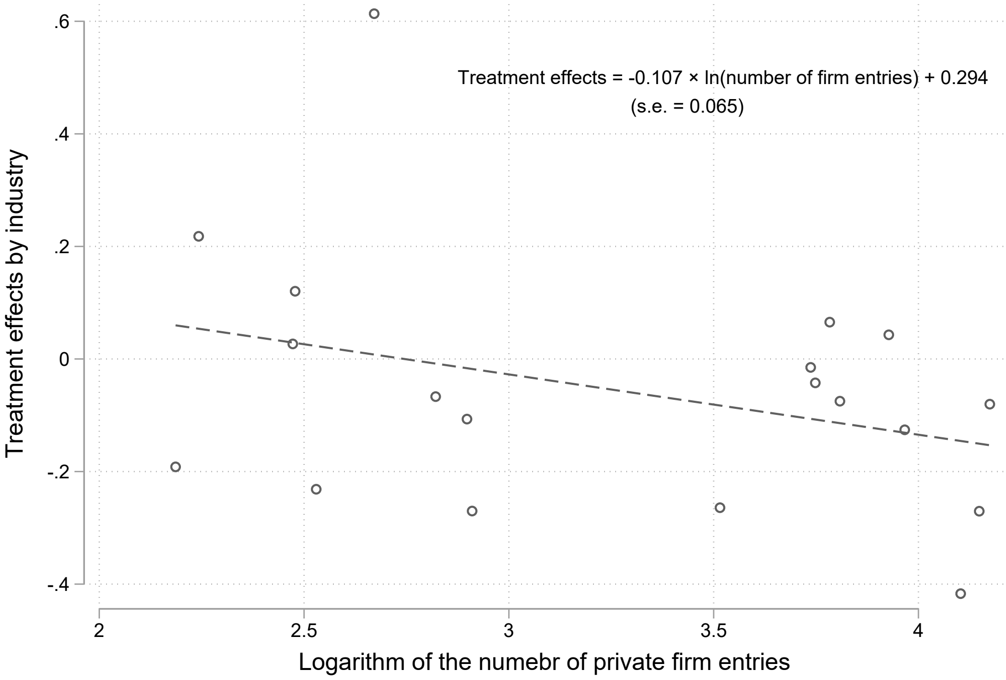

Figure 8: Treatment effects and private firm entries

Notes: This figure illustrates the relationship between treatment effects and firm entry, as measured by the number of private firm entries in the initial sample year (2008) for each industry. The dashed line indicates the fitted regression line. Point estimates and standard errors are presented within the figure.

quently employed to compute the HHI for each industry. [27]

Figure 9 illustrates the relationship between the HHI and the estimated policy effects, revealing an apparent "inverted-U" pattern. When the HHI is low, the increasingly negative policy effects observed with further decreases in HHI are intuitive, as a lower HHI typically corresponds to more active firm entry and intensified market competition. Thus, the initial upward trend in policy effects may be attributed to less pronounced discouragement through the firm-entry channel. As the HHI rises, the market tends to become concentrated among a few firms with similar levels of competitiveness. In such cases, subsidizing one of the leading firms may incentivize other firms near the productivity frontier to increase their R&D investments, as implied by the suggestive evidence in Figure 2. Notably, some industries within this range even exhibit positive policy effects. However, as the HHI increases further, the subsidized leading firm may acquire substantial monopolistic power and display significant productivity advantages over its competitors. Under these circumstances, the discouraging effects on competitor firms are likely to dominate, resulting in a return to negative policy effects.

Once again, due to the limited number of observations, the statistical significance of the estimates is relatively weak. I acknowledge that this relationship warrants further investigation and more robust identification when a more suitable empirical environment becomes available.

In summary, this section provides evidence that the NTIDF policy exerts negative effects on innovation outputs in the city–industry pairs where it is implemented. When considered alongside the divergence identified in the previous section—namely, the positive direct effects on subsidized leading firms versus the negative, discouraging effects on competitor firms and potential entrants—these findings suggest that the negative effects outweigh the direct positive effects of the policy. This interpretation is further

[27] Suppose $\mathcal{N}^i$ denotes the set of all listed firms operating in industry i, with each firm indexed by n and its market share denoted by s_n. The HHI for industry i is defined as $HHI^i \equiv \sum_{n\in\mathcal{N}^i} s_n^2$. The HHI is higher in markets where a small number of large firms dominate the market, indicating greater market concentration.

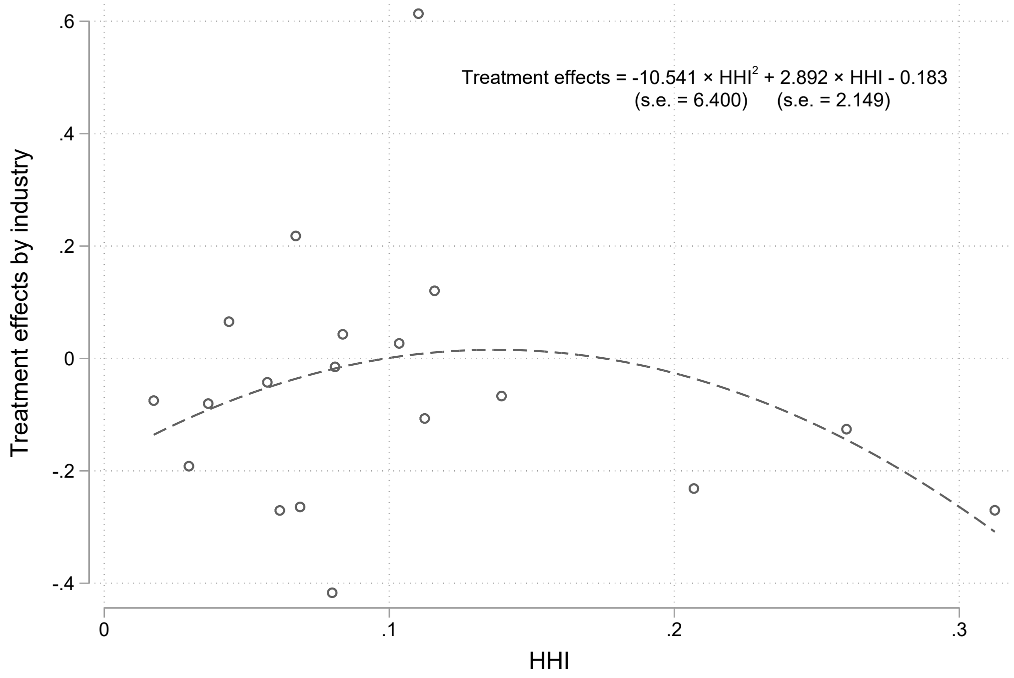

Figure 9: Treatment effects and market competition

Notes: This figure illustrates the relationship between treatment effects and market competition, as measured by HHI in 2008 for each industry. The dashed line indicates the fitted regression line. Point estimates and standard errors are presented within the figure.

reinforced by the observed heterogeneity, as the overall negative effects are more pronounced in industries characterized by higher levels of firm entry and market competition. Admittedly, my analysis in this section does not account for the existence of potential spillover effects, leaving the aggregate implications somewhat ambiguous. I explicitly address this limitation in the following section.

6 Spillover effects and aggregate implications

This section explores two distinct types of innovation spillover effects. The first pertains to inter-industry and spatial spillovers, which, as outlined in the previous section, may complicate the identification of the true ATT as well as the evaluation of nationwide impacts on innovation. The second type centers on local knowledge spillovers—specifically, whether demonstration firms produce positive externalities for other firms within the same industry and city. Analysis of this channel is directly relevant to one of the principal objectives of the NTIDF policy.

6.1 Inter-industry and spatial spillovers

When the NTIDF policy alters innovation outputs in treated city–industry pairs, it may also affect their productivity and overall market competitiveness, thereby generating spillover effects on other regions or industries. Two kinds of spillovers are considered in this section.

The first is inter-industry spillovers. Given the presence of input–output linkages and knowledge flows across industries, a negative productivity shock in one industry—caused by reduced innovation—may affect others through two potential channels. First, through cost shocks transmitted via input dependencies, which can lower the expected returns to R&D in downstream industries. Second, through weakened inter-industry knowledge spillovers. Due to persistent market segmentation across regions in China

(Young, 2000; Tombe and Zhu, 2019; Barwick et al., 2021), these spillovers, if present, are assumed to be more substantial within cities rather than across them. For this reason, and to ensure identification feasibility, I focus on potential intra-city inter-industry spillovers.

The second is spatial spillovers. On the one hand, firms in the same industry but located in different cities compete in a national market. A decline in innovation output in treated cities may improve the relative competitiveness of firms elsewhere, potentially encouraging greater R&D activity in untreated cities. On the other hand, reduced innovation in treated areas may hinder regional knowledge diffusion, thereby negatively affecting nearby cities. Therefore, the net spatial spillover effect of the policy is theoretically ambiguous and could potentially be positive.

It should be noted that spatial spillovers pose a more substantial challenge to identifying the overall policy effect than inter-industry spillovers. While the latter are theoretically negative and may result in conservative, downward-biased estimates of the ATT, they do not undermine the qualitative conclusions of the analysis. In contrast, spatial spillovers may be positive, increasing the risk of overstating the ATT and, consequently, the nationwide adverse impact of the NTIDF policy.

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 firms. Based on the analysis above, I assume that these control group samples are not experience any spillover effects.

2. *Inter-industry spillover control group:* City–industry pairs where demonstration firms 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 firms 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 firms 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 firms in their corresponding city or industry. This process again 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

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:

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

where $\mathbb{1}\{Treated^{city}\}_{c,t}$ takes the value of one after city c occurs the first demonstration firms. As this estimations relies on the variation at the city level, essentially comparing cities with demonstration firms to cities without any of them, I again replace city–year fixed effects by province–year fixed effects $\gamma_{p_c,t,s}$. To improve comparability, I restrict the estimation sample to city–industry pairs with more than 10 invention patent applications in the year preceding the treatment, consistent with the approach in the previous section.[28]

Table 5 presents the estimation results, using three-year citation-weighted invention patent counts, raw patent counts, and average citations per patent as dependent variables. Across all columns, the estimated coefficients are statistically insignificant. Despite the lack of statistical significance, the point estimates appear non-trivial in magnitude, and it is worth noting that the specification here differs from the baseline model. As a comparison, I re-estimate a similar specification in Appendix Table A.15, using the baseline sample while excluding all city–industry pairs belonging to either the mixed or inter-industry spillover control groups. This aims to mitigate potential bias arising from inter-industry spillovers. The results continue to show negative policy effects on innovation outcomes. The estimated effect is approximately -6.8%, comparable to the baseline estimates, suggesting that any bias due to inter-industry spillovers is likely limited. However, the effect on patent quality is no longer statistically significant, further supporting the notion that the NTIDF policy primarily reduces the quantity of innovation rather than its average quality.

Table 5: Estimating spillover effects by subgrouping control group city–industry pairs

	3-year citation-weighted	Patent quantity	Quality per patent
	(1)	(2)	(3)
Panel A. Inter-industry spillovers			
Treated	0.108	0.061	0.047
	(0.090)	(0.068)	(0.036)
City FEs × Industry FEs × Stack FEs	Yes	Yes	Yes
Industry FEs × Year FEs × Stack FEs	Yes	Yes	Yes
Province FEs × Year FEs × Stack FEs	Yes	Yes	Yes
# of clusters: city	285	285	285
# of clusters: industry	12	12	12
# of observations	25,879	25,879	25,879
Panel B. Spatial spillovers			
Treated	-0.115	0.017	-0.132***
	(0.087)	(0.082)	(0.036)
City FEs × Industry FEs × Stack FEs	Yes	Yes	Yes
Sector FEs × Year FEs × Stack FEs	Yes	Yes	Yes
City FEs × Year FEs × Stack FEs	Yes	Yes	Yes
# of clusters: city	135	135	135
# of clusters: industry	49	49	49
# of observations	24,430	24,430	24,430

Notes: This table reports estimates of spillover effects by regrouping control group city–industry pairs. In Panel A, inter-industry spillover effects are estimated by comparing the pure control group with the inter-industry spillover group. In Panel B, spatial spillover effects are estimated by comparing the pure control group with the spatial spillover group. The sample is restricted to city–industry pairs with more than 10 invention patent applications in the year prior to treatment within each stack. Standard errors are two-way clustered at the city and industry levels and reported in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6.1.2 Spatial spillover effects in innovation

Next, I address potential spatial spillover effects on innovation, which, as discussed earlier, are of particular importance for the implications of this study. I begin by employing a similar strategy to that used for inter-industry spillovers—restricting the sample to the comparison between the spatial spillover control

[28] Appendix Table A.14 reports invention patent application statistics for each control group subgroup. The table indicates that city–industry pairs in the pure control group systematically have fewer patent counts than those in the other two subgroups.

group and the pure control group—by estimating the following specification:

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

where $\mathbb{1}\{Treated^{ind}\}_{i,t}$ takes the value of one after the first demonstration firm emerges in industry i. Therefore, the identification relies on variation across industries. To avoid collinearity, I replace the industry-by-year fixed effects with sector-by-year fixed effects, denoted as $\rho_{I_i,t,s}$.[29]

Panel B of Table 5 reports the estimated spatial spillover effects. Columns (1) and (2) indicate that the overall impact on overall outcomes and patent quantity is statistically insignificant. Interestingly, a negative effect on average patent quality is observed in Column (3), and this pattern is also observed in the event study estimates reported in Appendix Figure A.20. This finding might reflect that the adverse policy effects on treated city–industry pairs may have hindered innovation and, in turn, weakened the diffusion of high-quality innovation to neighboring areas, ultimately reducing the quality of their newly produced patents. Reassuringly, these effects are negative, and thus likely to bias my core estimates in a conservative direction.

Following the strategy employed in the previous subsection, I re-estimate the model using the baseline sample, excluding all city–industry pairs classified into either the mixed or spatial spillover control groups. This exercise aims to assess the extent to which potential spatial spillovers may bias the main findings. As reported in Appendix Table A.16, the estimated effects remain robustly negative, with a larger average treatment effect of -12.3% on innovation outcomes. Notably, once the negative spatial spillovers on patent quality are largely accounted for, the estimated impact on average patent quality becomes considerably more pronounced than in earlier specifications, reaching a reduction of approximately 5.9%. Nevertheless, the magnitude remains smaller than that observed for patent quantity.

The preceding strategy essentially relies on comparisons across industries. However, if the structure of spatial spillovers is better understood, additional variation can be exploited for identification. For instance, under the knowledge diffusion channel—where negative effects on treated pairs may impede knowledge flow and thus suppress innovation in neighboring cities—it is reasonable to expect that geographically proximate cities are more susceptible to such spillover effects, given the spatial attenuation inherent in knowledge diffusion (Jaffe et al., 1993; Moretti, 2021; Atkin et al., 2022).

Based on this rationale, I identify city–industry pairs that are adjacent to treated pairs but not treated themselves, and assign each such pair a "spillover treatment year" corresponding to the earliest year in which any of their neighboring treated pairs received treatment.[30] This approach once again yields seven treatment cohorts, and a stacked sample is constructed accordingly. Estimation using this sample exploits not only cross-industry variation, but also variation between adjacent and non-adjacent cities.

The estimated results are presented in Panel A of Table 6, with the corresponding event study shown in Appendix Figure A.21. As expected, the point estimate for overall innovation outcomes is negative but statistically insignificant. Consistent with prior findings, I observe adverse effects on average patent quality in neighboring cities.

Another potential channel arises from inter-city competition over national market demand. Specifically, when treated city–industry pairs experience a decline in competitiveness due to slowed innovation, they may cede market share to firms in the same industry located in other cities. If spatial spillovers oper-

[29] According to the *Industrial Classification for National Economic Activities* (GB/T 4754–2017), 97 divisions (*dalei*)—the main industry categories used in this study—are grouped into 20 sectors (*menlei*). Among these, the 54 industries included in the patent analysis fall under 7 sectors.

[30] For example, the Metal Products Manufacturing industry in Beijing received its first demonstration firm certification in 2011 and is therefore considered treated beginning in 2012. Accordingly, the same industry in cities neighboring Beijing—including Baoding, Tianjin, Langfang, Chengde, and Zhangjiakou—is assumed to be exposed to spatial spillover effects starting in 2012.

ate through this channel, cities with larger initial market shares are expected to gain more.[31]

To capture this form of economic connection, I aggregate the output of each city–industry pair using the 2012 city-level input–output table constructed by Zheng et al. (2022). Within the control group, city–industry pairs with output shares in the top half of their respective industries—conditional on the industry having at least one demonstration firm—are classified as the "spillover group" and compared against all remaining control group pairs in the estimation. The estimated results are presented in Panel B of Table 6, with the corresponding event study estimates shown in Appendix Figure A.22. While I observe a minor upward trend in innovation outcomes following the treatment in the event study, all estimates remain statistically insignificant and modest in magnitude.

Taken together, the estimates presented in this subsection suggest that inter-industry and spatial spillover effects, if any, are minor and unlikely to meaningfully bias the baseline findings.

Table 6: Estimating spatial spillover effects by geographical and economic connections

	3-year citation-weighted	Patent quantity	Quality per patent
	(1)	(2)	(3)
Panel A. Geographical connection			
Treated	-0.030	-0.006	-0.024*
	(0.023)	(0.019)	(0.013)
# of clusters: city	316	216	316
# of clusters: industry	53	53	53
# of observations	332,812	332,812	332,812
Panel B. Economic connection			
Treated	-0.003	0.018	-0.021
	(0.032)	(0.023)	(0.022)
# of clusters: city	318	318	318
# of clusters: industry	53	53	53
# of observations	179,622	179,622	179,622
City FEs × Industry FEs × Stack FEs	Yes	Yes	Yes
Industry FEs × Year FEs × Stack FEs	Yes	Yes	Yes
City FEs × Year FEs × Stack FEs	Yes	Yes	Yes

Notes: This table reports estimates of spatial spillover effects through two channels—geographic and economic connections with treated pairs. Panel A identifies potentially affected city–industry pairs as those adjacent to treated pairs but not treated themselves; the control group includes the remaining untreated pairs. Panel B defines potentially affected pairs as untreated pairs with output shares in the top half within their respective industries in 2012, conditional on the industry having at least one demonstration firm; the control group comprises the remaining untreated pairs. All estimations restrict the sample to city–industry pairs with more than 10 invention patent applications in the year preceding the treatment within each stack. Standard errors, two-way clustered at the city and industry levels, are reported in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6.2 Local knowledge spillovers

Next, 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, as well as highlighting the rapid decay of knowledge spillover effects with distance (Jaffe et al., 1993; Moretti, 2021; Atkin et al., 2022). The NTIDF 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

[31] As implied by heterogeneous firm models with the independence of irrelevant alternatives (IIA) property, such as Eaton and Kortum (2002), a decline in one region's market share is redistributed proportionally to others based on their initial shares.

knowledge diffusion among other firms. Consequently, the net impact of the policy on local knowledge spillovers remains ambiguous.

Utilizing the patent citation network, I identify each patent's citations to other patents within the same city–industry pair. This approach enables me to construct two measures for each city–industry pair over time: the total number of local citations and the average number of local citations per patent. These measures serve as proxies for local knowledge spillovers. The first measure, total local citations, captures the overall magnitude of local knowledge spillovers and is informative for assessing the aggregate impact on local knowledge dissemination. In contrast, the second measure—the average number of local citations per patent—reflects the per-patent intensity of local knowledge spillovers.

I estimate the specification consistent with Equation (15), replacing the dependent variable with the logarithm of the two alternative measures. Table 7 presents the estimation results. In Column (1), the dependent variable is the logarithm of total local citations, for which I obtain a negative point estimate. This result is consistent with the observed decline in total patent outputs, although it is not statistically significant. Column (2) examines the effects on local citations per patent, where the point estimate becomes positive but small in magnitude and remains statistically insignificant. These findings indicate that the NTIDF policy does not enhance local knowledge spillovers, or, at best, has only a limited impact if any positive effects exist.

This finding carries two implications. First, the local knowledge spillover effects generated by subsidizing leading firms are weak. Demonstration firms 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 firms 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 7: Policy effects on local knowledge spillovers

	Total local citations	Local citations per patent
	(1)	(2)
Treated	-0.040	0.014
	(0.044)	(0.044)
City FEs × Ind. FEs × Stack FEs	Yes	Yes
Ind. FEs × Year FEs × Stack FEs	Yes	Yes
City FEs × Year FEs × Stack FEs	Yes	Yes
# of clusters: city	287	287
# of clusters: industry	53	53
# of observations	257,192	257,192

Notes: This table reports the estimated effects of the policy on local knowledge spillovers. The dependent variables in Columns (1) and (2) are the logarithm of total local citations and the logarithm of per-patent local citations, respectively. The sample is restricted to city–industry pairs where the number of invention patent applications in the year preceding the treatment exceeds 10 within each stack. Standard errors are two-way clustered at the city and industry levels and are presented in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

7 Quantifying policy effects on national economic outputs

Thus far, I have examined the potential spillover effects on innovation activities and determined that these effects are relatively minor. Nevertheless, even if the policy does not have a substantial impact on innovation in other cities or industries, it may still generate spillovers on economic output through the input–output linkages that connect cities and industries. In order to assess the national economic cost of the NTIDF policy for economic growth, it is essential to account for such spillover effects, which requires the application of a spatial equilibrium framework.

To address this, I construct a quantitative trade model that is based on the foundational frameworks developed by Eaton and Kortum (2002) and Caliendo and Parro (2015). The model incorporates firm-level productivity differences, sectoral heterogeneity, and trade in intermediate goods across cities and industries. In the counterfactual analysis, I treat the NTIDF policy as exogenous TFP shocks. With this spatial model, I can quantify how these shocks affect the national economic output and welfare.

7.1 Model

Suppose that there are N cities, index by $o, d \in \{1, \cdots, N\}$ and J industries (sectors), index by $j, k \in \{1, \cdots, J\}$. The subscript od of a variable represents the direction of goods trade from city o to city d. Each industry produces a continuum of intermediate goods, which can be aggregated into a industry-specific final good. Therefore, indices j and k are also used to represent products. For clarity, they are placed on the superscript when referring to products and on the subscript when referring to industries. All markets are assumed perfectly competitive. As city-level migration shares are unavailable, I assume that labor is immobile across cities but fully mobile across industries within a city. Each worker supply one unit of labor inelastically and homogeneously.

7.1.1 Household

In each city, there are L_d workers that maximize utility by consuming final goods C_d^j. The preference of workers in city d is given by

$$u_d = \prod_{j=1}^{J} \left(\frac{C_d^j}{\alpha_d^j} \right)^{\alpha_d^j}, \tag{19}$$

with $\sum_{j=1}^{J} \alpha_d^j = 1$. Letting w_d denote the nominal wage level in city d, the consumption on final goods j in city d is given by

$$P_d^j C_d^j = \alpha_d^j w_d L_d, \tag{20}$$

where P_d^j is the price of final good j in city d. Additionally, the indirect utility function is

$$v_d = \frac{w_d}{\prod_{j=1}^{J} \left(P_d^j \right)^{\alpha_d^j}}. \tag{21}$$

7.1.2 Intermediate goods

A continuum of intermediate goods $\omega^j \in \Omega^j$ is produced in each industry. Assume that firms in industry j of city o have a Cobb–Douglas production function:

$$y_{o,j}\left(\omega^j\right) = z_{o,j}\left(\omega^j\right) \left[L_{o,j}\left(\omega^j\right) \right]^{\gamma_{o,j}} \prod_{k=1}^{J} \left[Y_{o,j}^k \left(\omega^j\right) \right]^{\eta_{o,j}^k}, \tag{22}$$

where $L_{o,j}(\omega^j)$ and $Y_{o,j}^k(\omega^j)$ denote labor and the final good from industry k used for the production of intermediate goods ω^j. The parameters $\gamma_{o,j}$ and $\eta_{o,j}^k$ are the output elasticities of labor and final goods, respectively, varying among cities and sectors, with $\alpha_{o,j} + \sum_k \eta_{o,j}^k = 1$. According to the property of Cobb–Douglas production function, these elasticities also stand for the income share of each input factors.

Each firm in industry j located in city o produces intermediate goods ω^j with heterogeneous productivity levels, denoted by $z_{o,j}(\omega^j)$. Following Caliendo and Parro (2015), productivity is assumed to be independently drawn from a region- and sector-specific distribution given by $F_{o,j}(x) = \mathrm{e}^{-T_{o,j}x^{-\theta}}$, where the scale parameter $T_{o,j}$ reflects the average productivity in industry j of city o, and the shape parameter θ captures the degree of productivity dispersion. For a given θ, the expected productivity of firms in industry j of city o is determined as a function of $T_{o,j}$, expressed as

$$\mathbb{E}\left[z_{o,j}\right] = \Gamma\left(\frac{\theta-1}{\theta}\right) \cdot T_{o,j}{}^{1/\theta}, \tag{23}$$

where $\Gamma(\cdot)$ denotes the Gamma function. This relationship facilitates the quantitative conversion of TFP shocks into relative changes in $T_{o,j}$.

Firms in industry j of city o employ labor with wage w_o and buy final goods in industry k with price P_o^k. Solving the cost minimization problem of firms yields the cost of producing $z_{o,j}(\omega^j)$ units of products, given by

$$c_{o,j} = \Upsilon_{o,j} w_o{}^{\gamma_{o,j}} \prod_{k=1}^{J} \left(P_o^k\right)^{\eta_{o,j}^k}, \tag{24}$$

where $\Upsilon_{o,j} \equiv \gamma_{o,j}{}^{-\gamma_{o,j}} \prod_{k=1}^{J} (\eta_{o,j}^k)^{-\eta_{o,j}^k}$. As goods markets are assumed perfectly competitive, the local price (price without taking into account trade costs) is

$$p_o^j(\omega^j) = \frac{c_{o,j}}{z_{o,j}\left(\omega^j\right)}. \tag{25}$$

7.1.3 Final goods

Final goods are local-used and portrayed as a Dixit–Stiglitz aggregation of the intermediates in the corresponding industry that are produced locally or traded from other cities:

$$Y_{o,j} = \left[\int_{\omega^j \in \Omega^j} y_{o,j}\left(\omega^j\right)^{\frac{\sigma^j-1}{\sigma^j}} \mathrm{d}\omega^j\right]^{\frac{\sigma^j}{\sigma^j-1}}, \tag{26}$$

where σ^j is the elasticity of substitution across intermediate goods within industry j.

7.1.4 Inter-regional trade and prices

Goods trading encounters obstacles arising from various natural and institutional factors, including transportation distance and institutional local protectionism. In the model, I incorporate these trade costs in a unified manner using the Iceberg costs, where one unit of intermediates in industry j traded from city o to city d requires producing τ_{od}^j units in city o ($\tau_{od}^j \geq 1$ and $\tau_{oo}^j = 1$). A larger τ_{od}^j signifies greater trade costs from o to d. Accounting for the trade costs, the unit price of intermediates traded from o to d incurs a markup against the exporter local price, given by $p_{od}^j(\omega^j) = \tau_{od}^j p_o^j(\omega^j)$.

The final good sector in each province is responsible for seeking the cheapest intermediates nationwide and combining them into industry-specific final goods, which serve as either the consumption of residents or the input in the production of intermediates. As there is a random term in prices, the trade decision is characterized by a probability distribution:

$$\pi_{od}^j = \Pr\left\{\frac{c_{o,j}\tau_{od}^j}{z_{o,j}\left(\omega^j\right)} \leq \min_{o' \neq o}\left\{\frac{c_{o',j}\tau_{o'd}^j}{z_{o',j}\left(\omega^j\right)}\right\}\right\}. \tag{27}$$

With the CDF of Fréchet distribution, I yield:

$$\pi_{od}^{j} = \frac{T_{o,j}\left(\tau_{od}^{j}c_{o,j}\right)^{-\theta}}{\sum_{o'=1}^{N} T_{o',j}\left(\tau_{o'd}^{j}c_{o',j}\right)^{-\theta}}. \tag{28}$$

As the number of firms is sufficiently large under the continuum goods settings, the trade share from city o to city d will converge to this probability.

Given importer d, the price distribution is homogeneous across varieties. Therefore, the price of their composited final goods will converge to the expectation of the price of a variety:

$$P_{d}^{j} = \mathbb{E}\left[p_{od}^{j} \mid p_{od}^{j} \le \min_{o' \neq o}\left\{p_{o'd}^{j}\right\}\right] = \left[\Gamma\left(\frac{\theta+1-\sigma^{j}}{\theta}\right)\right]^{\frac{1}{1-\sigma^{j}}}\left[\sum_{o=1}^{N} T_{o,j}\left(\tau_{od}^{j}c_{o,j}\right)^{-\theta}\right]^{-\frac{1}{\theta}}, \tag{29}$$

where $\Gamma(\cdot)$ denotes the gamma function.

7.1.5 Market clearing

The total demand on final good j in city d, denoted by X_{d}^{j}, is the sum of the expenditure by firms for production and the expenditure by households for consumption, given by

$$X_{d}^{j} = \alpha_{d}^{j} w_{d} L_{d} + \sum_{k=1}^{J} \eta_{d,k}^{j} R_{d,k}, \tag{30}$$

where $R_{d,k}$ is the total output value of intermediates in industry k of city d. Since final goods are composited intermediate goods without value added, the total demand on final good is also the total demand of intermediates imported by or produced locally in city d.

The total supply of intermediate goods in industry j of city o is the sum of intermediates exported to all other countries or used locally for producing final goods, given by

$$R_{o,j} = \sum_{d=1}^{N} \pi_{od}^{j} X_{d}^{j}. \tag{31}$$

Combining Equations (30) and (31) forms the market clearing condition of this spatial model.

7.1.6 Equilibrium in relative changes

As my aim is to estimate the aggregate effects of productivity shocks resulted from the NTIDF policy, I are only interested in the relative changes of endogenous variables before and after the shock. As such, I can solve the model equilibrium in the relative form of each variable, which reduce the number of parameters that need to be calibrated (Dekle et al., 2008). Specifically, a variable with a "hat" is used to signify the relative change of its value under the baseline equilibrium (x) and the counterfactual equilibrium (x'), i.e., $\hat{x} = x'/x$. The equilibrium in the form of relative changes is defined as follows:

Definition 1. *Let* $\Theta \equiv \{\pi_{od}^{j}\}_{o=1,d=1,j=1}^{N,N,J}$ *denote the set of trade shares under baseline equilibrium, let* $\Lambda \equiv \{\alpha_{d}^{j}, \gamma_{o,j}, \eta_{o,j}^{k}, \theta\}_{o=1,j=1,k=1}^{N,J,J}$ *denote the set of parameters, and let* $\Upsilon \equiv \{\hat{T}_{o,j}\}_{o=1,d=1,j=1}^{N,N,J}$ *denote the relative changes in exogenous variables of the model. According to Equations* (24)(28)(29)(30)(31)*, given* $\{\Theta, \Lambda, \Upsilon\}$*, the relative change in the counterfactual equilibrium is a set of relative changes in nominal wages and final goods prices* $\{\hat{w}_{d}, \hat{P}_{d}^{j}\}_{d=1,j=1}^{N,J}$ *that satisfy:*

Price index:

$$\hat{c}_{o,j} = \hat{w}_o^{\gamma_{o,j}} \prod_{k=1}^{J} \left(\hat{P}_o^k\right)^{\eta_{o,j}^k}. \tag{32}$$

Final good price:

$$\hat{P}_d^j = \left[\sum_{o=1}^{N} \hat{T}_{o,j} \left(\hat{\tau}_{od}^j \hat{c}_{o,j}\right)^{-\theta} \pi_{od}^j\right]^{-\frac{1}{\theta}}. \tag{33}$$

Trade share:

$$\hat{\pi}_{od}^j = \frac{\hat{T}_{o,j} \left(\hat{\tau}_{od}^j \hat{c}_{o,j}\right)^{-\theta}}{\sum_{o'=1}^{N} \hat{T}_{o',j} \left(\hat{\tau}_{o'd}^j \hat{c}_{o',j}\right)^{-\theta} \pi_{o'd}^j}. \tag{34}$$

Total supply:

$$R_{o,j}' = \sum_{d=1}^{N} \pi_{od}^{j}{}' X_d^{j\prime}. \tag{35}$$

Total demand:

$$X_d^{j\prime} = \alpha_d^j \hat{w}_d w_d L_d + \sum_{k=1}^{J} \eta_{d,k}^j R_{d,k}', \tag{36}$$

where $w_d L_d = \sum_{j=1}^{J} \gamma_{d,j} R_{d,j}$ and $\{R_{d,j}\}_{d=1,j=1}^{N,J}$ are derived from solving the baseline equilibrium. To set a numeraire for each equilibrium, I normalize the sum of nominal wage to 1 (i.e., $\sum_d w_d L_d = \sum_d w_d' L_d' = 1$).

Accordingly, the relative change in welfare for workers in city d is

$$\hat{v}_d = \frac{\hat{w}_d}{\prod_{j=1}^{J} \left(\hat{P}_d^j\right)^{\alpha_d^j}}, \tag{37}$$

which is equal to the relative change in the real wage in city d. Given the assumption of labor immobility and its role as the sole value-adding input in production, this measure is equivalent to the relative change in local real GDP.

Furthermore, I aggregate these city-level relative changes to evaluate the national changes in welfare and real GDP:

$$\hat{V} = \frac{\sum_{d=1}^{N} v_d' L_d}{\sum_{d=1}^{N} v_d L_d} = \sum_{d=1}^{N} \hat{v}_d \cdot \frac{w_d L_d / P_d}{\sum_{d=1}^{N} w_{d'} L_{d'} / P_{d'}}, \tag{38}$$

where $\hat{V}$ represents a weighted average, with weights determined by each city's initial share in the national total of real wages.

7.2 Data and calibration

As indicated in Definition 1, determining the relative changes of variables under the counterfactual equilibrium necessitates data of the trade shares from the baseline equilibrium as well as certain parameters. To estimate the trade shares for industry-specific products across cities, I employ the 2012 city-level multi-regional input–output (MRIO) table constructed by Zheng et al. (2022). This dataset provides input–output linkages for intermediate goods covering 313 regions and 42 industries. To maintain consistency with the reduced-form analysis conducted earlier, I retain 302 city-level administrative units. Furthermore, I exclude 26 cities due to the lack of other data. Consequently, trade shares are computed among the remaining 276 cities.

Trade elasticity, θ, is a key parameter in quantitative spatial models, and a substantial body of literature provides estimates for it (Simonovska and Waugh, 2014; Caliendo and Parro, 2015; Tombe and Zhu, 2019). As the estimates in the literature tend to converge, I adopt the calibration results from Tombe and Zhu

(2019), setting θ to 4.

City-specific consumption shares of each final goods, α_d^j, the labor share in the production of each city–industry pair, $\gamma_{o,j}$, and intermediate shares in the production of each city–industry pair, $\eta_{o,j}^k$, can all be calculated based on the input–output table. As only labor and intermediates are considered as factors of production, I magnify these factor shares proportionally to ensure their sum is one.

Finally, the aggregation of national welfare changes requires data on each city's real wage in 2012. Wage and employment data are sourced from the *China City Statistical Yearbook (2013)*. Due to the unavailability of city-level consumer price indices, I use province-level indices instead. Specifically, the price index for each province is normalized to 1 for the year 1996, and cumulative price indices are computed up to 2012.

7.3 Counterfactual analysis

I model the NTIDF policy as exogenous shocks to averaged TFP in specific cities and industries. Using the proposed model and observed economic fundamentals from 2012—the year in which the NTIDF policy was implemented—I compute a counterfactual equilibrium that reflects the effect of these TFP shocks, thereby quantifying the relative changes in real GDP.

To quantify these exogenous TFP shocks, I draw on the quantitative findings of Kogan et al. (2017). In their study, the authors develop a patent-level innovation metric based on stock market reactions, which displays an elasticity of 0.174 with respect to the forward citations of a patent. Their analysis further demonstrates that a one standard deviation increase (approximately 85%) in their nationally-aggregated innovation measure leads to a 3.4% rise in aggregate productivity. Combined together, this implies a 1% decrease in annual citation-weighted patent outputs is estimated to result in a 0.00736% reduction in TFP.

Using this quantitative relationship, I consider three counterfactual shock scenarios. First, based on the baseline estimates reported in Table 4, I assume that the NTIDF policy induces a uniform 8.3% reduction in patent outputs, which translates into a 0.061% decrease in TFP for city–industry pairs that had at least one demonstration firm during the sample period.[32] The resulting counterfactual changes in real GDP are presented in Column (1) of Table 8. On average, these TFP shocks lead to a 0.05% reduction in real GDP for cities containing demonstration firms. Furthermore, trade linkages across cities and industries serve to propagate these negative shocks, resulting in an additional average decrease of 0.021% in real GDP in other cities. Collectively, the policy results in a 0.049% reduction in national real GDP.

It is important to emphasize that demonstration firms exist in only 3.3% of city–industry pairs, which together account for 14.1% of total national output. Therefore, while the estimated effect is relatively moderate under the current scope, the NTIDF policy could exert a substantially greater impact on aggregate output if extended nationwide. To illustrate this potential effect, I perform a counterfactual analysis in which the TFP in all city–industry pairs is assumed to decline uniformly by 0.061%. The resulting counterfactual equilibrium suggests that such a scenario would result in a 0.26% reduction in national real GDP, corresponding to approximately 22.55 trillion USD based on China's GDP in 2012.

The second scenario considers heterogeneous treatment effects across industries, as illustrated in Figure 7. To address possible estimation errors stemming from a small number of treated city–industry pairs, I replace the treatment effects of industries with fewer than five treated cities with the baseline average treatment effect of 8.3%. These estimated impacts on patent output are then similarly converted into TFP shocks within the quantitative model. The results for this scenario are reported in Column (2) of Table 8 and are similar to those in Column (1).

[32]The reduction in TFP is subsequently reflected as a relative change in the scale parameter of the distribution of firms' TFP (i.e., $\hat{T}_{o,j}$) according to Equation (23).

In the third scenario, I consider the possibility of spatial spillovers. In addition to a uniform 8.3% reduction in patent outputs for treated city–industry pairs, I also incorporate a negative spillover effect of 3% for the same industries in cities adjacent to the treated pairs, as estimated in Table 6. As illustrated in Column (3), accounting for spatial spillovers results in a more pronounced reduction in national real GDP, amounting to 0.06%.

Table 8: Equilibrium effects on real GDP

	Percentage change in real GDP		
	Uniform treatment effects	Industrial heterogeneity	Spatial spillovers
	(1)	(2)	(3)
Cities with demonstration firms	-0.050	-0.048	-0.061
Cities without demonstration firms	-0.021	-0.017	-0.036
Nation	-0.049	-0.046	-0.060

Notes: This table presents the percentage changes in real GDP resulting from TFP shocks induced by the NTIDF policy. The computation of these changes is based on the quantitative trade model.

8 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, potentially 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 like new entrances or small-to-medium enterprises (SMEs).

The theoretical predictions are corroborated by empirical evidence from the implementation of the "National Technology Innovation Demonstration Firm" policy in China, which primarily subsidizes leading local innovators. This study further evaluates the aggregate impacts of the policy and finds that it leads to a reduction in citation-weighted patent applications, both within the affected city–industry pairs and at the national level. These adverse effects are particularly pronounced in markets characterized by intense competition and frequent entry of new firms, which aligns with the theoretical expectation that the policy disproportionately discourages competitor firms and new entrants in such contexts. Moreover, I observe that spillover effects across industries are limited, while negative spatial spillovers do arise, plausibly due to diminished innovation outcomes restricting knowledge diffusion to neighboring cities. Additionally, there is no evidence to suggest that the policy enhances local knowledge spillovers. Finally, utilizing a quantitative trade model, I estimate the policy's effects on national equilibrium real GDP and underscore the potentially significant impact should the policy be extended nationwide.

Taken together, this study yields three important policy implications. First, governments should exercise caution regarding the potential discouraging effects of subsidizing leading firms. In particular, in industries characterized by frequent entry of new firms, selective R&D subsidy policies may produce adverse outcomes. Moreover, I identify evidence suggestive of an "inverted-U" relationship between market concentration and policy effects, indicating that superstar-oriented subsidies may be more effective when the market is predominantly occupied by a few large firms with comparable levels of competitiveness. Second, the observed negative aggregate effects suggest that new firms and SMEs, which are relatively distant from the productivity frontier, may play a more significant role in driving aggregate innovation in today's China. Consequently, governments should consider implementing measures to promote competition, facilitate firm entry, and support the development of SMEs. Third, given the interconnected nature of innovation competition among firms, selective innovation policies are vulnerable to unanticipated firm responses and unintended consequences. This finding resonates with the broader debate on industrial policy and the ability of governments to effectively identify future winners (Juhász et al., 2024). Therefore, governments may wish to consider non-selective approaches, such as investing in education and training or providing universal innovation support, to more effectively incentivize aggregate innovation.

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A Additional policy background

This appendix provides additional background on the National Technological Innovation Demonstration Firm (NTIDF) policy.

A.1 Submitted materials and criteria prioritized in certification

I begin by providing a more comprehensive summary of the materials that applicant firms 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, firms 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 firm'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 firms 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 firms. The application materials of the recommended firms, 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 Firms* 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 firms, the table includes detailed information on each firm'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 firms. 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 firms, the number of re-evaluated firms, the number of firms failing in the re-evaluation, the passing rate, and the cumulative number of demonstration firms at the end of the year from 2011 to 2017. On average, 71 demonstration firms were certified annually between 2011 and 2017. Demonstration firms are subject to a re-evaluation process every three years. For instance, the 55 demonstration firms certified in 2011 underwent two re-evaluations in 2014 and 2017, respectively. From 2014 to 2017, an average of 84.5 demonstration firms 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 firms in the treatment group lost the policy title. Consequently, in the main text, when estimating treatment effects, once an firm is certified as a demonstration firm or a city–industry pair experiences its first demonstration firm, 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 firms

Figure A.4 illustrates the industry distribution of demonstration firms. The left panel presents the distribution of the 494 demonstration firms 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 firms 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 firms are "Pharmaceutical Manufacturing," "Electronics Manufacturing," "Special Purpose Machinery Manufacturing," and "General Purpose Machinery 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 firms 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 12 demonstration firms, 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 firms

Appendix Figure A.5 presents the spatial distribution of demonstration firms, showing the year in which each city first received demonstration firm certification, regardless of industry. The figure reveals a clear pattern: earlier certifications were more likely granted to more developed cities, such as Beijing, Shanghai, Shenzhen, and Hangzhou. Across the seven certification rounds examined in this study, demonstration firms are largely concentrated in coastal provinces characterized by higher productivity and greater contributions to national economic growth. These patterns suggest substantial selection into treatment, which is consistent with the observed differences in initial invention patent application counts between treatment and control groups.

Another observation worth noting is that the distribution of demonstration firms is spatially dispersed. Appendix Figure A.6 shows each city's maximum number of demonstration firms within a single industry in 2018. Approximately 73% of treated cities hosted only one demonstration firm per treated industry.

Appendix Table A.2 further presents city–industry-level statistics, reporting the distribution of cumulative demonstration firms and examining the extent to which multiple demonstration firms were certified within the same city–industry pair. For example, as shown in the first row, among the 52 city–industry pairs treated in 2012 (with their first certification in 2011), 50 pairs had only one demonstration firm, accounting for 96.15% of the sample. Only two pairs had two demonstration firms, representing 3.85%.

Although the proportion of treated city–industry pairs with only one demonstration firm decreased over time, as of the 2017 certification, 83.71% of treated city–industry pairs still had only one demonstration firm. 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 firms, 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 firm program is unlikely to be signaling policy incentives by subsidizing "star firms" to attract innovation from other local firms. This is because city–industry pairs with an existing demonstration firm rarely have a second firm certified.

A.5 The market standing of demonstration firms

Finally, I examine the market standing of demonstration firms to support the conclusion in the main text that demonstration firms are typically leading firms within their local markets. Specifically, I calculate the percentile rankings of listed demonstration firms 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.7 presents the results. On average, demonstration firms rank between the 70th and 80th percentiles across the four evaluated variables. However, among the 32 industries with listed demonstration firms, some industries exhibit a high concentration of such firms. For example, in the Pharmaceutical Manufacturing industry (industry code: 27), there are 27 listed demonstration firms, including 4 in Zhejiang Province, 3 in Guangdong Province, and 3 in Jiangsu Province. Due to this concentration, the average percentile ranking of demonstration firms tends to be lower in these industries.

To better reflect the market standing of early-certified demonstration firms, I further restrict the sample to industries with no more than two listed demonstration firms nationwide. This restriction leaves 16 industries out of the original 32. This time, the average ranking of demonstration firms in terms of utility patent and invention patent applications rises to approximately the 98th and 88th percentiles, respectively, and their average ranking in R&D investment even reaches the 100th percentile. Meanwhile, the relevance of the asset size indicator diminishes. These findings suggest that demonstration firms are typically local industry leaders in innovation—so-called innovation "superstar" firms.

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 firms hold a significantly leading position within their respective industries and provinces. Additionally, the results suggest that, when certifying demonstration firms, 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:

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

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

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

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

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

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 $\tilde{x}$, such that for $x < \tilde{x}$, the partial derivative $\partial f_A \left(x \mid R_{o,t} \right) / \partial R_{o,t} < 0$, and for $x > \tilde{x}$, $\partial f_A \left(x \mid R_{o,t} \right) / \partial R_{o,t} > 0$. 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 $f_A^0(x)$ denote the baseline density function, which represents the density conditional on $R_{o,t} = 0$. Then, other conditional density functions can be expressed as

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

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 $\tilde{x} = m^0 + \mu\left(R_{o,t}\right)$. 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 The classification of government-provided subsidies

This appendix summarizes and discusses the method used to classify government-provided subsidies. In the main analysis, I adopt a keyword-based classification approach. However, a potential concern is that relying solely on a fixed set of ten keywords may result in a non-negligible rate of misclassification.

To assess the accuracy of this method, I leverage five large language models (LLMs) known for their strong performance in understanding Chinese text. These models are accessed via the API platform SiliconFlow (`https://www.siliconflow.com`), and include:

- **DeepSeek-V3-0324**: A mixture-of-experts LLM with approximately 671 billion total parameters and 37 billion active parameters per forward pass, developed by DeepSeek AI.
- **Qwen3-30B-A3B-Instruct-2507**: A mixture-of-experts LLM with approximately 30.5 billion total parameters and 3.3 billion active parameters per forward pass, developed by Alibaba Cloud's Qwen team.
- **Qwen3-235B-A22B-Instruct-2507**: A mixture-of-experts LLM with approximately 235 billion total parameters and 22 billion active parameters per forward pass, also developed by the Qwen team.
- **ERNIE-4.5-300B-A47B**: A mixture-of-experts LLM with approximately 300 billion total parameters and 47 billion active parameters per forward pass, developed by Baidu.
- **GLM-4.5**: A mixture-of-experts LLM with approximately 355 billion total parameters and 32 billion active parameters per forward pass, developed by Zhipu AI.

I randomly select a subsample of 3,000 subsidy records (approximately 1% of the full sample). Within this subsample, the keyword-based method classifies 32.23% of the records as R&D-related subsidies, a proportion closely aligned with that in the full sample (33.4%), indicating good representativeness. Each record is then independently assessed by various large language models (LLMs) to determine whether it constitutes an R&D-related subsidy. The LLM classification procedure is standardized across models using the following settings:

- `temperature`: Set to 0 to ensure deterministic and consistent outputs.
- `system_prompt`: "As a government subsidy classification expert, you are tasked with evaluating government subsidy records disclosed in the financial statement notes of listed companies. Based on the 'Project' and 'Description' fields of each record, determine whether it constitutes an R&D-related subsidy. Requirement: Return only '0' or '1,' where '0' indicates 'not an R&D subsidy' and '1' indicates 'R&D subsidy.' No further explanation should be provided." (original prompt issued in Chinese)
- `user_prompt`: The original Chinese textual content of each subsidy record, as disclosed in financial statement notes. For example: "Project: The Research and Development Project for Wafer-Level Chip Scale Packaging (WLCSP)," corresponding to a subsidy received by Tianshui Huatian Technology Company (ticker: 002185) in 2013. This record is classified as R&D-related by both the keyword-based and LLM-based methods.
- `max_tokens`: Set to 1 to restrict output to a single-digit (0 or 1) classification.
- `enable_thinking`: Set to `False` to reduce latency and accelerate output generation. (Applicable only to reasoning models such as ERNIE and GLM)

Table A.3 compares the classification outcomes across all pairs of methods. The keyword-based approach achieves over 85% consistency with each of the large language models, suggesting that the method provides a practically useful approximation for identifying R&D-related subsidies, despite some inconsistencies. As discussed in the main text, I rely primarily on the keyword-based method to ensure transparency and reproducibility. The comparison results offer some reassurance that this approach does not systematically deviate from LLM-based classifications.

LLMs employed here generally agree, with consistency rates typically above 90% but below 95%. This indicates that some variation in classification occurs even among different LLMs. Such inconsistencies mostly arise in records with relatively ambiguous descriptions—cases that fall into a gray area between R&D-related and non-R&D-related subsidies, where even human judgment can be challenging. Therefore, it is difficult to definitively determine which classification is best.

C.1 Strengths and limitations of keyword-based and LLM-based methods

There are some interesting observations regarding the strengths and limitations between keyword-based the LLM-based methods. Among the records classified as R&D-related by the LLM-based method but not by the keyword-based method, there seems to be a tendency for such subsidies to involve the commercialization of scientific and technological achievements. For instance, in 2014, the China Animal Husbandry Industry Company (ticker: 600195) received a subsidy of 500,000 CNY for the "Commercialization Project of Cefquinome Sulfate." While commercialization constitutes an essential stage in the innovation process, it is not equivalent to R&D itself. Therefore, whether such subsidies should be classified as R&D-related remains ambiguous.

In addition, LLMs occasionally makes classification errors. For example, in 2013, Guangzhou Echom Science & Technology Company (ticker: 002420) received a subsidy for a program described as the "Guangzhou Public Service Platform for LED Creative Design." This appears to relate more to the construction of a public service platform than to direct innovation activities. However, the presence of the word "creative" may have misled some models, resulting in a false positive classification as R&D-related.

On the other hand, the LLM-based method also demonstrates clear advantages over the simple keyword-based approach. A notable example is the subsidy described as "863 Program Government Grant," received by Guangzhou Improve Medical Instruments Company (ticker: 300030) in 2013. The full name of the "863 Program" is the "National High-tech R&D Program," and as such, this record should be classified as R&D-related. However, the keyword-based method fails to capture this implication, as it lacks the capacity to interpret the contextual meaning of terms like "863."

For records classified as R&D-related by the keyword-based method but not by the LLM-based method, misclassification may arise due to the presence of keywords in the names of government offices rather than in the content of the subsidy itself. For example, Beijing Easpring Material Technology Company (ticker: 300073) received subsidies described as "Policy Incentive Fulfillment for Enterprises in Zhongguancun Fengtai [Science and Technology] Park," with additional notes stating: "Issuing Authority: Fengtai Administrative Committee of Zhongguancun Science and Technology Park. Reason for Issuance: Incentive Award. Nature of Subsidy: Government grant obtained for engaging in state-encouraged and supported industries (legally acquired in accordance with national policies)." Based on this description, it is unclear whether the subsidy was intended to support innovation activities. However, merely due to the appearance of the word "technology" in the name of the issuing authority, the keyword-based method indiscriminately classifies it as R&D-related.

C.2 Robustness check using the classification by a LLM

While the above analysis suggests the keyword-based method is plausibly acceptable, there still exists the concern about those observed inconsistency. Therefore, as a robustness check complementing the keyword-based results, I use the lightest model—Qwen (30B)—to classify all over 300,000 subsidy records and aggregate annual R&D-related subsidies for each listed firm. Based on these data, I re-match treated firms to control firms and re-estimate the models reported in Table 1.

The re-estimation results are presented in Table A.4. Columns (1) and (3) present results using keyword-based method, which mirroring the estimates in Columns (2) and (4) in Table 1. Columns (2) and (4) present results based on LLM's classification. As R&D-related subsidy is also a covariate in the mathcing procedure, changing to another classification method indirectly the estimates on R&D expenditures by altering the matched sample. As observed, while the point estimates are somewhat smaller in magnitude in Columns (2) and (4), the results remain qualitatively consistent with those in the main analysis: the NTIDF policy appears to increase government-provided R&D-related subsidies and is associated with higher R&D investment by treated firms.

Additionally, I report the estimates using the event study specification in Figure A.11. The dynamic pattern of R&D-related subsidies closely mirrors my baseline results, exhibiting a significant increase during the first three years following certification. However, the trajectory of R&D expenditures appears somewhat different. Rather than a steadily increasing post-treatment trend as observed in the baseline, the growth in R&D expenditures seems to taper off after the third year, displaying a pattern more closely aligned with that of government-provided subsidies. This divergence may indicate a degree of dependence of innovation investment on external public funding. Despite these differences in dynamic patterns, the results consistently support my main conclusion: the NTIDF policy encourages higher R&D investment among treated firms.

D 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>

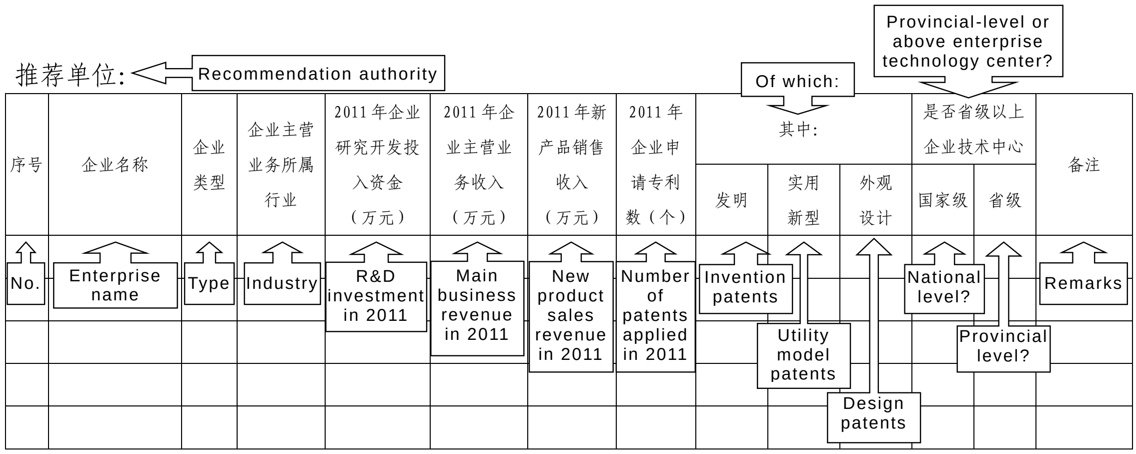
Note: The above indicators should be based on data as of the end of 2011.

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)


推荐单位:

序号	企业名称	企业类型	企业主营业务所属行业	2011年企业研究开发投入资金（万元）	2011年企业主营业务收入（万元）	2011年新产品销售收入（万元）	2011年企业申请专利数（个）	其中:			是否省级以上企业技术中心		备注
								发明	实用新型	外观设计	国家级	省级	

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

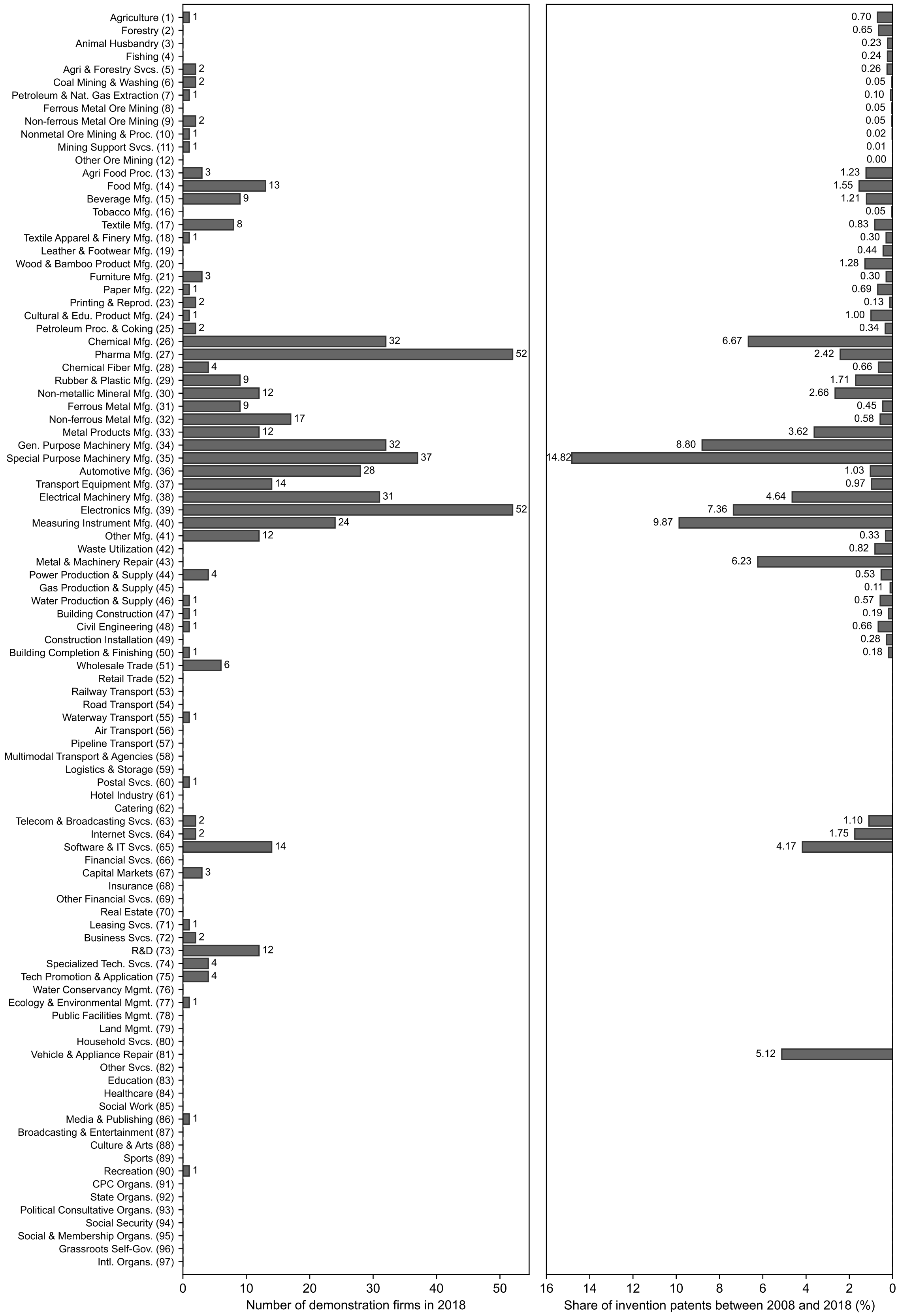


Figure A.4: Number of demonstration firms and share of invention patents by industry

Notes: This figure summarizes the industry distribution of demonstration firms and the share of invention patents by industry. The left panel displays the accumulated number of demonstration firms 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.

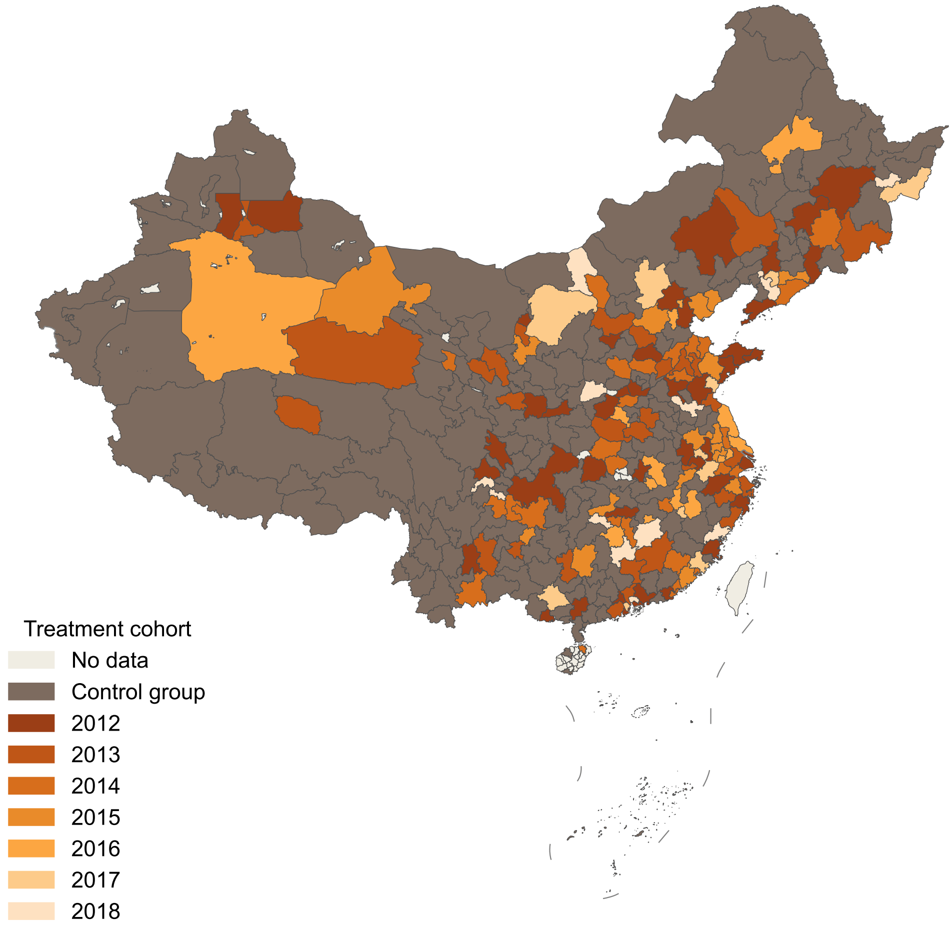


Figure A.5: The distribution of demonstration firms by treatment year

Notes: This figure displays the spatial distribution of cities with and without any demonstration firms in the last year of the sample period (i.e., 2018). Among the treatment cities, different colors indicate different treatment cohorts. For example, the "2012" group includes cities (such as Beijing and Shanghai) where the first demonstration firm was certified in 2012, regardless of industry.

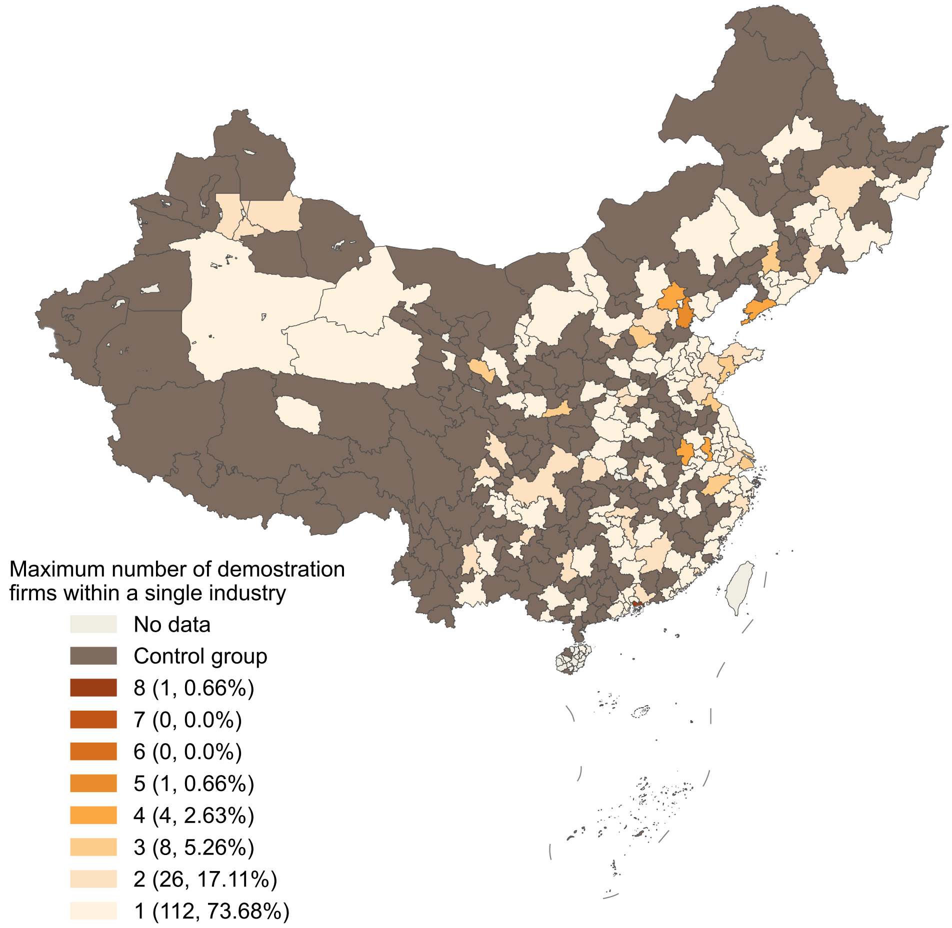


Figure A.6: Each city's maximum number of demonstration firms within a single industry

Notes: This figure displays each city's maximum number of demonstration firms within a single industry in 2018, based on all demonstration firms certified between 2011 and 2017. For example, by the end of 2017, Shenzhen had 14 demonstration firms across 6 industries, with the highest concentration—8 firms—in the Electronics Manufacturing (39) category. As a result, Shenzhen is the only city classified in the "8" group. The legend also reports the number and share of cities in each category among all treatment cities.

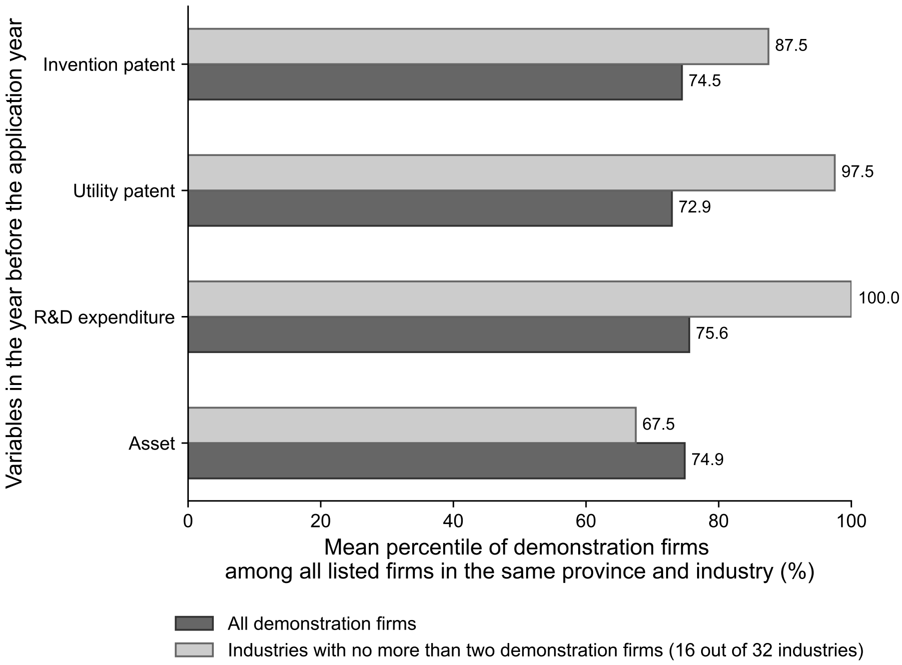


Figure A.7: The percentile of demonstrations firms in the local market

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 firms 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 firms, while the lighter bar represents the mean for demonstration firms in industries with no more than two listed demonstration firms (16 out of 32 industries).

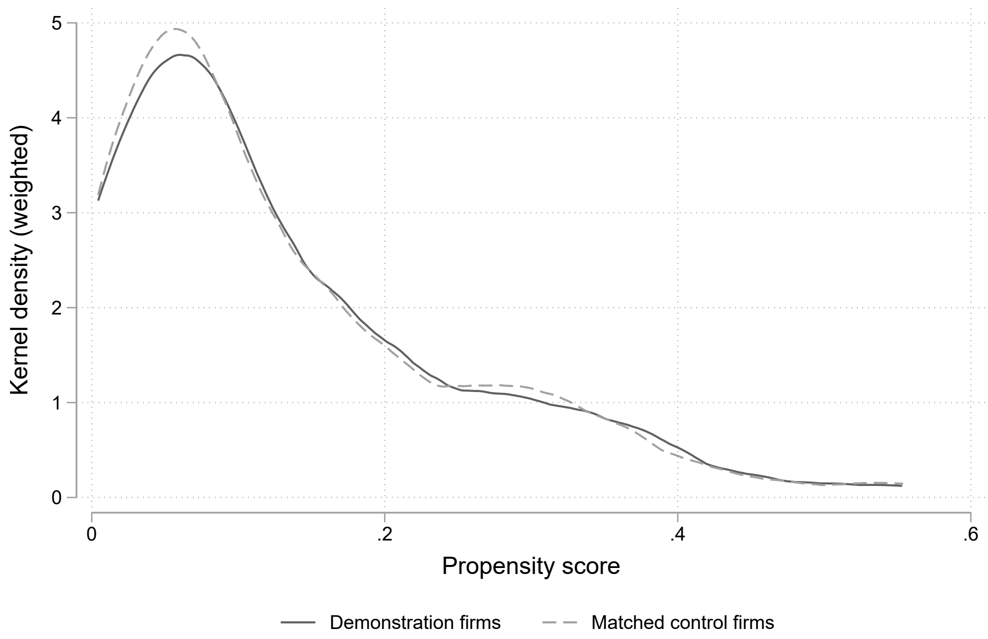


Figure A.8: The distribution of propensity scores of treated and control firms in the matched sample

Notes: This figure displays the kernel density distributions of propensity scores for treated and control firms in the matched sample based on 2-nearest-neighbor propensity score matching with a caliper of 0.05. The distribution for control firms is weighted by the matching weights derived from the matching procedure.

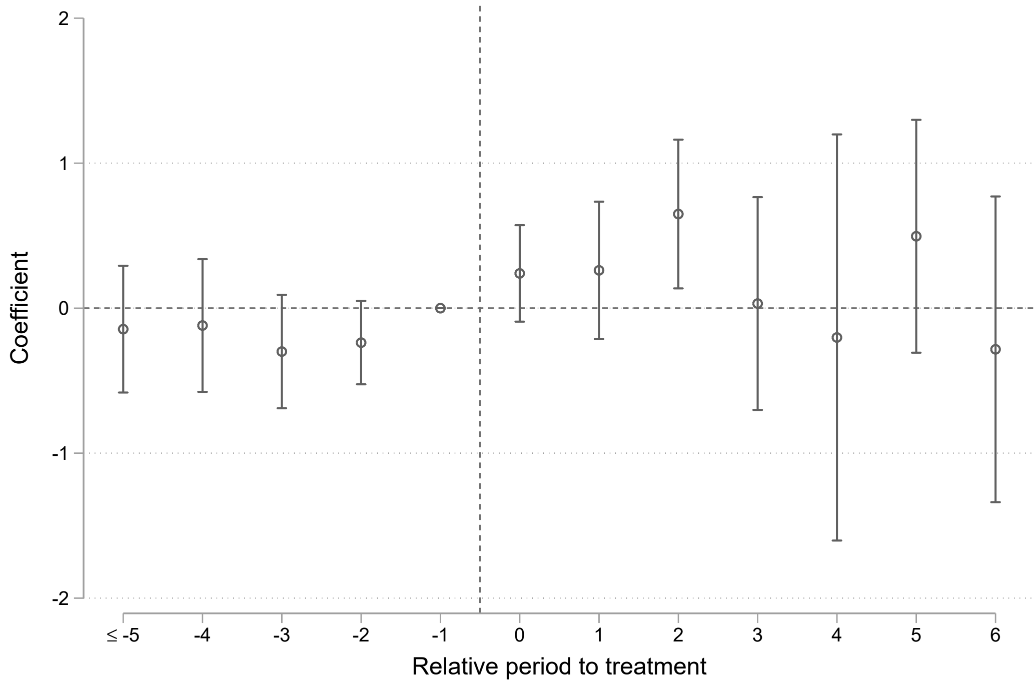


Figure A.9: Event study on R&D-related subsidies received by demonstration firms

Notes: This figure presents the results of an event study on government-provided R&D-related subsidies received by demonstration firms. The analysis is based on a matched sample constructed using 2-nearest-neighbor propensity score matching with a caliper of 0.05. Regressions are weighted by matching weights derived from the matching procedure. Circles represent point estimates, and lines denote 95% confidence intervals.

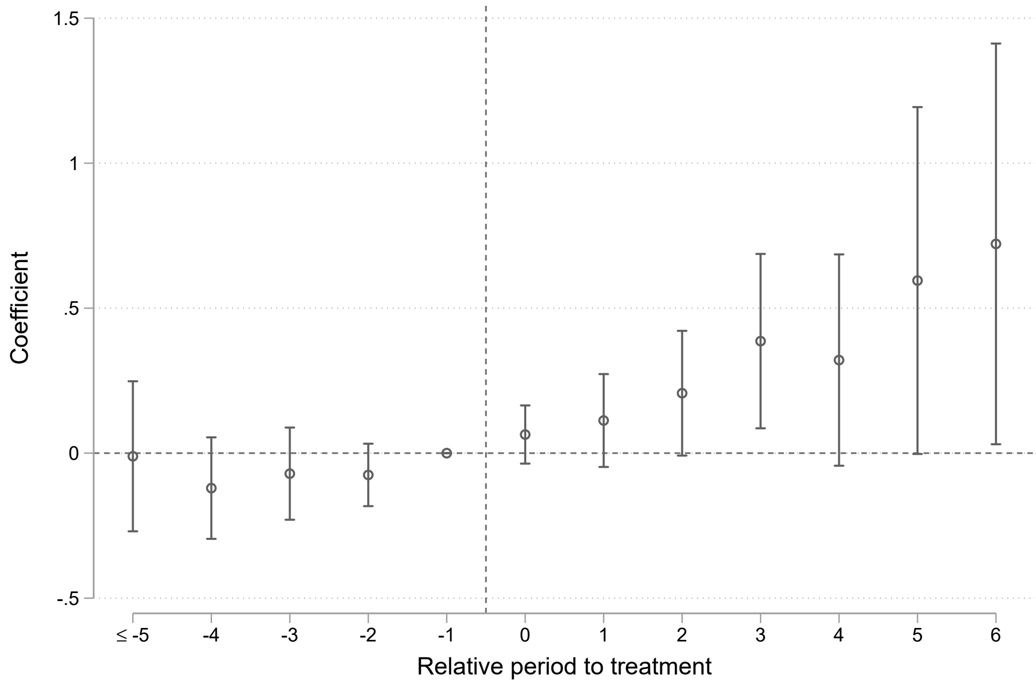


Figure A.10: Event study on R&D expenditures of demonstration firms

Notes: This figure presents the results of an event study on R&D expenditures of demonstration firms. The analysis is based on a matched sample constructed using 2-nearest-neighbor propensity score matching with a caliper of 0.05. Regressions are weighted by matching weights derived from the matching procedure. Circles represent point estimates, and lines denote 95% confidence intervals.

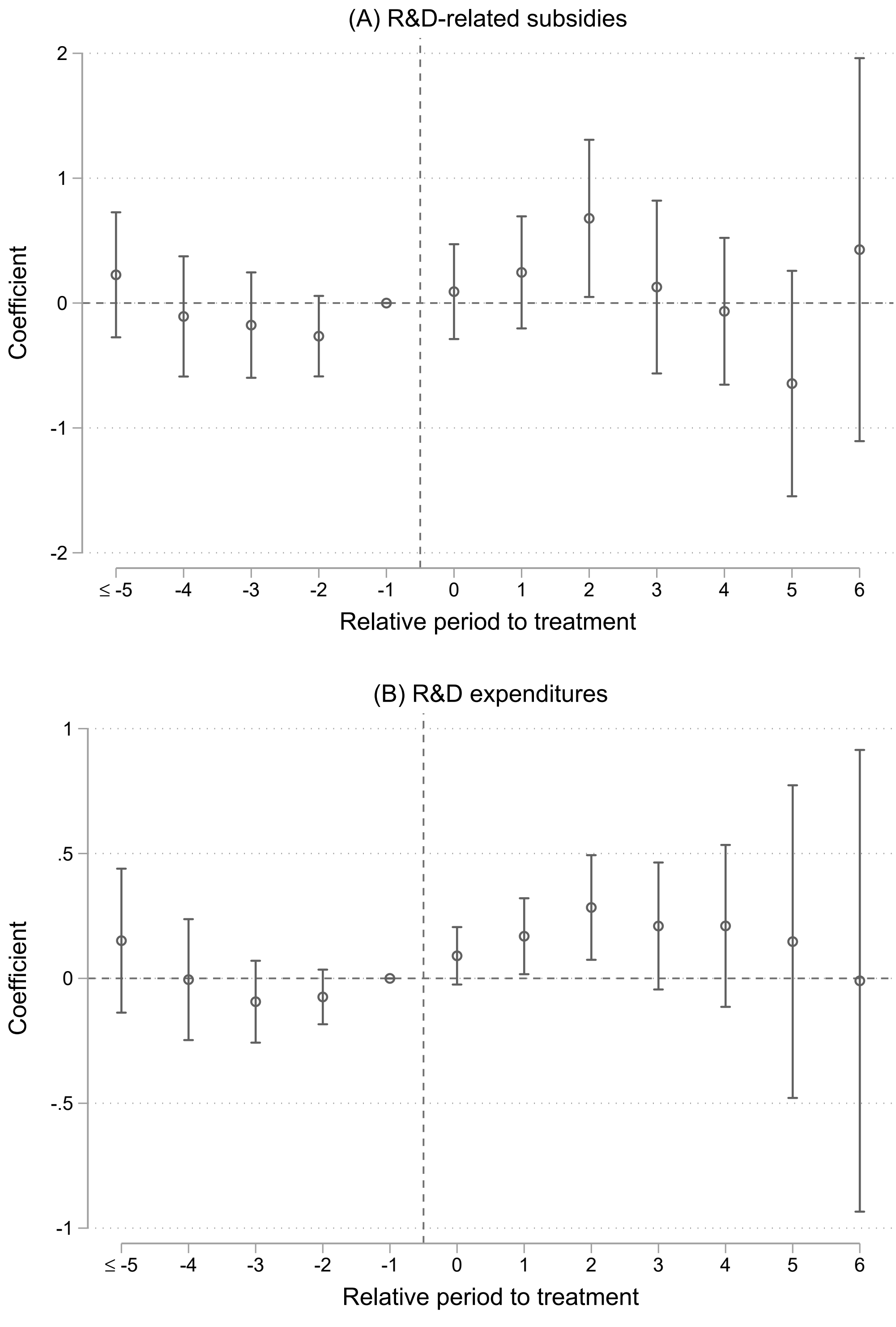


Figure A.11: Event study of demonstration firms using the LLM-based classification

Notes: This figure presents event study estimates of R&D-related subsidies and R&D expenditures for demonstration firms, where the classification of R&D-related subsidies is based on a LLM, as described in Appendix C. The analysis is conducted on a matched sample constructed using 2-nearest-neighbor propensity score matching with a caliper of 0.05. Regressions are weighted by the matching weights derived from the matching procedure. Circles indicate point estimates, and lines represent 95% confidence intervals.

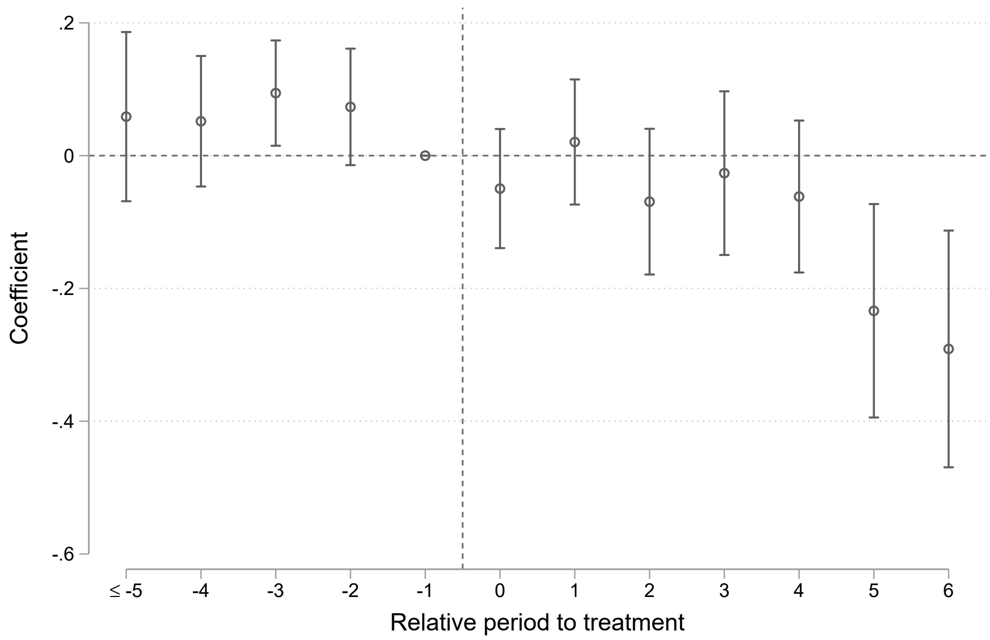


Figure A.12: Event study on the entry of foreign firms

Notes: This figure presents the estimated coefficients obtained from the event study on the entry of foreign firms using the OLS estimator. The circles represent the point estimates, and the lines indicate the 95% confidence intervals.

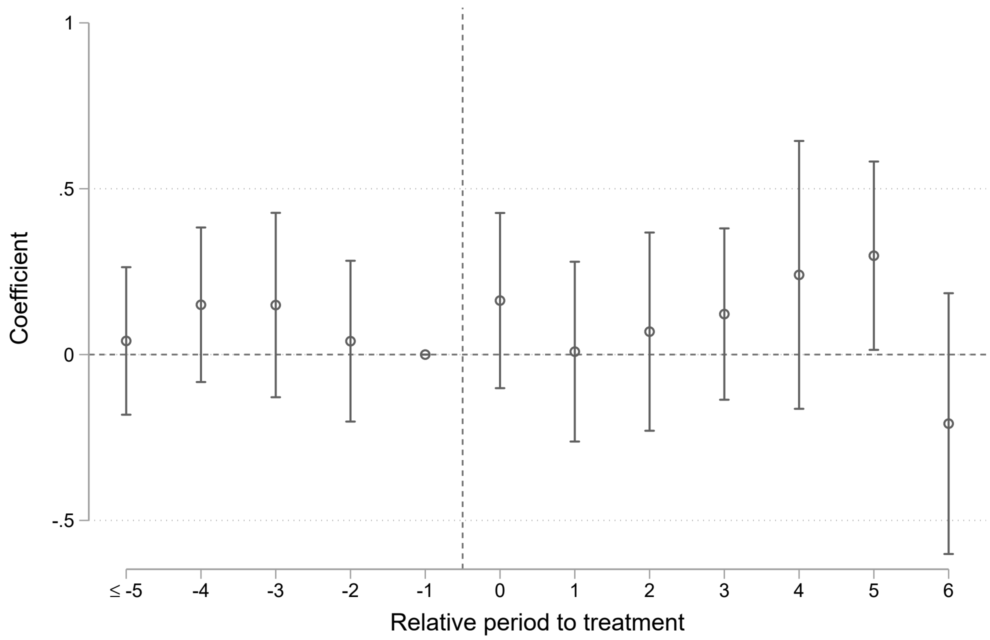


Figure A.13: Event study on the entry of public firms

Notes: This figure presents the estimated coefficients obtained from the event study on the entry of public firms using the OLS estimator. The circles represent the point estimates, and the lines indicate the 95% confidence intervals.

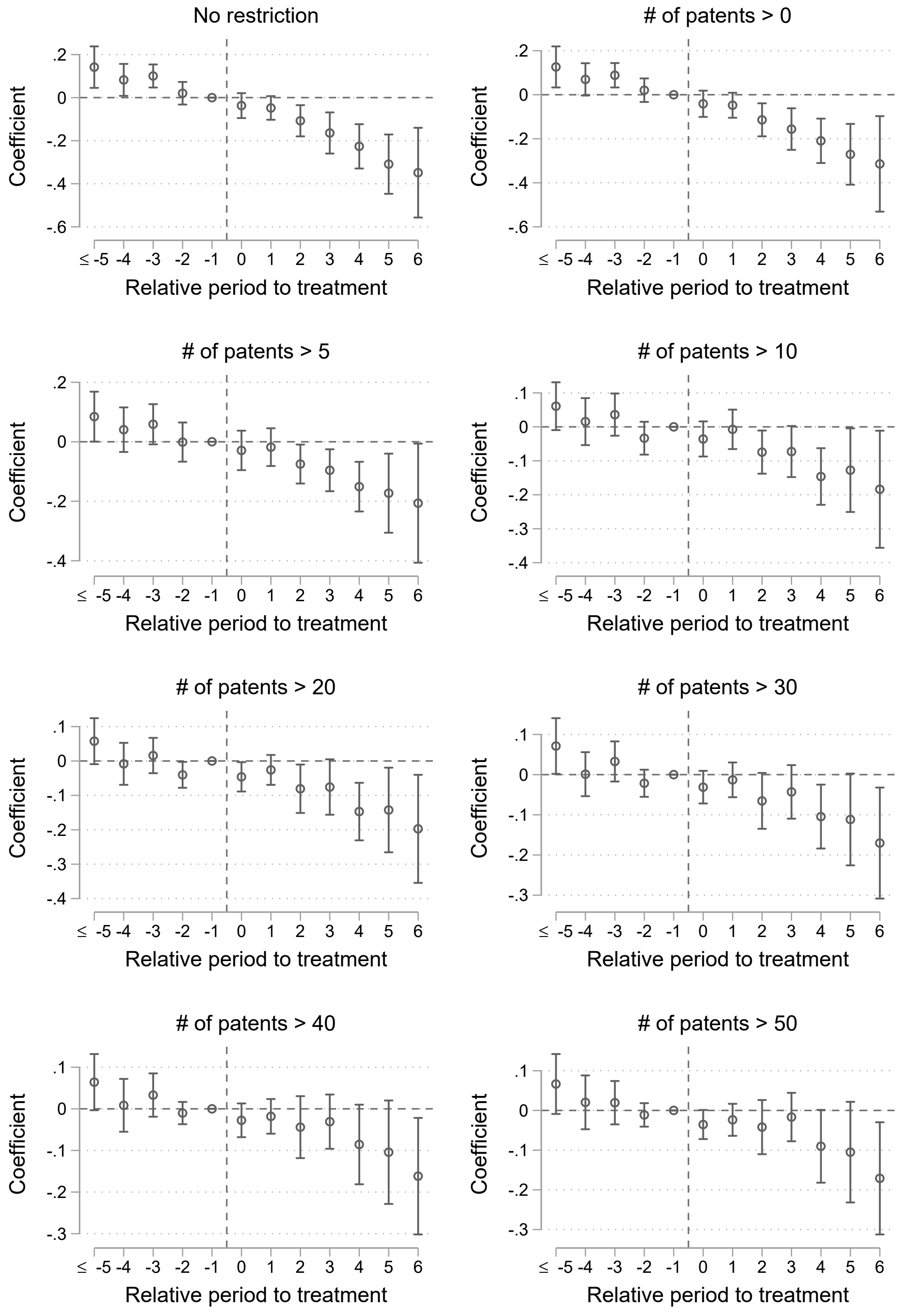


Figure A.14: Event study on patent outputs with different restrictions on pre-treatment patent counts

Notes: This figure presents the results of event study estimations under progressively more stringent restrictions on the number of invention patent applications in the year preceding treatment for city–industry pairs included in the estimation. The thresholds range from no restriction to a minimum of 50 patents. For example, the panel titled "# of patents > 10" includes only those city–industry pairs with more than 10 invention patent applications in the year prior to treatment—where the treatment year varies across stacks—and is the preferred one used in the main analysis. Circles indicate point estimates, and lines denote the 95% confidence intervals.

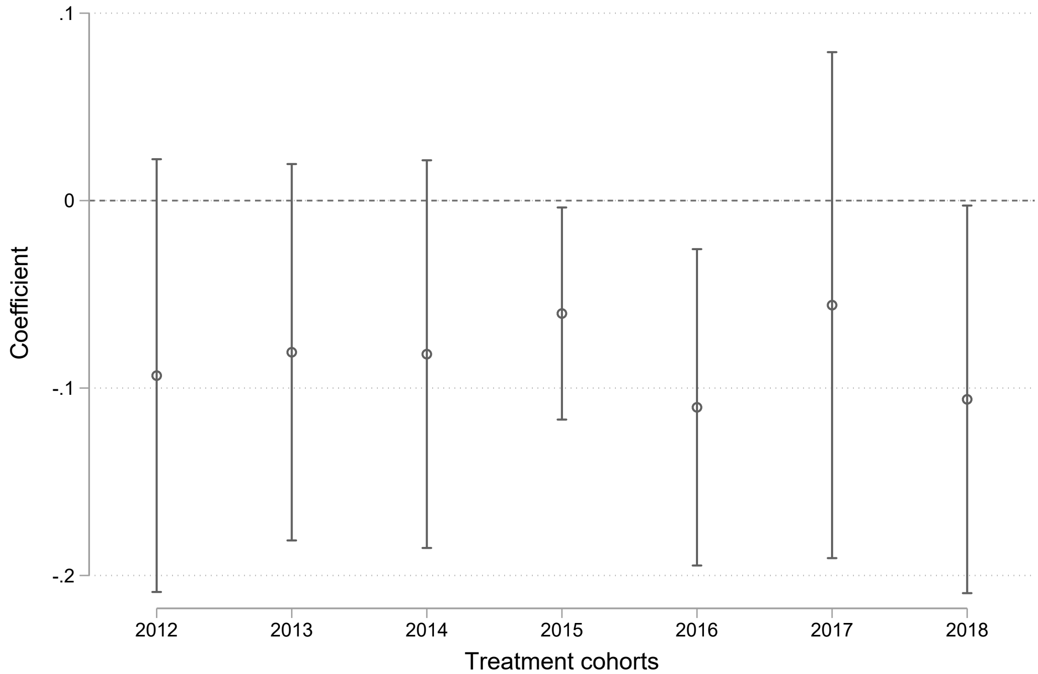


Figure A.15: Treatment effects on patent outputs by cohort

Notes: This figure presents the estimations of treatment effects on seven treatment cohorts from 2012 to 2018. The estimation model is consistent with Column (1) of Panel A in Table 4, with the only difference being that the estimation is conducted separately for each stack. The sample is restricted to city–industry pairs with invention patent applications in the year preceding the treatment exceeding 10. The circles represent the point estimates of the coefficients, while the lines represent the 90% confidence intervals.

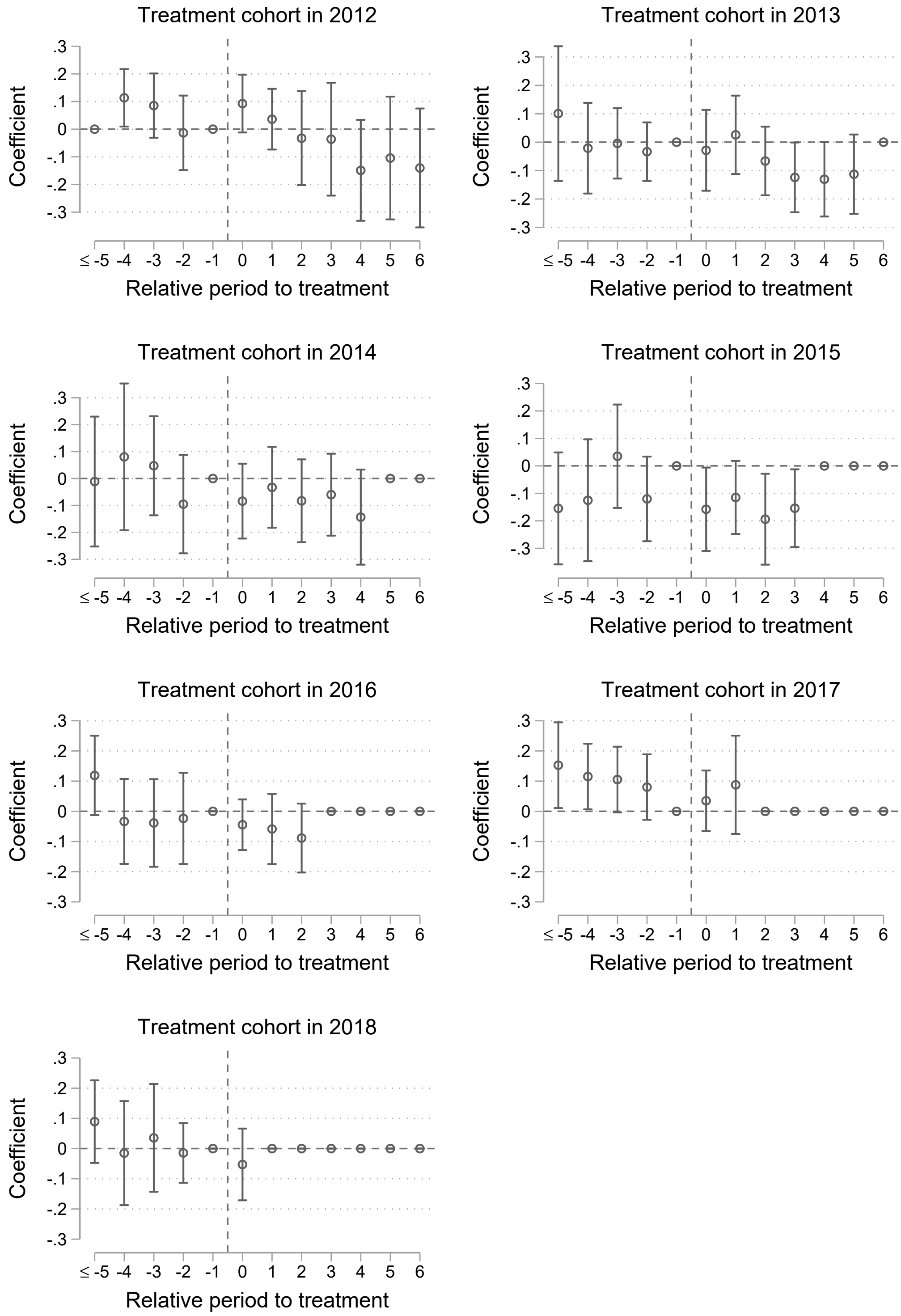


Figure A.16: Event study on patent outputs by cohort

Notes: This figure presents the estimates of event studies on seven treatment cohorts from 2012 to 2018, respectively. The estimation model is consistent with Figure 6, with the only difference being that the estimation is conducted separately for each stack. The sample is restricted to city–industry pairs with invention patent applications in the year preceding the treatment exceeding 10. The circles represent the point estimates of the coefficients, while the lines represent the 95% confidence intervals.

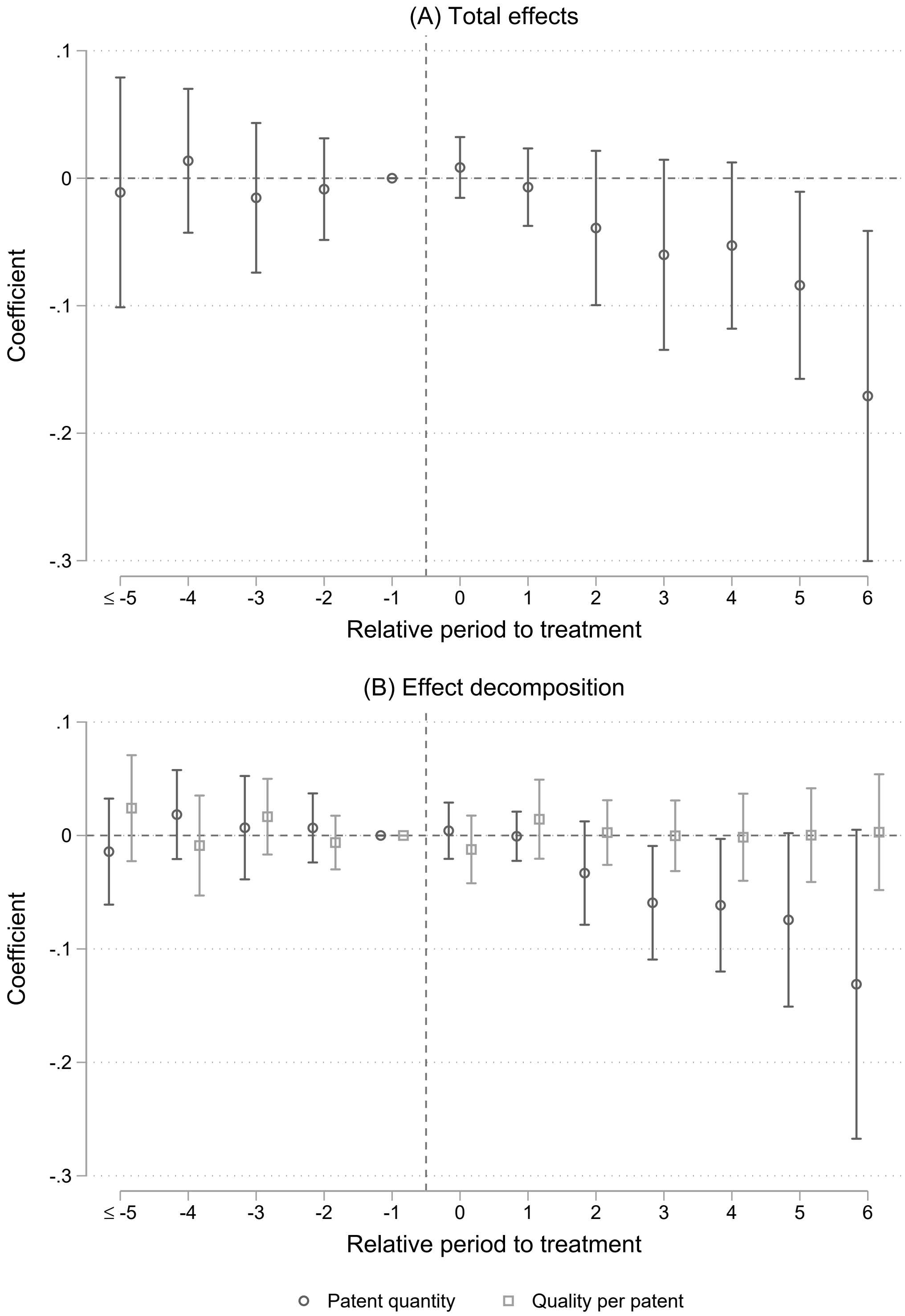


Figure A.17: Event study on patent outputs using the PPML estimator

Notes: This figure presents the estimation of the event study on patent outputs using the PPML estimator. The sample is restricted to city–industry pairs with invention patent applications in the year preceding the treatment exceeding 10 in each stack. The circles represent the point estimates, while the lines indicate the 95% confidence intervals.

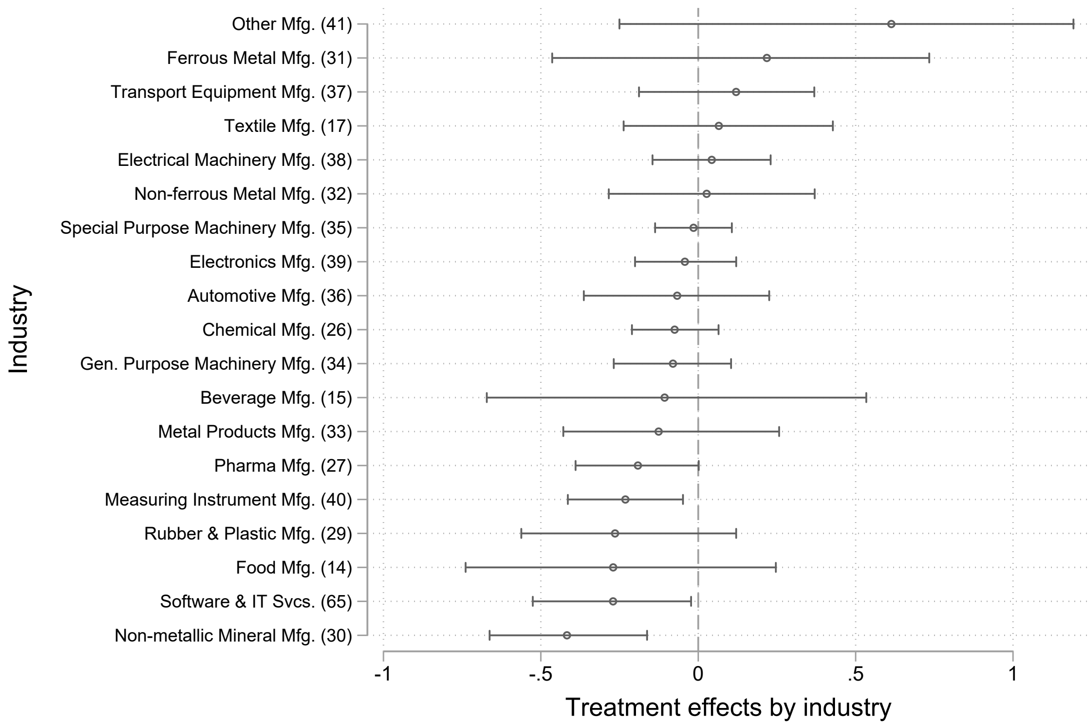


Figure A.18: Treatment effects on innovation outcomes by industry using restricted wild cluster bootstrap for inference

Notes: This figure serves as a robustness check for the inference in Figure 7, which reports the heterogeneous treatment effects of the NTIDF policy on patent outputs weighted by forward three-year citations. To mitigate potential estimation bias, the analysis is restricted to industries with more than five treated city–industry pairs. Circles represent point estimates, and lines denote 90% confidence intervals. The confidence intervals are constructed using the restricted wild cluster bootstrap method with 999 replications, employing Rademacher weights and clustering at the city level.

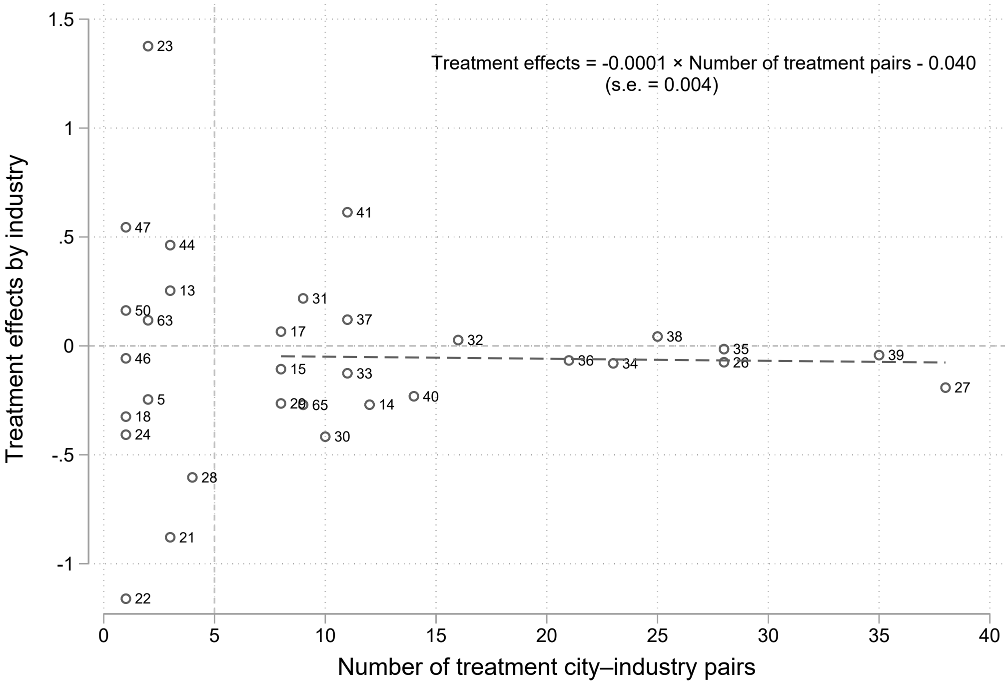


Figure A.19: Treatment effects and number of treatment pairs

Notes: This figure illustrates the relationship between the estimated treatment effects and the number of treatment city–industry pairs across industries. Each dot represents an industry, with its corresponding industry code labeled nearby. The mapping between industry codes and categories is provided in Figure A.4. The darker dashed line shows the fitted regression line based on industries with more than five treatment pairs.

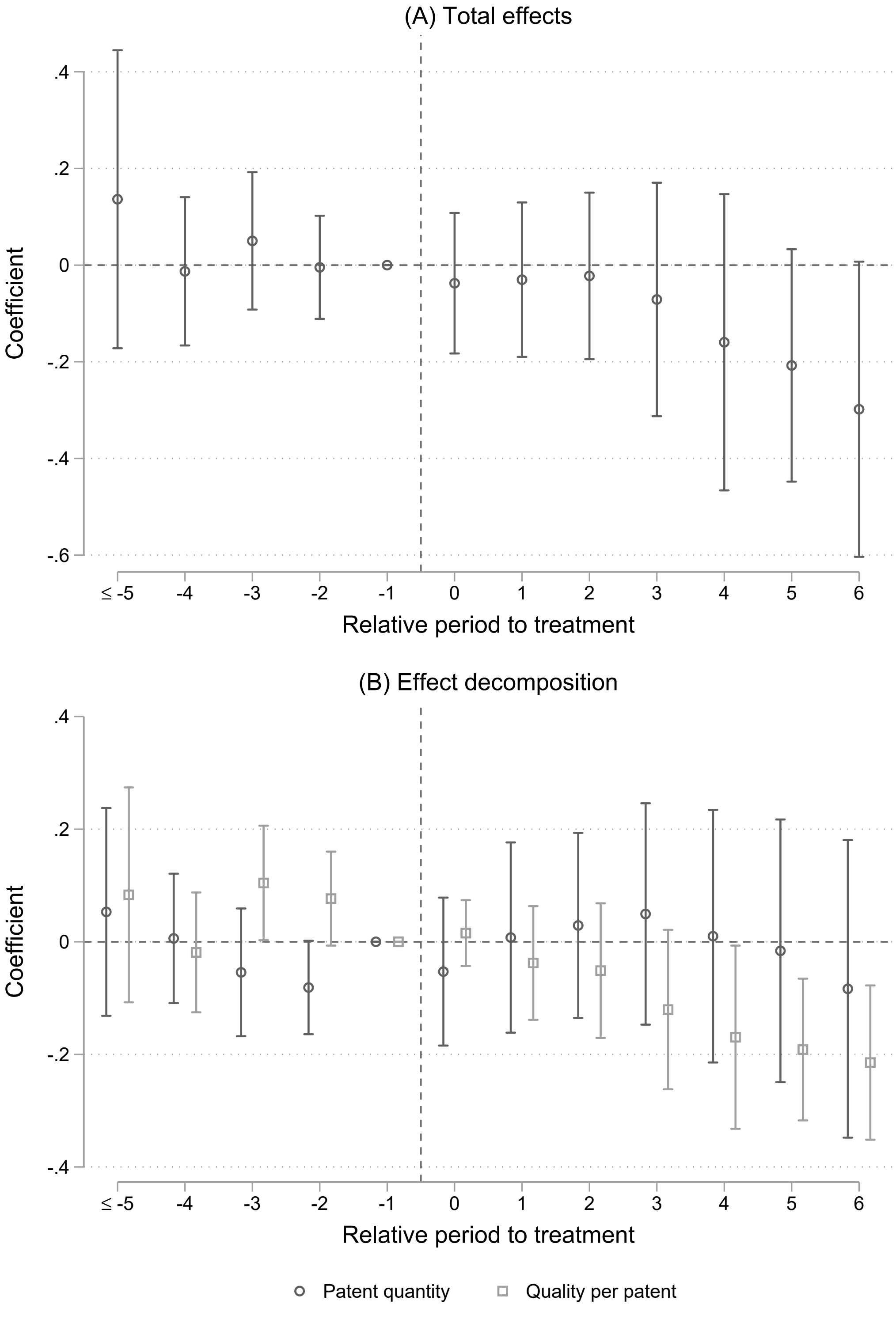


Figure A.20: Event study on spatial spillovers without controlling for linear time trend

Notes: This figure plots the estimated spatial spillover effects based on an event-study specification corresponding to Equation (18), excluding the linear time trend term. The sample is restricted to city–industry pairs with more than 10 invention patent applications in the year preceding the treatment within each stack. Circles denote point estimates, and the lines represent 95% confidence intervals.

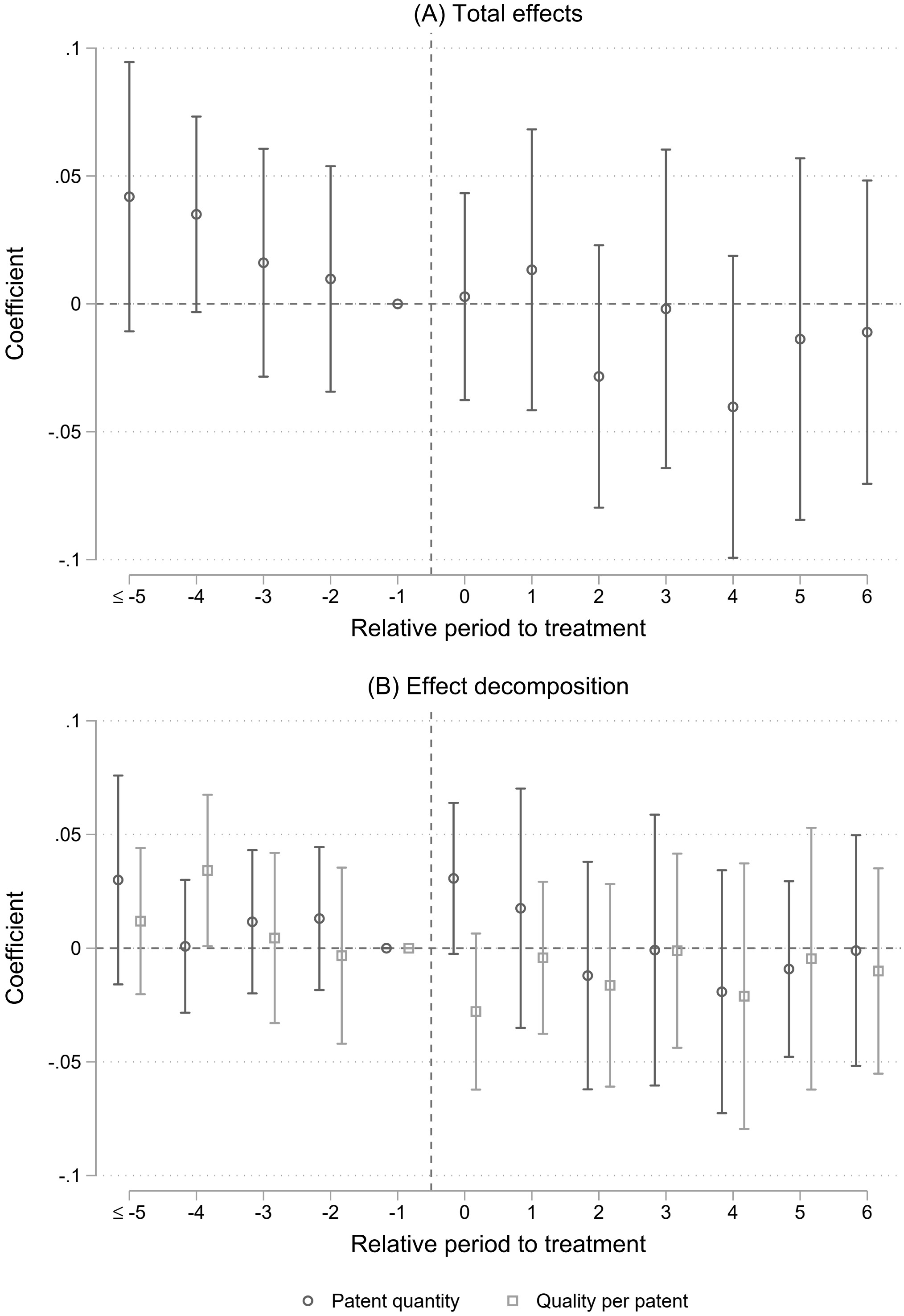


Figure A.21: Event study on spatial spillovers based on geographical proximity

Notes: This figure plots the estimated spatial spillover effects based on geographical proximity. City–industry pairs identified as potentially affected by spillovers are those adjacent to treated pairs but not treated themselves, while the control group consists of the remaining untreated pairs. The sample is restricted to pairs with more than 10 invention patent applications in the year preceding the treatment within each stack. Circles represent point estimates, and lines indicate 95% confidence intervals.

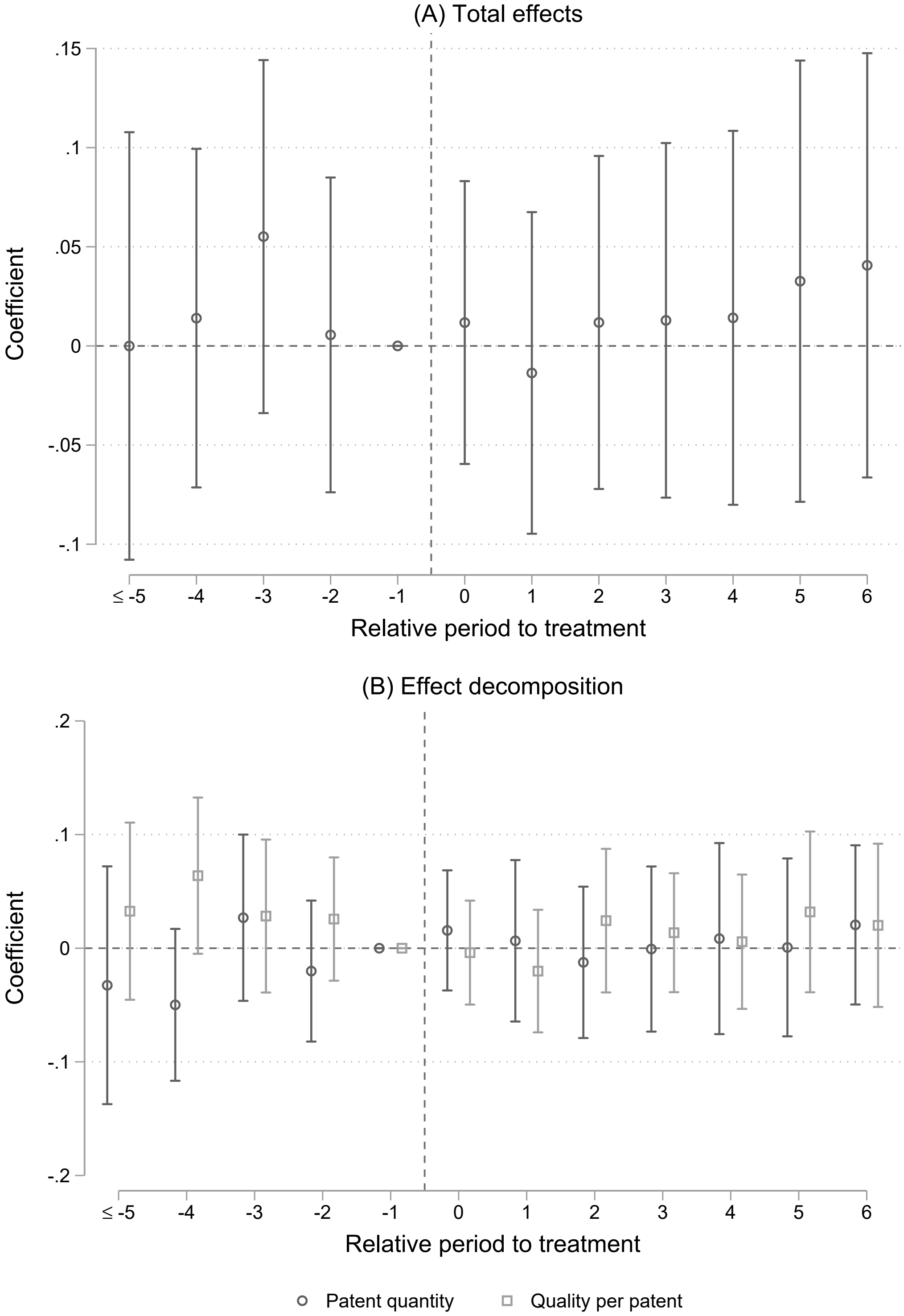


Figure A.22: Event study on spatial spillovers based on economic connections

Notes: This figure presents the estimated spatial spillover effects based on economic connections. City–industry pairs potentially affected by spillovers are defined as untreated pairs with output shares in the top half within their respective industries in 2012, conditional on the industry having at least one demonstration firm. The control group comprises the remaining untreated pairs. The sample is restricted to pairs with more than 10 invention patent applications in the year preceding the treatment within each stack. Circles represent point estimates, and lines indicate 95% confidence intervals.

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

		Re-evaluated firms			
Year (certification)	New certified	Total	# of failed	Passing rate (%)	Accumulation
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 firms, the number of re-evaluated firms, the number of firms failing in the re-evaluation, the passing rate, and the cumulative number of demonstration firms at the end of the year from 2011 to 2017 (corresponding to treatment cohorts from 2012 to 2018 as explained in Section 4.1). Since demonstration firms 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 firms

	Fraction of city–industry pairs for whose # of demonstration firms ≥ 1 (%)							
# of DEs =	1	2	3	4	5	6	7	8
2011	96.15	3.85	0	0	0	0	0	0
2012	93.39	5.79	0.83	0	0	0	0	0
2013	89.84	8.58	1.07	0.53	0	0	0	0
2014	88.11	9.43	2.05	0	0.41	0	0	0
2015	86.96	8.36	4.35	0	0	0	0.33	0
2016	84.30	10.47	4.07	0.58	0.29	0	0	0.29
2017	83.71	11.28	3.51	1.00	0.25	0	0	0.25

Notes: This table presents the distribution of the accumulated number of demonstration firms across city–industry pairs. The second to seventh columns present the fraction of treatment city–industry pairs for which the number of demonstration firms equals 1, 2, 3, 4, 5, 6, 7, and 8, respectively, during the period from 2011 to 2017.

Table A.3: Comparison of the classification using the keyword-based and LLM-based methods

	Keyword	DeepSeek	Qwen (30B)	Qwen (235B)	ERNIE
DeepSeek	89.47%				
Qwen (30B)	84.77%	92.17%			
Qwen (235B)	87.90%	92.63%	90.27%		
ERNIE	86.63%	94.90%	93.27%	94.07%	
GLM	86.57%	94.57%	93.27%	93.93%	98.93%

Notes: This table compares the classification results of R&D-related government subsidies using a keyword-based method and several large language models (LLMs). The comparison is based on a random sample of 3,000 subsidy records. Each cell reports the proportion of classification outcomes that are consistent between any two methods.

Table A.4: Policy effects on demonstration firms: comparing keyword-based and LLM-based methods

	Logarithm of R&D-related subsidies		Logarithm of R&D expenditures	
	Keyword	Qwen LLM	Keyword	Qwen LLM
	(1)	(2)	(3)	(4)
Treated	0.432**	0.281*	0.217**	0.163**
	(0.184)	(0.167)	(0.089)	(0.078)
Firm FEs × Stack FEs	Yes	Yes	Yes	Yes
Industry FEs × Year FEs × Stack FEs	Yes	Yes	Yes	Yes
# of treated firms	120	107	121	107
# of clusters	297	298	299	265
# of observations	2,634	2,393	2,906	2,646

Notes: This table compares the estimation results of Equation (12) using different methods for classifying R&D-related subsidies. Columns (1) and (3) report results based on the keyword-based classification method, which are identical to Columns (2) and (4) in Table 1. Columns (2) and (4) present results using the LLM-based classification method, as detailed in Appendix C. In both cases, matched samples are constructed using 2-nearest-neighbor propensity score matching with a caliper of 0.05. The regressions are weighted using the matching weights derived from the matching procedure. Standard errors clustered at the firm level are reported in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A.5: Comparison between treated and control firms in the matched sample

	Treatment group		Control group		Difference (t-statistics)	
	Obs.	Mean	Obs.	Weighted mean	Raw	Ind. FEs
	(1)	(2)	(3)	(4)	(5)	(6)
Invention patent	125	35.192	216	35.060	0.132	-1.254
					(0.018)	(-0.176)
Utility patent	125	44.464	216	40.956	3.508	3.092
					(0.300)	(0.282)
Operating revenue (log)	125	21.813	216	21.808	0.005	-0.123
					(0.035)	(-1.018)
R&D expenditure (log)	125	18.418	216	18.323	0.095	-0.055
					(0.652)	(-0.456)
R&D subsidies (log)	125	15.676	216	15.644	0.031	-0.063
					(0.190)	(-0.409)

Notes: This table compares five variables measured in the year prior to certification between treated and control firms in the matched sample based on 2-nearest-neighbor propensity score matching with a caliper of 0.05. Column (2) reports the means for treated firms, while Column (4) reports the means for control firms, weighted by the matching weights derived from the matching procedure. Column (5) presents the results from weighted regressions of each variable on a treatment indicator; the corresponding t-statistics are shown in parentheses. Stack-specific industry-by-year fixed effects are included in Column (6) to mirror the main estimation setup, where they help ensure comparisons are made within the same industry and account for time-varying industry-level shocks.

Table A.6: Policy effects on demonstration firms: robustness checks by different matching strategies

	Logarithm of R&D subsidies	Logarithm of R&D expenditures
	(1)	(2)
Panel A. 1-nearest-neighbor PSM (caliper of 0.05)		
Treated	0.473**	0.178*
	(0.190)	(0.096)
# of treated firms	114	115
# of clusters	224	226
# of observations	1,833	2,034
Panel B. 4-nearest-neighbor PSM (caliper of 0.05)		
Treated	0.350**	0.248***
	(0.154)	(0.079)
# of treated firms	110	111
# of clusters	376	379
# of observations	3,770	4,125
Panel C. 2-nearest-neighbor PSM (caliper of 0.01)		
Treated	0.476**	0.270***
	(0.197)	(0.100)
# of treated firms	92	93
# of clusters	224	246
# of observations	2,094	2,318
Panel D. 2-nearest-neighbor PSM (no caliper restriction)		
Treated	0.291*	0.139*
	(0.169)	(0.082)
# of treated firms	132	133
# of clusters	314	316
# of observations	2,867	3,149
Panel E. Triangle Kernel PSM (caliper of 0.05)		
Treated	0.186*	0.182***
	(0.108)	(0.061)
# of treated firms	130	131
# of clusters	1,070	1,091
# of observations	24,006	26,860
Panel F. Epanechnikov Kernel PSM (caliper of 0.05)		
Treated	0.176^{a}	0.181***
	(0.109)	(0.060)
# of treated firms	130	131
# of clusters	1,070	1,091
# of observations	24,006	26,860
Firm FEs × Stack FEs	Yes	Yes
Industry FEs × Year FEs × Stack FEs	Yes	Yes

Notes: This table reports estimation results of Equation (12) using the different matching strategies. Panel A employs 1-nearest-neighbor PSM with a caliper of 0.05. Panel B employs 4-nearest-neighbor PSM with a caliper of 0.05. Panel C employs 2-nearest-neighbor PSM with a smaller caliper of 0.01. Panel D employs 2-nearest-neighbor PSM without any restriction on caliper. Panel E uses PSM with a Triangle kernel function and a caliper of 0.05. Panel F employs PSM with a Epanechnikov kernel function and a caliper of 0.05. All regressions are weighted using the matching weights derived from the matching procedure. Standard errors, clustered at the firm level, are reported in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, $^{a}p < 0.11$.

Table A.7: Heterogeneous policy effects on firm entries in respect to baseline entry intensity

	Logarithm of the number of private firm entries		
	From 2009	From 2010	From 2011
	(1)	(2)	(3)
Treated	-0.068**	-0.059**	-0.053**
	(0.028)	(0.026)	(0.025)
Treated × Firm entries in 2008 (thousands)	-0.020***	-0.024***	-0.027***
	(0.006)	(0.006)	(0.007)
City FEs × Industry FEs × Stack FEs	Yes	Yes	Yes
Industry FEs × Year FEs × Stack FEs	Yes	Yes	Yes
City FEs × Year FEs × Stack FEs	Yes	Yes	Yes
# of clusters: city	337	337	337
# of clusters: industry	89	89	89
# of observations	1,804,849	1,633,048	1,458,905

Notes: This table reports the results from estimating Equation (14), incorporating an interaction term between the treatment indicator and the number of private firm entries in the initial sample year (i.e., 2008) for each city–industry pair. To mitigate concerns about dynamic endogeneity, the estimation sample is restricted to observations from 2009 onward in Column (1), from 2010 onward in Column (2), and from 2011 onward in Column (3). Standard errors are two-way clustered at the city and industry levels and reported in parentheses.
*** p < 0.01, ** p < 0.05, * p < 0.1.

Table A.8: Policy effects on the entry of foreign firms and public firms

	Logarithm of the number of firm entries			
	Foreign firms		Public firms	
	(1)	(2)	(3)	(4)
Treated	-0.213***	-0.108**	-0.076	0.048
	(0.051)	(0.041)	(0.108)	(0.070)
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	326	301	335	334
# of clusters: industry	87	85	89	88
# of observations	242,401	238,618	309,577	308,808

Notes: This table presents the estimated treatment effects of the NTIDF policy on the logarithm of annual entry for foreign firms and public firms (comprising state-owned and collectively owned firms). The analysis of foreign firm entry provides supplementary evidence supporting the main findings for private firms, as foreign firm entry is typically profit-motivated. In contrast, public firm entry in China is predominantly driven by policy objectives rather than market incentives, making it an appropriate 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.9: The distribution of the number of invention patent applications in treatment and control city–industry pairs

	Fraction of samples (%)	
# of invention patents in the year preceding the treatment	Treatment city–industry pairs	control city–industry pairs
0	1.10 (1.10)	41.56 (41.56)
1–10	11.02 (12.12)	37.21 (78.77)
11–20	5.79 (17.91)	6.56 (85.33)
21–30	2.75 (20.66)	3.23 (88.56)
31–40	4.41 (25.07)	1.85 (90.41)
41–50	2.48 (27.55)	1.46 (91.87)
51–100	10.74 (38.29)	3.41 (95.28)
101–200	14.05 (52.34)	2.14 (97.42)
201–500	16.81 (69.15)	1.53 (98.95)
501–1000	9.64 (78.79)	0.63 (99.58)
> 1000	21.21 (100.00)	0.42 (100.00)

Notes: This table summarizes the distribution of the number of invention patent applications for treatment and control city–industry pairs in the year preceding the treatment in each stack. The values outside the parentheses denote the sample proportions for each group, and the values inside the parentheses represent the cumulative proportions.

Table A.10: Estimating overall effects with the continuous treatment variable

	Logarithm of citation-weighted patent counts			
	(1)	(2)	(3)	(4)
Panel A: 3-year citation-weighted				
# of demonstration firms	-0.065***	-0.055**	-0.109***	-0.135**
	(0.020)	(0.021)	(0.038)	(0.062)
(# of demonstration firms)^2		-0.004	0.038^a	0.071
		(0.007)	(0.023)	(0.059)
(# of demonstration firms)^3			-0.005**	-0.015
			(0.002)	(0.015)
(# of demonstration firms)^4				0.001
				(0.001)
# of clusters: city	319	319	319	319
# of clusters: industry	53	53	53	53
# of observations	391,081	391,081	391,081	391,081
Panel B: 5-year citation-weighted				
# of demonstration firms	-0.059**	-0.045*	-0.096**	-0.127**
	(0.023)	(0.023)	(0.039)	(0.063)
(# of demonstration firms)^2		-0.006	0.034^b	0.074
		(0.006)	(0.022)	(0.059)
(# of demonstration firms)^3			-0.005**	-0.017
			(0.002)	(0.015)
(# of demonstration firms)^4				0.001
				(0.001)
# of clusters: city	320	320	320	320
# of clusters: industry	53	53	53	53
# of observations	395,900	395,900	395,900	395,900
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

Notes: This table presents the estimation results using the number of demonstration firms as the core explanatory variable. The sample is restricted to city–industry pairs with invention patent applications in the year preceding the treatment exceeding 10 in each stack. Column (1) replicates the results from Columns (2) and (4) of Table 4, while Columns (2)–(4) progressively incorporate second-, third-, and fourth-order polynomials into the specification. Panel A reports estimates using 3-year citation-weighted patent counts as the dependent variable, while Panel B presents those using 5-year citation-weighted patent counts.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, $^a p < 0.11$, $^b p < 0.14$.

Table A.11: Policy effects on the annual application number of utility model patents and eventually granted invention patents

	Logarithm of the number of patents			
	Utility model patents		Granted invention patents	
	(1)	(2)	(3)	(4)
Treated	-0.059**		-0.105	
	(0.025)		(0.074)	
# of demonstration firms		-0.048***		-0.127***
		(0.017)		(0.043)
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	317	317	312	312
# of clusters: industry	53	53	53	53
# of observations	391,409	391,409	155,522	155,522

Notes: This table reports the treatment effects of the NTIDF policy on the logarithm of annual application number of utility model patents and eventually granted invention patents. The sample is restricted to city–industry pairs with invention patent applications in the year preceding the treatment exceeding 10 in each stack. 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.12: Estimating policy effects with the matched sample

	Logarithm of the number of 3-year citation-weighted invention patents				
	Preceding year	Preceding two years	All pre-treatment years		
			1-NN	2-NN	4-NN
	(1)	(2)	(3)	(4)	(5)
Treated	-0.048*	-0.089***	-0.053*	-0.053*	-0.053**
	(0.028)	(0.028)	(0.027)	(0.031)	(0.023)
City FEs × Industry FEs × Stack FEs	Yes	Yes	Yes	Yes	Yes
Industry FEs × Year FEs × Stack FEs	Yes	Yes	Yes	Yes	Yes
City FEs × Year FEs × Stack FEs	Yes	Yes	Yes	Yes	Yes
# of clusters: city	333	332	327	327	327
# of clusters: industry	54	54	54	54	54
# of observations	225,274	131,512	66,830	69,969	75,138
t-statistics (the preceding year)	0.34	0.54	0.38	0.36	0.58
t-statistics (all pre-treatment years)	0.39	0.58	0.23	0.36	0.58

Notes: This table reports the estimated treatment effects of the NTIDF policy using matched samples. Each treated city–industry pair is matched to one or more control pairs with the closest pre-treatment invention patent counts. Column (1) matches based on patent counts in the year immediately preceding treatment; Column (2) uses the average over the two years prior to treatment; and Columns (3)–(5) use averages over all available pre-treatment years. The treatment timing varies across stacks. When multiple control pairs have equally close patent counts to a treated pair, all are included with proportionally smaller weights. This explains why Columns (1) and (2) include more observations, despite employing one-nearest-neighbor matching. Columns (3)–(5) implement one-, two-, and four-nearest-neighbor matching, respectively. Standard errors, clustered two-way at the city and industry levels, are reported in parentheses. t-statistics for the balance tests comparing pre-treatment invention patent counts between treated and control groups—based on the year preceding the treatment and the full pre-treatment average, respectively—are also reported in the table.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.13: Placebo test on the 2019 and 2020 cohorts

	Logarithm of the number of 3-year citation-weighted invention patents	
	(1)	(2)
Treated	-0.031	
	(0.074)	
$\mathbb{1}\{T^R = -9\} \times \mathbb{1}\{\text{Treatment group}\}$		0.049
		(0.086)
$\mathbb{1}\{T^R = -8\} \times \mathbb{1}\{\text{Treatment group}\}$		0.098
		(0.097)
$\mathbb{1}\{T^R = -7\} \times \mathbb{1}\{\text{Treatment group}\}$		0.003
		(0.068)
$\mathbb{1}\{T^R = -6\} \times \mathbb{1}\{\text{Treatment group}\}$		0.118
		(0.084)
$\mathbb{1}\{T^R = -5\} \times \mathbb{1}\{\text{Treatment group}\}$		0.037
		(0.112)
$\mathbb{1}\{T^R = -4\} \times \mathbb{1}\{\text{Treatment group}\}$		0.038
		(0.074)
$\mathbb{1}\{T^R = -3\} \times \mathbb{1}\{\text{Treatment group}\}$		-0.007
		(0.094)
$\mathbb{1}\{T^R = -2\} \times \mathbb{1}\{\text{Treatment group}\}$		-0.020
		(0.088)
$\mathbb{1}\{T^R = -1\} \times \mathbb{1}\{\text{Treatment group}\}$		0.017
		(0.112)
City FEs × Industry FEs	Yes	Yes
Industry FEs × Year FEs	Yes	Yes
City FEs × Year FEs	Yes	Yes
# of clusters: city	333	333
# of clusters: industry	54	54
# of observations	213,021	213,021

Notes: This table reports the results of a placebo test using city–industry pairs whose first demonstration firms were certified in 2018 or 2019. The two stacks corresponding to these cohorts are constructed and stacked in the same manner as in the baseline estimation. Column (1) estimates Equation (15), where the treatment indicator $\mathbb{1}\{Treated\}_{c,i,t}$ is set to 1 after 2012 for both cohorts, mirroring the treatment timing of the 2012 cohort. Column (2) reports results from an event study specification. For the 2018 treatment cohort, the year 2018 is coded as the year preceding the treatment and is denoted by $\mathbb{1}\{T^R = -1\}_{t,s}$, and so forth for other relative time indicators. A similar coding approach is applied to the 2019 cohort. All years that fall ten or more years before treatment are grouped together and serve as the reference period. Standard errors are two-way clustered at the city and industry levels and reported in parentheses.

*** p < 0.01, ** p < 0.05, * p < 0.1.

Table A.14: Summary of the number of patent applications in different control groups

	Obs.	Mean	Median	Std. Dev.	Min.	Max.
Panel A. The initial sample year (2008)						
Pure control group	2,405	0.772	0	2.518	0	44
Spatial-spillover control group	7,585	1.832	0	5.981	0	117
Inter-industry spillover control group	1,976	26.602	1	238.713	0	8,238
Panel B. The year preceding the treatment						
Pure control group	16,835	5.889	0	23.431	0	796
Spatial-spillover control group	7,585	5.706	1	17.070	0	538
Inter-industry spillover control group	1,976	73.927	4	385.321	0	9,267
Panel C. All sample years						
Pure control group	26,455	5.394	0	23.292	0	796
Spatial-spillover control group	87,318	13.101	1	69.377	0	4,781
Inter-industry spillover control group	21,736	96.265	4	607.589	0	30,805

Notes: Notes: This table presents descriptive statistics on the number of invention patent applications for different types of control groups, categorized based on the presence of spillover effects. Panel A reports statistics for the year 2008, Panel B uses data from the year immediately preceding each treatment, and Panel C covers the full sample period from 2008 to 2018. Since the year preceding the treatment varies across different stacks, each city–industry pair classified as part of the pure control group may have different pre-treatment patent counts in different stacks. Therefore, Panel B treats them as distinct observations. In contrast, Panels A and C remove duplicate city–industry pairs. The pure control group consists of city–industry pairs that differ from both the industries and cities of all demonstration firms. The inter-industry-spillover control group consists of city–industry pairs where demonstration firms are present in the city but not in the industry. The spatial-spillover control group consists of city–industry pairs where demonstration firms are present in the industry but not in the city.

Table A.15: Re-estimating treatment effects with accounting for inter-industry spillovers

	3-year citation-weighted	Patent quantity	Quality per patent
	(1)	(2)	(3)
Treated	-0.068*	-0.097***	0.029
	(0.037)	(0.034)	(0.022)
City FEs × Industry FEs × Stack FEs	Yes	Yes	Yes
Industry FEs × Year FEs × Stack FEs	Yes	Yes	Yes
Province FEs × Year FEs × Stack FEs	Yes	Yes	Yes
# of clusters: city	302	302	302
# of clusters: industry	51	51	51
# of observations	118,649	118,649	118,649

Notes: This table reports estimation results based on the same specification as Panel A in Table 5. The estimated sample excludes city–industry pairs belonging to either the mixed spillover or inter-industry spillover control groups to mitigate potential bias arising from inter-industry spillovers. The sample is restricted to pairs with more than 20 invention patent applications in the year preceding the treatment within each stack. Jackknife 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.16: Re-estimating treatment effects with accounting for spatial spillovers

	3-year citation-weighted	Patent quantity	Quality per patent
	(1)	(2)	(3)
Treated	-0.123***	-0.064**	-0.059***
	(0.033)	(0.025)	(0.019)
City FEs × Industry FEs × Stack FEs	Yes	Yes	Yes
Industry FEs × Year FEs × Stack FEs	Yes	Yes	Yes
Province FEs × Year FEs × Stack FEs	Yes	Yes	Yes
# of clusters: city	265	265	265
# of clusters: industry	47	47	47
# of observations	74,148	74,148	74,148

Notes: This table reports estimation results based on the same specification as Panel B in Table 5. The estimated sample excludes city–industry pairs belonging to either the mixed spillover or spatial spillover control groups to mitigate potential bias arising from spatial spillovers. The sample is also restricted to pairs with more than 20 invention patent applications in the year preceding the treatment within each stack. Jackknife standard errors, two-way clustered at the city and industry levels, are reported in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.