Zombies in the Zone: R&D Subsidies and Innovation Misallocation in China's Development Zones [*]

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Abstract

Governments subsidize firms in designated zones to promote innovation. This paper evaluates China's development zones using near-universe administrative data on Shanghai technology enterprises from 2008 to 2018. Despite much higher R&D subsidies, state-level development zones do not generate larger increases in patenting than provincial-level development zones. We develop a zombie measure for technology firms based on excess government support and show that SDZs sustain subsidy-dependent zombies that crowd out subsidies and depress neighboring firms' R&D investment and patenting, especially among small firms. Exploiting staggered zone upgrades that tighten oversight, we find that improved governance significantly reduces zombies and increases innovation.

Key words: Place-based Policy; R&D Subsidy; Innovation; zombie firms

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1 Introduction

A large literature in economics has examined the determinants of innovation and the role of government support in promoting technological progress (e.g., Cohen, 2010; Bloom et al., 2019; Howell, 2024). In recent decades, place-based industrial policies have become a central tool through which governments seek to promote innovation and regional growth.[1] By design, these policies concentrate subsidies and other incentives in specific locations to overcome market failures in innovation and stimulate technological progress. Yet despite their widespread use and substantial public spending, it remains unclear when place-based policies successfully foster innovation and when they instead generate misallocation.

In this paper, we provide new evidence on the effects of place-based policies. We examine whether development zones foster innovation and how these effects differ across firms. By focusing on firm-level heterogeneity, our analysis highlights how subsidy provision within development zones shapes innovation outcomes beyond average treatment effects.

China provides a useful setting because development zones are a core policy instrument and vary sharply in administrative rank and governance. We use a comprehensive annual survey of Shanghai Science and Technology Enterprises (SSTE) from 2008 to 2018.[2] Unlike analyses that rely on aggregate outcomes or focus on listed firms, our data cover about 99 percent of technology enterprises reported in the Shanghai Statistical Yearbook, including a large population of small and medium-sized firms. Crucially, the SSTE survey reports firm-level government R&D subsidies and procurement, which allows us to observe how innovation support is allocated across firms within and outside zones. Over our sample period, total government support in the survey exceeded 95 billion RMB and reached more than 20,000 firms.

We first examine whether development zones foster firm-level innovation. Using propensity score matching to address selection into zones, we find that entry into a development zone increases patenting on average by about 7.1 percent. However, these gains are concentrated in provincial-level development zones (PDZs). For PDZ entrants, patenting rises by 12.6 percent and remains robust across specifications. In con-

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[1] Place-based policies, including special economic zones, industrial parks, and technology hubs, have been widely adopted across countries. The U.S. innovation system provides a prominent contemporary example, with substantial federal support for regional technology clusters (Chatterji et al., 2014; Gross and Sampat, 2023). See Neumark and Simpson (2015) for a comprehensive review. Agglomeration-based mechanisms for innovation are discussed in Carlino and Kerr (2015).

[2] Recent advances in the micro spatial innovation literature suggest that focusing on a single, innovation-intensive city like Shanghai does not meaningfully limit external validity. A large body of work shows that knowledge flows, collaboration networks, and innovation spillovers operate at extremely fine spatial scales and often change sharply at administrative or organizational boundaries (Jaffe et al., 1993; Gross and Sampat, 2023).

trast, the higher patenting observed in state-level development zones (SDZs) largely disappears once selection is controlled for, even though SDZ firms receive much larger R&D subsidies, more than 5 times those of comparable firms in PDZs. This divergence points to a composition mechanism: zones can raise innovation by attracting high-potential firms, but generous support may also distort selection and exit, allowing subsidy-dependent firms to persist and crowd out resources for marginal innovators.

We next open the black box of policy implementation inside zones. We show that SDZs host a polarized firm mix. They concentrate on high-performing firms, but they also sustain a nontrivial mass of low-performing, subsidy-dependent firms, which we define as zombies. For example, entry into an SDZ increases the probability that a firm is classified as a zombie by about 8.3 percent, whereas the corresponding effect in PDZs is insignificant. These zombie firms receive more government R&D support, yet they spend less on internal R&D, employ fewer R&D workers, and file fewer patents than comparable non-zombie firms. Measuring such firms is challenging in technology industries, where temporary losses can reflect long-horizon R&D rather than nonviability. Standard definitions based on losses or profitability net of subsidies may therefore misclassify innovative young firms as zombies (Caballero et al., 2008; Fukuda and Nakamura, 2011). We address this challenge by constructing a micro-founded, subsidy-based zombie measure that isolates excess government support relative to predicted, performance-based support, using high-dimensional LASSO predictions.

Third, we show how within-zone composition translates into spillovers and policy performance. A higher share of zombies within an SDZ crowds out public support for otherwise healthy firms and reduces their innovation investment. Quantitatively, a one percentage point increase in the zombie share is associated with about 4.3 percent lower R&D subsidies and 6.7 percent lower internal R&D expenditures among non-zombie firms. The average effect on patenting is not statistically significant, but the innovation losses are concentrated among smaller firms, which are more dependent on external finance and more exposed to subsidy rationing. The results indicate that intensive zone policies can generate negative externalities when they sustain subsidy-dependent firms that absorb fiscal resources and weaken innovation incentives for marginal innovators.

Finally, we test whether improving governance mitigates these distortions by exploiting staggered upgrades of several Shanghai zones from provincial to state-level status. We estimate a staggered difference-in-differences design that compares firms in upgraded zones to firms in never-upgraded zones, complemented by event-study specifications that confirm parallel pre-trends. We find that upgrading reduces zombie prevalence by about 8.4 percent and leads to significant increases in innovation inputs and outputs, including higher internal R&D expenditure, expanded R&D staffing, and increased patenting. Importantly, the dynamic estimates show that these gains build gradually after the upgrade, consistent with a governance mechanism operating through improved screening and monitoring rather than a discrete fiscal expansion. These findings suggest that strengthening oversight and performance-based allocation within zones may be as important as increasing subsidy generosity for raising the innovation returns to place-based industrial policy.

Our paper contributes to three strands of literature: research on zombie firms and their economic consequences, the evaluation of place-based industrial policies, and the role of government support in firm-level innovation. We also build on recent theoretical work emphasizing firm heterogeneity and market selection in shaping the effectiveness of industrial policy.

First, we relate to the extensive literature on zombie firms. In their seminal analysis of Japan, Caballero et al. (2008) show that nonviable firms distort market selection by depressing investment and employment growth among healthier firms. Subsequent work documents broader distortions from zombie lending: Schmidt et al. (2019) find that Spanish industries with more zombies exhibit lower innovation when banks face capital constraints, while Acharya et al. (2024) show that zombie lending in Europe distorts prices and contributes to inflationary pressures. In China, Li and Ponticelli (2021) link zombie prevalence to weak legal enforcement, and Charoenwong et al. (2025) show that banks' concealment of nonperforming assets weakens credit allocation. Acharya et al. (2022) provide a comprehensive overview. We extend this literature by highlighting a distinct channel through which zombie-like firms can persist: geographically targeted R&D subsidies inside development zones. This policy-induced survival channel has received limited empirical attention despite its relevance for industrial policy in emerging economies.

Second, we contribute to evaluations of place-based policies. Evidence from U.S. and European programs shows that geographically targeted incentives can generate gains, with impacts that vary across places and program designs (Busso et al., 2013; Kline and Moretti, 2014; Criscuolo et al., 2019; Givord et al., 2013). Work on China's SEZs documents gains through investment and employment (Wang, 2013; Alder et al., 2016; Lu et al., 2019), and recent studies examine development zones and innovation (Tian and Xu, 2022; Jia et al., 2020). We move beyond average zone effects by opening the black box of policy implementation inside zones, using microdata to study how within-zone interactions among heterogeneous firms generate both positive spillovers and negative externalities.

Third, we speak to research on innovation policy. Classic work studies whether public R&D support crowds out or stimulates private investment (Lerner, 1999; Wallsten, 2000), while recent quasi-experimental evidence finds large innovation gains from targeted grants, especially for financially constrained firms (Howell, 2017). Bloom et al. (2013) emphasize the importance of spillovers, and surveys review mixed evidence on tax incentives (Hall and Van Reenen, 2000; Becker, 2015); for China, Chen et al. (2021) highlights both real and reporting responses to R&D tax incentives. Our setting combines localized innovation support with variation in governance, allowing us to study not only direct effects on innovation but also how misallocation toward low-productivity firms can undermine innovative activity among healthier firms.

Finally, our paper connects to emerging work emphasizing the importance of firm heterogeneity in shaping the effects of industrial policy. Recent theoretical and empirical studies show that policy interventions interact strongly with the distribution of firm capabilities. Juhász et al. (2024) illustrates how early entrants in the British cotton industry bore the fixed costs of experimentation, while late entrants benefited disproportionately. Related work by Akcigit and Kerr (2018); Akcigit et al. (2022) highlights how innovation policies can unintentionally favor established firms, reinforcing incumbency advantages. Consistent with these insights, our findings show that development zones reshape the composition of firms operating within them: they can simultaneously foster high-performing star firms and sustain low-performing zombie firms, so that the net effect on local innovation depends critically on firm heterogeneity and the governance quality within each zone.

The remainder of the paper is organized as follows. Section 2 provides an overview of development zones and government subsidies, while Section 3 describes the data and the construction of key variables. Section 4 presents baseline results on the effects of place-based policies on innovation. Section 5 examines firm composition within development zones, distinguishing star and zombie firms, and studies how zombie prevalence generates spillovers that affect subsidies, R&D investment, and patenting among non-zombie firms. Section 6 exploits staggered zone upgrades to test whether improving governance mitigates misallocation and raises innovation. Section 7 concludes.

2 Institutional Background

2.1 Development Zones in China and Shanghai

China has promoted geographically targeted development zones since the Reform and Opening-up era. Early Special Economic Zones (SEZs), created in the late 1970s, used preferential policies such as tax incentives, trade facilitation, and support for land access and financing to attract investment and expand trade (Alder et al., 2016;

Wang, 2013). Building on these successes, cities across China established smaller-scale zones modeled on SEZs. These are commonly referred to as development zones, delimited areas in which local governments concentrate infrastructure investment and provide policy incentives to firms. Over time, the policy orientation of development zones has shifted from export promotion and investment attraction toward innovation and technological upgrading. Development zones are now widely viewed as key engines of regional growth and innovation (Zheng et al., 2016; Li et al., 2021). Official statistics report 552 SDZs and 1,991 PDZs nationwide.[3]

Development zones are commonly classified by administrative rank. We focus on SDZs, approved by the central government and typically receiving more generous incentives, and PDZs, approved by subnational governments with comparatively limited policy packages (Lu et al., 2019). SDZs and PDZs are mutually exclusive administratively, and this distinction maps directly into differences in policy intensity and oversight that are central to our analysis.[4]

Shanghai is an informative setting for studying innovation policy inside development zones for three reasons. First, development zones play an outsized role in the city's innovation ecosystem. Despite covering only 1.8 percent of Shanghai's land area, they account for 46.9 percent of industrial output, 15.8 percent of tax revenue, and 70.5 percent of invention patents in force.[5] Second, Shanghai hosts a rich cross-section of zones, with 7 SDZs and 23 PDZs, enabling comparisons across administrative rank within the same city. Table B.1 provides the full list of development zones. Third, SDZs and PDZs differ sharply in scale and innovative activity. Table B.2 in Appendix B reports summary statistics for the two zone types. SDZs are larger and exhibit substantially higher R&D inputs and patent stocks, with divergence widening over time. For example, the SDZ–PDZ ratio in R&D expenditure rises from 7.0 in 2014 to 16.4 in 2018.

2.2 Preferential Policy in Development Zones

Development zones offer firms a bundle of preferential policies intended to promote growth and, increasingly, innovation. In our setting, the main instruments are R&D subsidies, tax incentives, and (for a subset of firms) preferential access to government

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[3] China Development Zone Audit Announcement Catalog (2018 edition) (Announcement No. 4 of 2018 by the National Development and Reform Commission).

[4] Zones can also be classified by functional objectives. High-tech and Industrial Development Zones (HIDZs) and Economic and Technological Development Zones (ETDZs) are the categories most closely linked to innovation policy, while bonded or export-processing zones primarily facilitate trade. In our Shanghai sample, functional types can overlap with administrative rank (e.g., an HIDZ that is also an SDZ).

[5] Shanghai Development Park Statistical Manual 2018 (Shanghai Bureau of Statistics) and China Patent Statistical Yearbook 2018 (CNIPA).

procurement. A defining feature is that many zones operate policy programs explicitly targeted to firms located within zone boundaries, layering zone-specific support on top of broader city- or national-level innovation policies.

R&D subsidies are the central component of this bundle and the primary focus of our analysis. Zone administrations commonly run dedicated subsidy programs that support research activities, technology upgrading, and commercialization, and these programs are often more generous in higher-ranked zones. Government procurement can provide an additional, demand-side channel of support, but it is received by only a small fraction of firms in our data. Accordingly, we treat procurement as a complementary policy margin rather than a core instrument.

Development zones are also associated with tax incentives, such as reduced corporate income tax rates, tax holidays, and exemptions or rebates on value-added and local taxes, with more favorable terms typically offered in higher-level zones (Wang, 2013). However, for technology-oriented firms, the incremental effect of zone-based tax incentives may be limited because many innovative firms qualify for the High and New Technology Enterprise (HNTE) designation. The HNTE program reduces the corporate income tax rate from 25 percent to 15 percent for eligible firms and represents one of China's most important tax-based innovation policies (Chen et al., 2021). Since HNTE eligibility is determined primarily by firm-level innovation characteristics rather than location, these tax benefits apply broadly to innovative firms both inside and outside development zones. This institutional feature helps motivate our emphasis on zone-targeted R&D subsidies as the policy instrument most directly tied to zone membership.

3 Data and Summary Statistics

3.1 Sample Construction

Our primary data source is the Shanghai Science and Technology Enterprise (SSTE) Survey, an annual administrative survey conducted by the Shanghai Municipal Government from 2008 to 2018, covering technology enterprises in Shanghai. The survey is jointly administered by the Shanghai Municipal Science and Technology Commission and the Shanghai Municipal Bureau of Statistics and is designed to track the universe of officially certified technology enterprises in the city. A firm is classified as a technology enterprise if it is meaningfully engaged in technology-related activities. In practice, certification is based on a firm's involvement in R&D, the presence of technical personnel, the importance of technology-based products or services in its revenues, and the use or ownership of intellectual property. Certified firms are required to report detailed information on these R&D inputs and outputs annually through the SSTE survey, allowing the classification criteria to be consistently observed in the data.[6]

The SSTE Survey additionally provides detailed firm-level information, including firm identifiers, industry and business activities, geographic location, key balance sheet variables, employment, profits, and government support received, including R&D subsidies and procurement. We use the full set of available survey waves to construct an unbalanced firm-year panel containing 178,517 observations. Aggregate firm counts in our data match 99.9 percent of the corresponding figures reported in the Shanghai Statistical Yearbook (Table B.3 in Appendix B), indicating near-complete coverage of the target population. Importantly, the SSTE includes both state-owned and private firms, many of which fall below the standard "above-scale" cutoff, allowing us to study a broad segment of technology enterprises that are typically underrepresented in firm-level datasets.

We supplement the SSTE survey with firm-level patent data from the IncoPat Database, the largest commercial provider of patent information in China. The data cover the universe of Chinese invention patents, utility models, and design patents filed during our sample period. For each patent, IncoPat reports the patent type, application year, applicant names, grant status, and citation information.

We link patents to firms in the SSTE sample using standardized applicant names provided by IncoPat and further harmonize firm names to ensure consistent matching over time. When patents list multiple applicants, we assign the patent to all co-applicants and aggregate outcomes to the firm-year level. After removing duplicate records, the final patent dataset contains 787,821 patent applications and 83,799 granted invention patents between 2008 and 2018. Using these data, we construct annual measures of firms' innovative output.

3.2 Key Variables

Our analysis focuses on how place-based industrial policies affect firms with very different underlying economic fundamentals. To capture this heterogeneity, we classify firms into two conceptually distinct groups: zombie firms, which remain in operation despite weak fundamentals and rely heavily on government support, and star firms, which represent the upper tail of the productivity and innovation distribution. These classifications are not outcomes of interest themselves, but serve to organize firms by

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[6] Firms are classified as technology enterprises based on officially issued eligibility criteria specified in the Shanghai Technology Enterprise Classification Reference Standard. Eligible firms are required to submit annual reports through the official "Shanghai Science and Technology" online reporting platform. Submissions are verified by local technology authorities and summarized in the Shanghai Statistical Yearbook under the table "Technology Enterprise Status in Key Years."

their economic viability and innovation potential. Distinguishing between zombie and star firms allows us to examine whether development zones and subsidy policies differentially affect firms at opposite ends of the performance distribution.

3.2.1 Measuring zombie firms

The concept of zombie firms originates from Kane (1987), who examined insolvent U.S. savings and loan institutions that continued to operate despite negative net worth. Traditional approaches to identifying zombie firms include the credit subsidy method (CHK) and the excessive borrowing method (FN-CHK) (Caballero et al., 2008; Fukuda and Nakamura, 2011). In China, the State Council defines zombie firms as those recording losses for more than three consecutive years and failing to meet structural adjustment requirements.

A central challenge is measurement. Zombie status is not directly observed, and standard proxies can misclassify firms in technology intensive sectors where temporary losses often reflect long horizon R&D investment rather than nonviability. At the same time, genuinely unviable firms may appear solvent when supported by large explicit or implicit assistance. These concerns motivate our construction of multiple measures and our use of observable firm characteristics to validate a benchmark definition.

Following the logic of Fukuda and Nakamura (2011), a natural approach is to classify a firm as a zombie if profitability becomes nonpositive after removing government assistance. The difficulty in our setting is that subtracting all observed support can label innovative young firms as zombies simply because they are temporarily unprofitable. We therefore refine this approach by separating excess support from support that is predictable given a firm's innovation inputs and economic fundamentals. Intuitively, conditional on observable characteristics, excess support captures the component most plausibly linked to policy driven survival rather than to performance based innovation funding.

We estimate theoretical subsidy values using LASSO regressions, which are well suited for predictive settings with high-dimensional covariates (Tibshirani, 1996; Lee et al., 2022). Specifically, we regress government R&D subsidies and procurement on 22 candidate predictors, including total invention patents, design patents, R&D employees, internal R&D expenditures, R&D outsourcing, R&D assets, profit, revenue, debt, firm age, high-tech industry classification, and their interactions, to obtain predicted subsidy values $Gov\_RD'_{it}$ and $Gov\_IS'_{it}$. The adaptive LASSO selects 10 of these covariates, with a cross-validated out-of-sample R^2 of 0.277.[7] This mod-

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[7] The top predictors entering the model are R&D outsourcing expenditure, revenue, patent applications, R&D personnel, and high-tech industry classification. Full LASSO selection results are available upon

erate fit is expected given the partly discretionary nature of subsidy allocation, and implies that our excess support measure captures a meaningful residual component beyond what firm-level innovation characteristics predict. Letting actual subsidies be Gov_RD_{it} and Gov_IS_{it}, we define a zombie firm as:

$$Zombie_{it} = \begin{cases} 1 & \text{if } EBIT_{it} - (Gov\_RD_{it} - Gov\_RD'_{it}) - (Gov\_IS_{it} - Gov\_IS'_{it}) \leq 0, \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

We also construct two alternative definitions as comparisons. The first follows the State Council definition (SC-measure). Because our data form an unbalanced panel, which prevents a strict implementation of the three-year loss criterion, we classify a firm as a zombie if its EBIT is non-positive:

$$Zombie\_SC_{it} = \begin{cases} 1 & \text{if } EBIT_{it} \leq 0, \\ 0 & \text{if } EBIT_{it} > 0. \end{cases} \tag{2}$$

The second follows Fukuda and Nakamura (2011) and Caballero et al. (2008) (FK-measure), and labels firms with negative profitability net of all government assistance as zombies:

$$Zombie\_FK_{it} = \begin{cases} 1 & \text{if } EBIT_{it} - Gov\_RD_{it} - Gov\_IS_{it} \leq 0, \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

Table 2 summarizes firm characteristics under our benchmark definition and two commonly used alternatives. The contrast is informative. Under the SC and FK rules, firms classified as zombies continue to display economically meaningful innovative activity and R&D capacity. For example, they file about 1.3–1.5 patents on average and employ sizable R&D teams. This pattern is consistent with the concern that profitability-based definitions may capture many technology firms that are temporarily loss-making while undertaking long-horizon investment, rather than firms whose continued operation reflects weak fundamentals.

By comparison, firms classified as zombies under our benchmark measure appear systematically weaker on both innovation and fundamentals. They file fewer patents (1.1 versus 2.7), are much smaller (33.4 versus 120.1 employees), and spend less on internal R&D (1.95 versus 7.93). They are also younger and smaller in assets (45.4 versus 217.6), yet substantially more leveraged (DA of 1.416 versus 0.742) and less profitable. At the same time, they receive more government support on average, both in R&D subsidies (0.64 versus 0.45), consistent with a notion of subsidy-dependent

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request.

survival.

To assess whether the benchmark classification is associated with economically meaningful distortions beyond these level differences, we examine subsequent innovation inputs, outputs, and productivity. Table 3 compares government support, innovation investment, and performance between zombie and non-zombie firms, controlling for firm fixed effects and district industry year fixed effects. Several patterns stand out. Column (1) shows zombie status is positively related to government R&D subsidies, reflecting that our measure identifies firms whose earnings become non-positive after netting out the excess component of observed support.[8] In contrast, Columns (2)–(5) show that zombies invest substantially less in internal R&D, employ fewer R&D personnel, generate fewer patent applications in the following year, and they also exhibit markedly lower productivity. These results suggest that the benchmark measure tends to select firms that absorb public support but translate it weakly into innovation inputs and outputs.

These descriptive and within-firm patterns do not imply that any proxy perfectly identifies zombie status. They do, however, indicate that netting out predicted, performance-based support helps separate subsidy-dependent, low-performing firms from innovative firms that are temporarily unprofitable, which is the key measurement challenge in technology-intensive settings.

3.2.2 Measuring star firms

We proxy for high-performing star firms using Shanghai's "Little Giant" enterprise program, a city-level predecessor to the national "Specialized, Refined, Distinctive, and Innovative" (SRDI) system later formalized by the Ministry of Industry and Information Technology (MIIT). Long before MIIT launched the first national cohort in 2019, Shanghai had established a technology-oriented cultivation system that identified and supported firms with strong innovation capacity and growth potential. The program evaluates candidates using stringent criteria that emphasize R&D intensity, core technological capabilities, intellectual property, and leading performance in specialized market segments.

This institutional setting makes the Shanghai Little Giant designation a useful proxy for frontier firms in our 2008–2018 sample period. The designation is based on multi-dimensional assessments of innovative capability rather than short-run profitability, and it is determined within a stable local framework that predates the 2019

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[8] Because the benchmark definition uses excess subsidy receipt, the positive association between zombie status and R&D subsidies in Column (1) is primarily diagnostic. The negative relationships with internal R&D inputs, patenting, and productivity in Columns (2)–(5) are not implied by construction, but firms selected on weak net profitability may also tend to be smaller and less innovative.

national policy rollout. As a result, the measure is well-suited to capture firms in the upper tail of the productivity and innovation distribution in our setting, without being mechanically driven by the later national SRDI expansion.

To construct the star firm indicator, we compile annual official directories of certified Shanghai Little Giant firms released by the relevant municipal authority and match firm names to the SSTE database using standardized identifiers and harmonized names. We then define a firm-year indicator equal to one from the certification year onward (and zero otherwise). This variable serves as our baseline measure of star status throughout the empirical analysis.

3.2.3 Defining development zones and other control variables

We use a GIS-based approach to precisely identify whether firms are located within development zones. We compile spatial data on Shanghai's development zones. We start from the official list of 30 development zones reported in the 2019 Shanghai Development Zone Statistical Yearbook.[9] Using publicly available boundary information and satellite imagery from Gaode Maps, we digitize polygon boundaries for each zone and construct a spatial database of development zone locations. We then geocode firm registered addresses from the SSTE survey and spatially match firms to development zones based on geographic location.[10]This procedure allows us to determine whether a firm is located inside a development zone in each year of the sample. Figure 1 illustrates the spatial distribution of development zones across Shanghai.

Our primary measure of innovative activity is the total number of patent applications filed in year t ($Patent$). We also construct disaggregated measures for invention patents ($Invention$), utility model patents ($Utility$), and design patents ($Design$), which capture different dimensions of firms' technological output.[11]

Information on firms' R&D inputs is drawn from the SSTE survey. We distinguish between internal R&D investment, measured by firms' own R&D expenditures, and external R&D support, captured by government R&D subsidies received in each year.

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[9] Data are sourced from the *Announcement on the Demarcation of State-Level Development Zones* issued by the Ministry of Natural Resources and the Ministry of Housing and Urban–Rural Development (Announcement No. 15 of 2018), available at `https://www.gov.cn/zhengce/zhengceku/2019-10/14/content_5439616.htm`.

[10] Eligibility for preferential policies typically depends on a firm's registered rather than operational address. For instance, Zhangjiang Park requires firms to maintain their registered address inside the park throughout the subsidy application and payout period, and terminates funding if the firm relocates prematurely.

[11] Under Chinese patent law, patents are classified into three categories: invention, utility model, and design patents. Invention patents cover novel technical solutions related to products or processes; utility model patents protect practical technical solutions concerning a product's shape or structure; and design patents protect the aesthetic design of a product, including its shape, pattern, or color combinations suitable for industrial application.

This distinction allows us to separately examine firms' self-financed innovation efforts and policy-induced R&D inputs. For a complete set of variable definitions and construction details, please refer to Table A.1.

3.3 Summary Statistics

Table 1 reports summary statistics for the main firm-level variables described in Table A.1. The sample consists of 178,517 firm-year observations for 63,028 Shanghai technology enterprises between 2008 and 2018.

Innovation output is highly skewed. The average firm files 2 patent applications per year, including 0.9 invention patents, 0.9 utility model patents, and 0.2 design patents. Median patenting activity is zero across all categories, while the large standard deviations indicate that innovative output is concentrated among a relatively small subset of firms. This pattern is consistent with a firm population characterized by many low-innovation firms and a small number of highly innovative leaders.

Firm characteristics exhibit similarly wide dispersion. Average employment is 83 workers, with a standard deviation exceeding 370, reflecting the coexistence of small startups and substantially larger enterprises. R&D inputs vary sharply across firms: the mean firm employs 26 R&D personnel and spends 5.4 million RMB annually on R&D, yet the median R&D expenditure is close to zero. About 28 percent of firm-year observations are located in development zones. State ownership and public listing are rare, accounting for only 2.4 percent and 0.7 percent of observations, respectively, indicating that analyses restricted to listed firms would capture only a small and unrepresentative subset of Shanghai's technology enterprises.

Financial measures also display pronounced heterogeneity. The average firm holds 144 million RMB in assets and 82 million RMB in liabilities, but both variables exhibit extremely large dispersion, indicating substantial variation in firm scale and leverage. Profitability is low on average, with a mean return on assets close to zero and a nontrivial share of firms experiencing losses. These patterns point to the presence of financially fragile firms alongside more productive and outward-oriented enterprises. Government support is present but unevenly distributed. The average firm receives 0.53 million RMB per year in government R&D subsidies but the 90th percentile is still 0.05 million RMB.

The descriptive statistics highlight two key features of Shanghai's technology enterprise sector. First, firms exhibit substantial heterogeneity in innovation output, size, and financial performance, with economic activity concentrated among a small subset of firms. Second, exposure to government support, particularly R&D subsidies, varies widely across firms, indicating significant heterogeneity in policy intensity. This joint variation in firm characteristics and policy exposure provides a rich empirical setting for examining how development zones influence innovation outcomes.

4 Empirical Findings

4.1 Policy Intensity across Development Zones

Before turning to innovation outcomes, we document how government support differs across locations. Table 4 reports descriptive statistics for firms in SDZs, PDZs, and outside zones. Panel A summarizes the level and dispersion of government R&D subsidies, government procurement, and effective tax rates. Panel B relates R&D subsidies to firms' own R&D spending and reports indicators of unusually high subsidy intensity.

Two facts stand out. First, SDZs deliver substantially larger R&D subsidies than PDZs. Conditional on receiving subsidies, the mean award in SDZs is 7.404 million RMB, compared with 1.497 million RMB in PDZs. The SDZ distribution is also much more dispersed: the standard deviation is 62.216, and the upper tail is thicker (P90 of 5.842 in SDZs versus 2.160 in PDZs). The mean exceeding the P90 reflects a small set of extremely large awards in SDZs. Firms outside zones also receive sizable subsidies on average (mean 4.379), but SDZs stand out in both generosity and tail risk.

Second, other policy margins exhibit much weaker differences across locations. Procurement amounts overlap substantially across areas, and effective tax rates are nearly identical (0.054 in SDZs, 0.056 in PDZs, and 0.056 outside zones). Thus, during our sample period, R&D subsidies are the primary dimension along which policy intensity differs across zones.

Panel B shows that the greater generosity of SDZs is also visible relative to private effort. Among firm-years with positive internal R&D spending, the mean subsidy share (subsidies divided by internal R&D expenditures) is 8 percent in SDZs, compared with 5.5 percent in PDZs and 6.6 percent outside zones, and the upper tail is substantially thicker in SDZs. Panel B further reports two extreme cases. The share of firm-years in which subsidies exceed reported internal R&D spending is small overall but highest in SDZs (1.30% versus 0.85% in PDZs). Likewise, the share receiving positive R&D subsidies while reporting zero internal R&D is highest in SDZs (2.10% versus 1.33% in PDZs). These patterns underscore that SDZs combine higher average generosity with a higher incidence of subsidy receipt that is not mirrored by measured internal R&D inputs.

4.2 Effects of Development Zones on Innovation

The descriptive evidence establishes a clear policy-intensity gradient: SDZs deliver substantially more R&D support than PDZs. We next test whether innovation outcomes follow the same gradient. We estimate firm-level panel regressions of next-period innovation outcomes on indicators for location in development zones, exploiting within-firm variation over time arising from changes in zone status.

$$\ln\left(\text{Patent}_{i,t+1} + 1\right) = \beta_1 \, \text{Zone}_{i,t} + X'_{i,t-1}\gamma + \mu_i + \lambda_{d\times j\times t} + \varepsilon_{i,t}, \tag{4}$$

Here, $\text{Patent}_{i,t+1}$ denotes the number of patent applications filed by firm i in year $t+1$, and $\text{Zone}_{i,t}$ is an indicator for whether the firm is located in a development zone in year t. The vector $X_{i,t-1}$ includes lagged firm size, and leverage, capturing differences in firm scale, and financial conditions.

The specifications include firm fixed effects μ_i, which absorb time-invariant heterogeneity in firms' innovation capacity, managerial quality, and technology orientation, as well as administrative district–industry–year fixed effects $\lambda_{d\times j\times t}$, which flexibly control for local policy environments, industry-specific shocks, and region–industry trends that may jointly affect innovation outcomes and zone placement. The dependent variable is measured in period $t+1$, while all firm-level controls are lagged to period $t-1$, mitigating concerns about simultaneity between innovation outcomes and firm characteristics. Standard errors are clustered at the administrative district–industry–year level to allow for arbitrary correlation in shocks within local industry–year cells.

To address potential selection into development zones, we combine OLS with propensity score matching (PSM) based on pre-entry characteristics. A natural concern is that firms with stronger innovation potential may self-select into development zones, so that estimates from fixed-effects OLS may partly reflect selection rather than the causal impact of zone location. We therefore implement PSM to align treated and untreated firms along observable pre-entry characteristics before comparing innovation outcomes. Importantly, comparing estimates from the fixed-effects OLS specifications and the matched sample provides a useful benchmark for assessing the role of selection. Differences between the two sets of estimates help assess the extent to which observed innovation premiums reflect pre-existing firm characteristics versus innovation responses induced by zone entry.

We conduct PSM separately for SDZs and PDZs. Treated firms, those located in SDZs or PDZs, are matched to control firms outside development zones using 1:2 nearest-neighbor matching with replacement, implemented separately for each year. Matching covariates include employment and workforce composition, balance sheet characteristics, firm age, leverage, revenue, export status, and profitability. After discarding unmatched observations, the matched sample contains 82,515 firm-year observations. Table C.1 reports post-matching balance statistics. Differences in covariates between treated and control firms are statistically insignificant at the 5 percent level for all matching variables, indicating good balance. Within the matched sample, we define treated firms as those that enter development zones during the sample period and never exit, and control firms as those that remain outside zones throughout. This yields 37,159 firm-year observations for the main matched-sample analysis. This restriction ensures that identification relies on clean within-firm pre- and post-entry variation, consistent with the fixed-effects design.

Despite these large differences in subsidy intensity, innovation outcomes do not follow the same ranking. Table 5 examines whether locating in a development zone fosters firm-level innovation, measured by patenting activity. Column 1 reports the baseline effects of locating in a development zone on firm innovation. Across all firms, entry into a development zone is associated with approximately an 7.1 percent increase in patenting activity.

However, a more nuanced pattern emerges when distinguishing between SDZs and PDZs. While SDZs exhibit a sizable innovation premium in the raw OLS estimates, this effect becomes smaller and statistically insignificant once firms are matched on pre-entry characteristics. By contrast, PDZs display robust innovation effects of 12.6 percent across specifications. These results suggest that SDZs disproportionately attract firms with stronger pre-existing innovation capacity, whereas the innovation gains observed in PDZs are more plausibly attributable to zone entry itself.

The estimated magnitudes are smaller than those reported in macro-level studies, such as Tian and Xu (2022), who document a 36.9 percent increase in city-level patenting following the establishment of High-Tech Development Zones. This difference likely reflects both the more targeted scope of high-tech zones and key differences in empirical design. In particular, our analysis focuses on firm-level outcomes, incorporates firm fixed effects and granular district–industry–year fixed effects, and isolates the direct effects on treated firms rather than capturing city-wide spillovers.

Because patenting is sparse and highly skewed in our firm population, we assess robustness to functional form. The mean number of patent applications is only 2.023 per firm-year and the median is zero, so log specifications can be sensitive to the mass at zero and to outliers among prolific patentees. We therefore re-estimate the baseline specifications using the inverse hyperbolic sine transformation, $asinh(Patent)$, which accommodates zeros while behaving similarly to the logarithm for larger values. The results in Table C.2 are consistent with the baseline findings: PDZs exhibit robust innovation effects, whereas SDZ effects attenuate once selection is addressed. These checks indicate that our main conclusions are not an artifact of log-transforming a sparse count outcome.

Our findings speak to a broader debate over whether development zones primarily *select* productive firms or *foster* productivity and innovation after entry. Several studies emphasize selection, showing that zone authorities tend to attract or designate areas with already strong technological foundations (Fontagné et al., 2013; Yu and Wan, 2022). Other research finds fostering effects, suggesting that industrial policies and agglomeration advantages in zones can stimulate firm upgrading and innovation (Brandt et al., 2012; Criscuolo et al., 2019). Our findings suggest that both mechanisms operate: PDZs exhibit consistent fostering effects, whereas SDZ premiums largely reflect pre-existing differences.

Why move beyond average effects? The divergence between SDZs and PDZs raises a conceptual question central to theories of industrial policy: why do zones with stronger fiscal support not necessarily deliver larger causal fostering effects? A key insight is that the impact of place-based programs depends not only on the average treatment effect for an individual firm but also on the composition of firms operating within the policy boundary. If development zones attract technologically capable "star" firms, knowledge spillovers and agglomeration forces may strengthen innovation capacity. However, if zones also subsidize low-productivity incumbents that would otherwise exit, these zombie firms may absorb resources, weaken competitive pressures, and suppress dynamic efficiency.

This logic implies that the average effect of zone entry reflects a net outcome of positive spillovers from high-performing firms and negative spillovers from subsidy-dependent firms. Guided by this mechanism, the next section studies how zones shape the upper and lower tails of the firm distribution and how the presence of star and zombie firms affects subsidy allocation and innovation inside zones.

5 Firm Composition and Spillovers inside Development Zones

This section examines how development zones reshape the composition of firms they host and how interactions among firms within zones generate spillovers that help explain why SDZs do not deliver stronger innovation effects despite more generous policy support.

5.1 Firm Composition: Star Firms and Zombie Firms

We begin by examining whether zones change the composition of firms they host, focusing on the upper tail (star firms) and the lower tail (zombie firms). This heterogeneity is central to explaining why SDZs, despite much greater policy intensity, do not exhibit larger innovation gains in Section 4.

Appendix Table D.1 reports the effects of zone location on subsequent star firm certification, measured by an indicator for being certified as a Little Giant firm in year $t + 1$. In the OLS specifications, firms located in zones are more likely to receive certification in the next year in both SDZs and PDZs. After matching firms on pre-entry characteristics, the point estimates remain positive but are no longer statistically significant. Overall, the star-firm results are consistent with an important role for selection, rather than strong evidence of systematic upgrading into star status after zone entry.

Table 6 shows a contrasting pattern for zombie formation. Firms located in SDZs are significantly more likely to be identified as zombies in the next year (an increase of about 8.3 percent), and this effect remains statistically significant after matching, suggesting it is not driven solely by selection on observables. In contrast, PDZs exhibit no meaningful increase in zombie incidence: the coefficients are small and statistically insignificant across specifications.

Taken together, SDZs concentrate high-performing star firms, largely through selection, but also sustain a nontrivial mass of low-productivity zombie firms by distorting exit decisions. PDZs, by contrast, increase the presence of star firms without generating a corresponding rise in zombie firms. While SDZs host highly capable firms that raise average innovative output, Table 3 shows that they also support firms that absorb subsidies without contributing to innovation or productivity. These countervailing forces help explain why SDZs appear highly innovative in raw comparisons yet exhibit much smaller effects once selection is controlled for.

5.2 Spillovers within Development Zones

A large literature emphasizes that agglomeration forces and spillovers are central to productivity gains in innovation clusters. In our setting, zones contain both high-performing star firms and subsidy-dependent zombies, implying that the net effect of place-based support may depend on within-zone composition. Knowledge spillovers from frontier firms can raise innovation, while a larger zombie presence may generate negative externalities by absorbing public support and weakening incentives for marginal innovators.

We study within-zone spillovers using firm-level panel regressions in which the key explanatory variable is the zombie share in a given zone–year cell, denoted $ZombieShare_{zt}$. We construct $ZombieShare_{zt}$ as the fraction of firms identified as zombies among all firms operating in zone z in year t, and we estimate the regressions on the sample of *non-zombie* firms. The dependent variables capture innovation-related outcomes of these non-zombie firms, including government R&D subsidies received, internal R&D expenditures, and patent applications.

All specifications include firm fixed effects, which absorb time-invariant differences in innovation capacity and managerial quality, and industry–year fixed effects, which flexibly control for common shocks and national innovation trends at the industry level. We also include the same set of time-varying firm controls used in Section 4. Standard errors are clustered at the zone–industry–year level to allow for correlated shocks within local policy and competitive environments.

Table 7 relates zombie prevalence within a zone to outcomes of non-zombie firms. Two main patterns emerge, and they are concentrated in SDZs. First, in Panel A, higher zombie prevalence is associated with lower government R&D subsidies received by non-zombie firms. A one percentage point increase in the zombie share is associated with a 4.3 percent decline in subsidies for non-zombie firms in SDZs.[12] Second, Panel B shows that non-zombie firms in SDZs with greater zombie prevalence also reduce internal R&D expenditures, with a one percentage point increase in the zombie share associated with a 6.7 percent decline, consistent with subsidy rationing and weaker innovation incentives.

Panel C examines whether these input distortions translate into lower innovation output, measured by patent applications in the following year. The point estimates in SDZs are small and statistically insignificant, suggesting that the crowd-out of subsidies and R&D spending does not produce a detectable average effect on patenting in the short run. This pattern is consistent with the lumpy and lagged nature of patent production: reductions in innovation inputs may take several years to appear in measurable patent output. Moreover, firms facing subsidy rationing may partially substitute toward internal financing, attenuating the immediate innovation response. As we show in Section 5.2.1, this insignificant average masks significant heterogeneity: the patent losses from zombie prevalence fall disproportionately on small firms, while larger firms are largely insulated.

In PDZs, the corresponding coefficients are small and statistically indistinguishable from zero across all three panels. Overall, the evidence suggests that SDZs with high zombie prevalence are environments in which public R&D support and innovation investment shift away from otherwise viable firms, with the strongest patterns

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[12] *ZombieShare* and *GiantShare* is measured on a 0–100 scale. A one-unit change corresponds to a one percentage point change in the share.

arising where policy intensity is greatest.

For completeness, Appendix Table D.2 reports analogous regressions using the star share (the within-zone share of Little Giant firms). A higher star share is associated with modestly lower subsidies received by non-star firms in SDZs, consistent with competition for limited public funds. The effects on R&D expenditures and patenting are small and statistically insignificant. These patterns suggest that the presence of star firms does not generate the same kind of uniformly negative fiscal externality associated with zombie prevalence, a distinction we explore further when examining heterogeneous effects below.

As in much of the spillover literature, these estimates should be interpreted as descriptive of equilibrium responses within zones rather than fully causal spillover effects. Nevertheless, they are informative about how development zones reallocate innovation opportunities across firms and help explain why zones with the most intensive policy support do not necessarily deliver the strongest causal innovation gains.

5.2.1 Heterogeneous Spillover Effects by Firm Size

Agglomeration and industrial organization theories emphasize that the ability to benefit from local externalities is highly heterogeneous across firms. Large firms typically possess stronger absorptive capacity, better access to finance, and more flexible organizational structures, enabling them to leverage knowledge spillovers and withstand competitive pressure. Smaller firms, by contrast, are more dependent on public support and more vulnerable to resource crowding out. To capture these mechanisms, we allow spillover effects to vary with firm size by interacting the local share of zombie firms with the logarithm of firm assets.

Panel A of Table 8 shows that the negative spillover effects of zombie firms on subsidy allocation are driven almost entirely by SDZs. In these zones, a higher zombie prevalence substantially reduces the government R&D subsidies received by other firms. Importantly, this effect is size dependent: the main effect is large and negative, while the interaction with lagged firm assets is positive and statistically significant, indicating that the crowding-out effect is steepest for smaller firms and attenuates with scale.

Panel B examines internal R&D expenditures. Unlike the subsidy channel, the heterogeneous pattern for R&D spending is less pronounced: the interaction with firm size is weakly negative and only marginally significant in the pooled sample. This asymmetry suggests that the primary constraint imposed by zombie prevalence operates through the fiscal channel—by reducing access to public R&D support—rather than through direct competitive pressure on private R&D investment.

Panel C turns to innovation output. While Table 7 shows no significant average effect of zombie prevalence on patenting, the heterogeneous specification reveals that this null average masks a meaningful distributional pattern. In SDZs, the main effect on next-period patent applications is negative and marginally significant, while the interaction with firm assets is positive and significant. This indicates that the patent losses from zombie prevalence fall disproportionately on small firms, which are more dependent on public support and less able to substitute across funding sources. Larger firms, by contrast, are largely insulated. The opposing responses across the size distribution wash out in the average, explaining the insignificant coefficients in Table 7.

By contrast, these heterogeneous spillovers are considerably weaker or absent in PDZs across all three panels, consistent with their lower subsidy intensity and more limited scope for misallocation.

These results show that the negative externalities associated with zombie firms operate primarily through the fiscal channel and fall on the lower tail of the firm size distribution in SDZs. Generous policy support in these zones disproportionately harms small, potentially viable firms by crowding them out of subsidies and concentrating innovation losses among the firms least equipped to absorb them. This provides a concrete mechanism through which high policy intensity can translate into weaker aggregate innovation performance.

Table D.3 reports the analogous heterogeneous specification for star firms. The patterns differ qualitatively from those for zombies and suggest a more complex set of externalities. In Panel A, the subsidy crowd-out from star prevalence is negative but statistically insignificant once heterogeneity is allowed for, indicating that competition for public funds near star firms is not strongly size dependent. Panel B, however, reveals a striking pattern: star prevalence is associated with significantly higher internal R&D expenditures among non-star firms, with the effect strongest for smaller firms. This is consistent with knowledge spillovers or competitive pressure from frontier firms stimulating private R&D investment, particularly among firms closest to the margin. Yet Panel C shows that this increased R&D effort does not translate into higher patenting for small firms. In SDZs, star prevalence is associated with significantly lower patent output among small firms, with the effect attenuating for larger firms. Small firms near the frontier invest more in R&D but face a higher threshold for converting that effort into measurable innovation output.

Taken together, the heterogeneous spillover results reveal a stratified innovation environment within development zones. Zombie firms generate a purely negative fiscal externality, absorbing public support and depressing innovation among small, financially constrained firms. Star firms generate a more nuanced dual externality: they stimulate private R&D investment, especially among small firms, but the innovation output gains accrue primarily to larger firms with sufficient absorptive capacity to compete near the frontier. These asymmetric spillovers help explain why average innovation gains from development zones—particularly SDZs—are modest despite the presence of highly innovative firms.

6 Policy Upgrading and the Quality of Development Zones

The preceding results suggest that weak innovation performance in some SDZs reflects not a lack of policy support, but distortions in firm selection and exit that reshape the composition of firms operating within zones. In this section, we examine whether strengthening governance can mitigate zombie-firm misallocation, improve within-zone spillovers, and raise the innovation returns to place-based industrial policy.

6.1 Background and Conceptual Motivation

Beginning in the early 2010s, several municipal and provincial governments initiated a formal upgrading process under which selected PDZs were elevated to SDZs. Table 9 lists the Shanghai zones that experienced upgrading over our sample period, highlighting their industrial focus and timing of policy changes. Upgrading entails a comprehensive assessment of a zone's governance and performance, including administrative capacity, land-use efficiency, industrial structure, environmental compliance, and the effectiveness of innovation support. Only zones that satisfy stringent benchmarks, spanning both management quality and firm-level performance indicators, obtain SDZ designation.

The economic rationale for upgrading is twofold. First, SDZ status typically comes with stronger regulatory authority, including more frequent audits, stricter monitoring of firms receiving public support, and tighter screening of new entrants. Second, upgrading can change how fiscal and administrative resources are allocated within the zone by strengthening oversight and shifting support away from low-productivity firms toward firms with higher innovation potential. If governance frictions are a key source of zombie-firm persistence, upgrading should reduce the prevalence of zombies, strengthen incentives for high-performing firms, and improve aggregate innovative output.

We use the upgrading process as a policy shock to test whether improvements in governance translate into changes in zone composition and firm-level innovation outcomes. This analysis complements earlier sections documenting substantial heterogeneity within zones and showing that the presence of star firms and zombie firms shapes spillovers. If upgrading raises regulatory quality, it should attenuate the negative externalities associated with zombie congestion and amplify the positive spillovers associated with agglomeration of innovative firms.

6.2 Effects of Regulatory Upgrading on Firm Composition and Innovation

Our identification strategy exploits the staggered timing of development-zone upgrades in Shanghai. Because upgraded zones were themselves PDZs prior to receiving state-level status, we restrict the control group to firms located in PDZs that were never upgraded during the sample period, ensuring that treated and control firms share a comparable pre-upgrade policy environment.

We first examine whether upgrading reshapes the mix of firms within zones. We estimate the following difference-in-differences specification at the zone-year level:

$$Y_{zt} = \alpha + \beta \, \text{Regulation}_{zt} + X'_{zt}\theta + \lambda_z + \delta_t + \varepsilon_{zt}, \tag{5}$$

where Y_{zt} denotes the outcome of interest in zone z and year t, the within-zone shares of star and zombie firms. Regulation_{zt} equals one for zone-years after zone z is upgraded to state-level status. The specification includes zone fixed effects (λ_z) and year fixed effects (δ_t), along with zone-level controls. We complement this with an event-study specification:

$$Y_{zt} = \alpha + \sum_{k \neq -1} \beta_k \, \mathbf{1}\{t - T_z = k\} + \lambda_z + \delta_t + \varepsilon_{zt}, \tag{6}$$

where T_z is the upgrade year for zone z and $k = -1$ is the omitted reference period. The coefficients β_k trace the dynamic evolution of zone composition relative to the year before the upgrade and provide a statistical assessment of pre-trends.

Table 10 reports the effects of zone upgrading on within-zone composition at the zone-year level. Columns (1)–(2) show that upgrading is associated with a higher share of star firms and a lower share of zombie firms: the point estimates imply an increase of 3.2 percentage points in the star share and a decline of 8.4 percentage points in the zombie share, consistent with improved selection and a reduced survival margin for low-productivity firms. Columns (3)–(4) report the corresponding event-study estimates. Pre-upgrade coefficients at $k = -2$ are small and statistically insignificant for both outcomes, supporting the parallel trends assumption. The reduction in zombie prevalence builds gradually after the upgrade, becoming statistically significant at the third and fourth year, consistent with a process in which tighter screening and oversight progressively reduce the survival margin for subsidy-dependent firms rather than producing a discrete one-time exit. The increase in star share is positive throughout the post-upgrade period but individually imprecise, suggesting that the cultivation of high-performing firms is a slower process than the removal of low performers.

We then ask whether upgrading affects innovation inputs and outputs at the firm level. We estimate:

$$Y_{izt} = \alpha + \beta \, \text{Regulation}_{zt} + X'_{izt}\theta + \gamma_i + \lambda_z + \delta_{jt} + \varepsilon_{izt},$$

X_{izt} includes the same firm-level controls as in the baseline analysis. The specification includes firm fixed effects (γ_i), zone fixed effects (λ_z), and industry-by-year fixed effects (δ_{jt}), absorbing time-invariant firm heterogeneity, permanent differences across zones, and common shocks at the industry-year level. We again complement this with an event-study analogue replacing Regulation_{zt} with leads and lags relative to the upgrade year. Standard errors in both the zone- and firm-level specifications are clustered at the zone level.

Figure 2 reports event-study estimates for firm-level innovation outcomes. All four panels show coefficients that are economically small and statistically indistinguishable from zero in the pre-upgrade period, consistent with parallel pre-trends. In the upgrade year and subsequent years, the coefficients increase across all outcomes. The response of R&D subsidies and R&D staff is immediate and persistent, indicating that upgraded zones quickly redirect public support and expand research capacity. R&D expenditures spike at the time of upgrading and remain elevated, though with wider confidence intervals. The patent response emerges more gradually, consistent with lags between innovation inputs and observable outputs.

These dynamic patterns point to a governance mechanism rather than a pure fiscal expansion. Our earlier results show that existing SDZs deliver substantially larger R&D subsidies yet do not produce correspondingly larger innovation gains, precisely because generous support without effective oversight sustains zombie firms. The upgrade process combines SDZ-level resources with the regulatory scrutiny required for promotion. The gradual decline in zombie prevalence and the simultaneous increase in innovation inputs suggest that the mechanism operates through improved screening of subsidy recipients and stricter monitoring of supported firms, reallocating resources toward firms with higher marginal returns to innovation and attenuating the negative spillovers documented in Section 5.

Notably, the reduction in zombie prevalence attenuates by the fifth year after upgrading, with the coefficient becoming smaller and statistically insignificant. One interpretation is mechanical: fewer zone-year observations contribute to later event-time bins, reducing statistical power. However, the pattern is also consistent with a gradual erosion of governance intensity as upgraded zones settle into routine SDZ administration, precisely the institutional environment that our earlier results show is associated with higher zombie prevalence. This finding underscores that the binding constraint on zone performance may not be fiscal generosity but the sustained quality of oversight, and that the innovation returns to place-based policies depend on continued enforcement rather than one-time institutional reform.

7 Conclusion

This paper studies how China's development zones affect firm-level innovation and the allocation of public R&D support. Using near-universe administrative data on Shanghai technology enterprises from 2008 to 2018 matched to GIS-based zone assignment, we provide evidence on how zone entry shapes innovation outcomes, the composition of firms operating within zones, and the equilibrium environment faced by incumbent firms.

First, development zones raise patenting on average, but the gains are not monotone in policy intensity. SDZs deliver substantially larger R&D subsidies than PDZs yet produce no larger causal innovation effects once selection is addressed. The reason lies in within-zone composition: SDZs sustain a nontrivial mass of subsidy-dependent zombie firms that absorb public resources while contributing little to innovation or productivity. Higher zombie prevalence within a zone crowds out R&D subsidies for non-zombie firms, depresses their internal R&D investment, and reduces patenting among smaller, financially constrained firms, precisely those most dependent on public support.

Second, governance matters. Exploiting staggered upgrades of Shanghai zones from provincial to state-level status, we find that tighter oversight reduces zombie prevalence, increases the share of high-performing firms, and generates sustained gains in R&D inputs and patenting. That these effects attenuate several years after upgrading suggests that the returns to institutional reform depend on continued enforcement, not one-time intervention.

Overall, the results imply that the binding constraint on development-zone performance is not fiscal generosity but the quality of subsidy allocation. Policies that strengthen screening, link support to measurable innovation performance, and prevent the accumulation of subsidy-dependent firms may substantially raise the innovation returns to place-based industrial policy.

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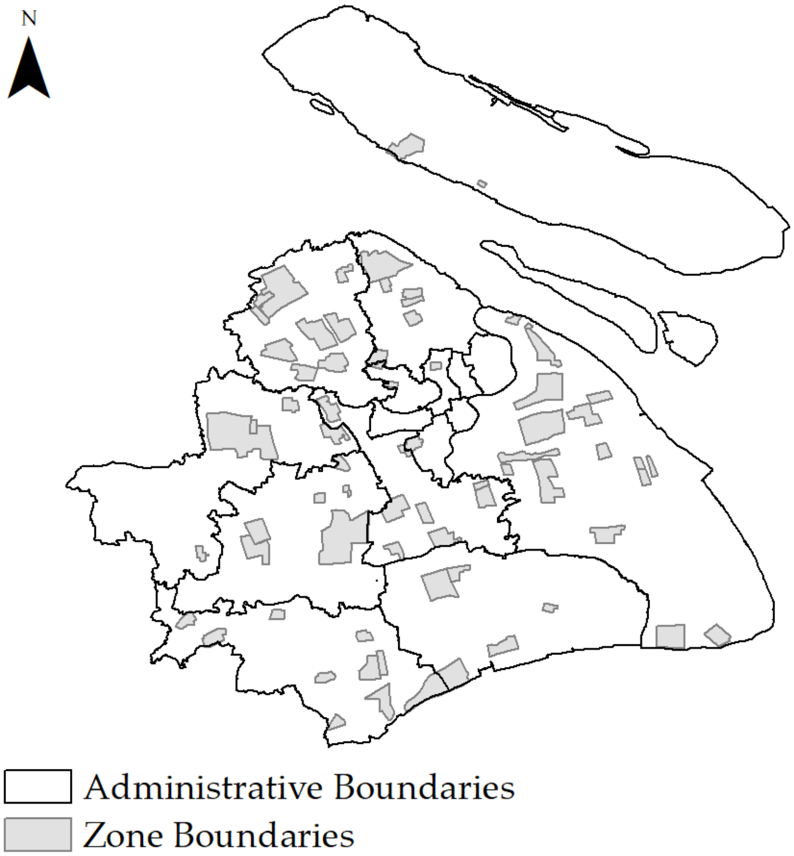
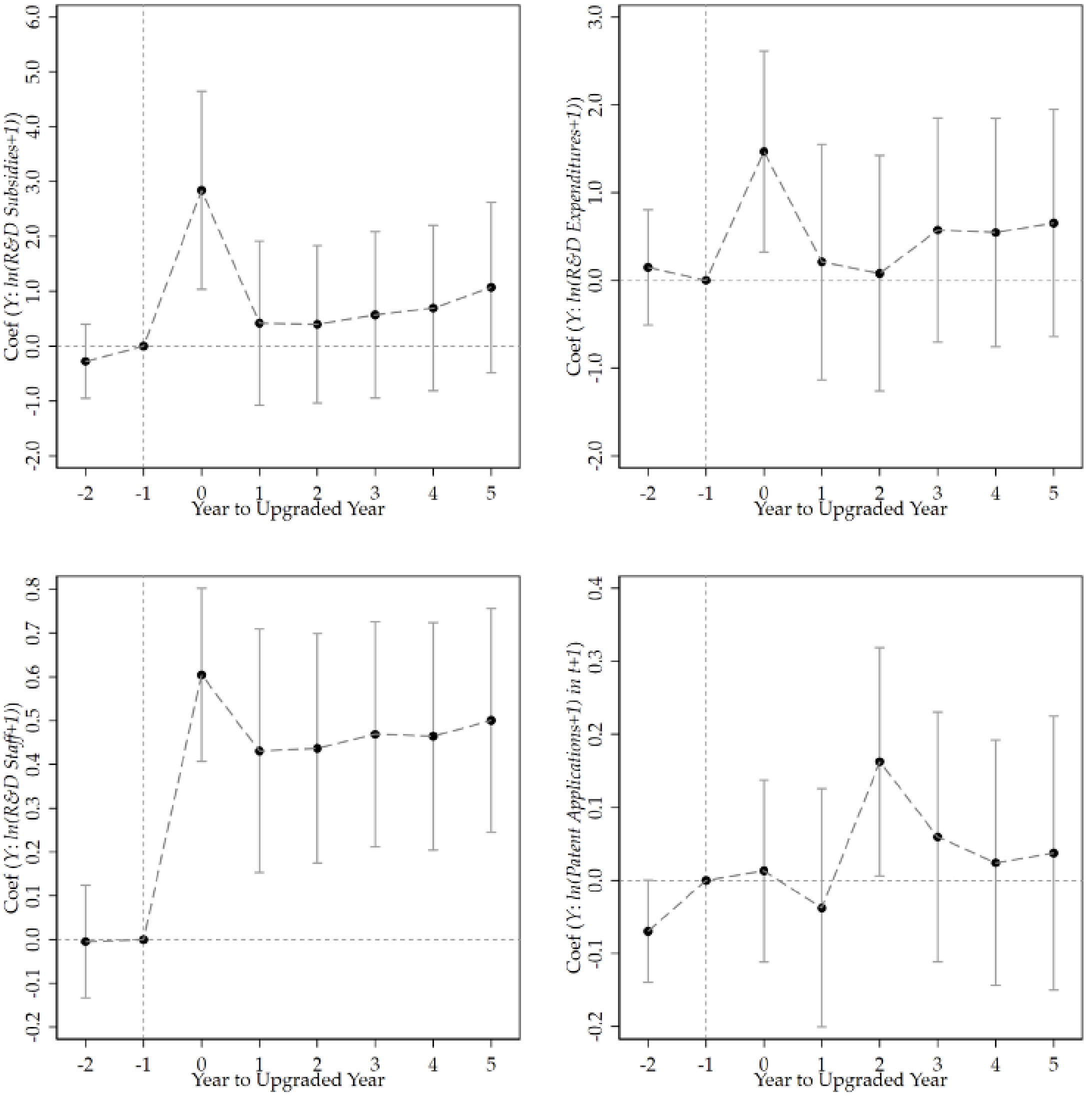


Notes: (1) Black lines indicate administrative boundaries between 16 districts in Shanghai. (2) Shaded gray areas indicate the locations of the 30 state-level and provincial-level development zones.

Figure 1: Spatial distribution of development zones in Shanghai



Notes: Each panel plots the estimated coefficients β_k from the event-study specification described in Equation 6, with $k = -1$ as the omitted reference period. The sample period spans two years before to five years after the upgrade. The dependent variables are the natural logarithm of one plus government R&D subsidies (top left), the natural logarithm of one plus R&D expenditures (top right), the natural logarithm of one plus R&D staff (bottom left), and the natural logarithm of one plus patent applications in $t + 1$ (bottom right). All specifications include firm fixed effects, zone fixed effects, industry-by-year fixed effects, and firm-level controls (natural logarithm of one plus employees and leverage, both lagged one period). Gray vertical bars indicate 95% confidence intervals. Standard errors are clustered at the zone level.

Figure 2: Event study: Effects of zone upgrading on firm-level innovation

Table 1: Variables and statistics

Variables	Obs.	Mean	S.D.	P10	P50	P90
Patent Measures						
Patent	178,510	2.023	15.635	0.000	0.000	4.000
Invention	178,510	0.931	10.786	0.000	0.000	1.000
Model	178,510	0.899	5.787	0.000	0.000	2.000
Design	178,510	0.193	4.898	0.000	0.000	0.000
Firm Characteristics						
Zone	178,517	0.280	0.449	0.000	0.000	1.000
Emp	178,517	83.131	374.512	4.000	17.000	164.000
Emp_RD	178,517	26.494	120.981	0.000	6.000	51.000
Emp_Edu	178,517	27.082	140.032	0.000	6.000	46.000
Emp_Exp	178,517	5.589	46.652	0.000	0.000	9.000
Age	176,704	7.795	5.947	1.333	6.583	16.083
Zombie	178,517	0.426	0.495	0.000	0.000	1.000
Giant	178,517	0.043	0.203	0.000	0.000	0.000
SOE	178,517	0.024	0.152	0.000	0.000	0.000
Listed	178,517	0.007	0.084	0.000	0.000	0.000
Financial Measures						
Asset	178,517	144.198	1894.189	0.176	4.274	157.434
Debt	178,517	82.351	2477.904	0.000	1.494	68.996
RD	178,517	5.384	56.166	0.000	0.170	6.961
DA	171,651	1.024	20.088	0.004	0.402	1.000
ROA	171,651	-0.273	20.390	-0.300	0.007	0.202
Ex	178,517	3.522	69.049	0.000	0.000	0.001
Rev	178,517	102.003	1062.342	0.000	3.450	125.004
Profit	178,516	8.339	173.970	-0.960	0.015	8.992
Government Support						
Gov_Sub	178,517	0.533	18.372	0.000	0.000	0.050
Gov_Pro	178,517	0.014	0.565	0.000	0.000	0.000

Notes: (1) This table presents descriptive statistics for the sample firms. (2) The sample consists of 178,517 firm-year observations for 63,028 firms over a 11-year period from 2008 to 2018. (3) The Listed indicator equals one if a firm is publicly listed as of 2018, the end of the sample period, and zero otherwise.

Table 2: Statistics of zombies and healthy firms

Variables	Benchmark measure		SC-measure		FK-measure	
	Non-zombies	Zombies	Non-zombies	Zombies	Non-zombies	Zombies
Patent Measures						
Patent	2.690	1.126	2.373	1.286	2.315	1.469
Invention	1.171	0.608	1.058	0.664	0.995	0.809
Model	1.255	0.419	1.084	0.509	1.085	0.545
Design	0.264	0.099	0.231	0.113	0.235	0.114
Firm Characteristics						
Zone	0.287	0.271	0.275	0.291	0.274	0.292
Emp	120.067	33.396	102.901	41.479	103.826	43.816
Emp_RD	37.239	12.024	31.879	15.146	31.462	17.054
Emp_Edu	37.802	12.648	32.448	15.777	32.573	16.652
Emp_Exp	8.002	2.339	6.924	2.775	6.770	3.344
Age	10.603	4.081	8.609	6.086	8.639	6.196
Financial Measures						
Asset	217.581	45.386	184.478	59.334	185.945	64.887
Debt	121.954	29.026	103.171	38.487	104.190	40.862
RD	7.932	1.952	6.715	2.578	6.523	3.218
DA	0.742	1.416	0.722	1.629	0.730	1.554
ROA	0.273	-1.033	0.270	-1.361	0.279	-1.269
Ex	5.372	1.032	4.539	1.382	4.652	1.377
Rev	160.227	23.603	136.529	29.262	139.219	31.300
Profit	17.232	-3.636	14.706	-5.077	15.141	-4.585
Government Support						
Gov_Sub	0.453	0.642	0.624	0.343	0.194	1.1773
Gov_Pro	0.007	0.024	0.019	0.005	0.004	0.033
Obs.	102,440	76,077	121,058	57,459	116,955	61,562

Notes: (1) This table presents descriptive statistics for the sample firms, identified as zombies and healthy firms under three measures. (2) Equations 1, 2 and 3 present the construction of benchmark measure, SC-measure, and FK-measure, respectively. (3) R&D staff (*Emp_RD*), highly educated employees (*Emp_Edu*), highly experienced (*Emp_Exp*) are measured in personnel. (4) Assets (*Asset*), debt (*Debt*), R&D expenditures (*RD*), exports (*Ex*), revenue (*Rev*), profit (*Profit*), government R&D subsidies (*Gov_Sub*), and government procurement (*Gov_Pro*) are measured in millions of RMB.

Table 3: Innovation performance of zombie firms

D.V.	ln(R&D Subsidies+1) (1)	ln(R&D Expenditure+1) (2)	ln(R&D Staff+1) (3)	ln(Patent Applications+1) in t+1 (4)	TFP (5)
Zombie	0.692***	-0.715***	-0.130***	-0.049***	-0.437***
	(0.058)	(0.060)	(0.008)	(0.008)	(0.028)
Firm-level controls	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Dist.-Ind.-Year FE	YES	YES	YES	YES	YES
Obs.	89,633	89,633	89,633	89,631	89,624
R^2	0.566	0.844	0.908	0.737	0.734

Notes: (1) The dependent variables in Columns 1-5 are the natural logarithm of one plus government R&D subsidies received by the firm, R&D expenditure, the number of R&D personnel, the number of patent applications in the next year, and total factor productivity. (2) TFP is constructed as the residual from regressing the natural logarithm of total revenue on the natural logarithm of total assets and total employees, with industry and year controlled for. (3) The key explanatory variable is an indicator for whether the firm is identified as a zombie firm in that year by Equation 1. (4) All specifications include firm-level controls (natural logarithm of one plus employees and leverage in the last year), firm fixed effects, and administrative district–industry–year fixed effects. (5) Standard errors are clustered at the administrative district–industry–year level. (6) Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 4: Statistics of state-level and provincial-level development zones

Panel A. Statistics for subsidies across zones

Variables	Obs.	Mean	S.D.	P10	P50	P90
Government R&D subsidy						
SDZs	4,404	7.404	62.216	0.050	0.321	5.842
PDZs	3,585	1.497	13.364	0.030	0.210	2.160
Outside DZs	13,071	4.379	56.771	0.020	0.200	2.450
Government procurement						
SDZs	264	1.537	7.215	0.005	0.100	1.140
PDZs	279	0.864	3.577	0.003	0.080	1.871
Outside DZs	1,620	1.169	4.765	0.004	0.070	1.646
Government Tax Rate						
SDZs	20,110	0.054	0.082	0.000	0.031	0.126
PDZs	26,356	0.056	0.083	0.000	0.033	0.123
Outside DZs	113,279	0.056	0.087	0.000	0.034	0.117

Panel B. Statistics for subsidies and firms' R&D across zones

Variables	Obs.	Mean	P50	P75	P90
Share of R&D subsidies in R&D expenditures					
SDZs	17,248	0.080	0.000	0.000	0.167
PDZs	19,287	0.055	0.000	0.000	0.077
Outside DZs	76,358	0.066	0.000	0.000	0.088
R&D Subsidy Share > 1					
SDZs	17,248	1.30%			
PDZs	19,287	0.85%			
Outside DZs	76,358	1.12%			
R&D subsidies > 0 while R&D expenditures $= 0$					
SDZs	21,741	2.10%			
PDZs	28,275	1.33%			
Outside DZs	128,501	0.69%			

Notes: (1) This table presents descriptive statistics for the sample firms. (2) The sample consists of 178,517 firm-year observations for 63,028 firms over a 11-year period from 2008 to 2018. (3) On average, 20.26%, 12.68%, and 15.97% of firms located in SDZs, PDZs, and outside development zones, respectively, receive government R&D subsidies each year. Descriptive statistics for government R&D subsidies reported in this table are calculated conditional on firms that receive such subsidies. (4) 1.21%, 0.99%, and 1.09% of firms in SDZs, PDZs, and outside development zones, respectively, receive government procurement each year, and descriptive statistics for government procurement are reported conditional on recipient firms only. (5) Government R&D subsidies (*Gov_Sub*) and government procurement (*Gov_Pro*) are measured in millions of RMB. (6) Descriptive statistics for the tax rate are reported for firms with positive total revenue; the tax rate is calculated as the ratio of total taxes paid to total revenue in a given year. (7) Descriptive statistics for the R&D subsidies share are reported for firms with positive R&D expenditures in a given year; the share is measured by the ratio of R&D subsidies received to R&D expenditures, and winsorized at the 0.1% to mitigate the impact of extreme values.

Table 5: Effects of development zones on innovation

D.V.	ln(Patent Applications +1) in t+1					
	All zones		State-level Zones		Prov.-level Zones	
Est.	OLS	OLS	OLS	PSM	OLS	PSM
	(1)	(2)	(3)	(4)	(5)	(6)
Zone	0.071**					
	(0.031)					
SDZ		0.062	0.092**	0.085		
		(0.041)	(0.044)	(0.066)		
PDZ		0.077**			0.053	0.126*
		(0.039)			(0.043)	(0.068)
Firm-level controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Dist.-Ind.-Year FE	YES	YES	YES	YES	YES	YES
Obs.	89,631	89,631	75,184	23,634	77,086	28,166
R^2	0.737	0.737	0.741	0.766	0.737	0.744

Notes: (1) The dependent variable is the natural logarithm of one plus the number of patent applications filed by the firm in the next year. (2) The key explanatory variable is an indicator for whether the firm is located in a development zone in the previous year. (3) All specifications include firm-level controls (natural logarithm of one plus employees and leverage in the last year), firm fixed effects, and administrative district–industry–year fixed effects. (4) Standard errors are clustered at the administrative district–industry–year level. (5) Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 6: Effects of development zones on zombie firm formation

D.V.	Identified as a zombie firm (dummy) in t+1					
	All zones		State-level zones		Prov.-level zones	
Est.	OLS	OLS	OLS	PSM	OLS	PSM
	(1)	(2)	(3)	(4)	(5)	(6)
Zone	0.057***					
	(0.019)					
SDZ		0.074***	0.079***	0.083*		
		(0.025)	(0.029)	(0.046)		
PDZ		0.043*			0.030	-0.026
		(0.024)			(0.026)	(0.046)
Firm-level controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Dist.-Ind.-Year FE	YES	YES	YES	YES	YES	YES
Obs.	56,265	56,265	48,208	14,166	47,950	16,974
R^2	0.639	0.639	0.625	0.662	0.649	0.684

Notes: (1) The dependent variable is the dummy of whether the firm is identified as a zombie in the next year. (2) The key explanatory variable is an indicator for whether the firm is located in a development zone in the previous year. (3) All specifications include firm-level controls (firm age, natural logarithm of one plus employees and leverage in the last year), firm fixed effects, and administrative district–finer industry–year fixed effects. (4) Standard errors are clustered at the administrative district–industry–year level. (5) Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 7: Spillover effects of zombie firms

	Dependent Variable		
Sample	All zones (1)	State-level zones (2)	Prov.-level zones (3)
Panel A. ln(R&D Subsidies+1)			
Zombie%	-0.011	-0.043**	0.009
	(0.009)	(0.019)	(0.009)
Obs.	17,608	7,437	10,086
R2	0.552	0.572	0.530
Panel B. ln(R&D Expenditures+1)			
Zombie%	-0.008	-0.067***	0.010
	(0.008)	(0.018)	(0.008)
Obs.	17,608	7,437	10,086
R2	0.875	0.883	0.875
Panel C. ln(Patent Applications+1) in t+1			
Zombie%	0.001	0.001	0.002
	(0.001)	(0.002)	(0.002)
Obs.	17,608	7,437	10,086
R2	0.727	0.753	0.711
Firm-level controls	YES	YES	YES
zone-level controls	YES	YES	YES
Firm FE	YES	YES	YES
Ind.-Year FE	YES	YES	YES

Notes: (1) Panel A reports the effects on government R&D subsidies, Panel B on R&D expenditures, and Panel C on patent applications in $t+1$ of non-zombie firms in development zones. (2) The key explanatory variable is the share of zombie firms in the development zone, relative to the total number of firms. (3) The sample is restricted to non-zombie firms located within development zones. (4) All specifications include firm-level controls (natural logarithm of one plus employees and leverage, both lagged one period), zone-level controls (natural logarithm of firm count and aggregate R&D expenditures), firm fixed effects, and industry–year fixed effects. (5) Standard errors are clustered at the zone–industry–year level. (6) Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 8: Heterogeneous spillover effects of zombie firms

	Dependent variable		
Sample	All zones (1)	State-level zones (2)	Prov.-level zones (3)
Panel A. ln(R&D Subsidies+1)			
Zombie%	-0.077**	-0.134***	-0.016
	(0.031)	(0.048)	(0.035)
Zombie% × lnAsset	0.004**	0.005**	0.001
	(0.002)	(0.002)	(0.002)
Obs.	17,608	7,437	10,086
R2	0.552	0.573	0.530
Panel B. ln(R&D Expenditures+1)			
Zombie%	0.052	-0.023	0.072
	(0.035)	(0.040)	(0.052)
Zombie% × lnAsset	-0.003*	-0.003	-0.003
	(0.002)	(0.002)	(0.003)
Obs.	17,608	7,437	10,086
R2	0.875	0.883	0.875
Panel C. ln(Patent Applications+1) in t+1			
Zombie%	-0.008*	-0.012*	-0.002
	(0.005)	(0.006)	(0.007)
Zombie% × lnAsset	0.001**	0.001**	0.000
	(0.000)	(0.000)	(0.000)
Obs.	17,608	7,437	10,086
R2	0.727	0.753	0.711
Firm-level controls	YES	YES	YES
zone-level controls	YES	YES	YES
Firm FE	YES	YES	YES
Ind.-Year FE	YES	YES	YES

Notes: (1) Panel A reports the effects on government R&D subsidies, Panel B on R&D expenditures, and Panel C on patent applications in $t + 1$ of non-zombie firms in development zones. (2) The key explanatory variable is the share of zombie firms in the development zone, relative to the total number of firms. (3) Interaction terms are constructed by interacting the key explanatory variable with the natural logarithm of one plus the firm's lagged total assets. (4) The sample is restricted to non-zombie firms located within development zones. (5) All specifications include firm-level controls (natural logarithm of one plus employees and leverage, both lagged one period), zone-level controls (natural logarithm of firm count and aggregate R&D expenditures), firm fixed effects, and industry–year fixed effects. (6) Standard errors are clustered at the zone–industry–year level. (7) Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 9: Upgraded Development Zones in Shanghai

No.	Development Zone	Year			Leading Industries
		Est.	PDZ	SDZ	
1	SH Jinqiao Economic and Technological Zone	1990		2011	New energy vehicles, robotics
2	SH Zizhu Hi-Tech Zone	2002	2006	2011	Integrated circuits, software development, new energy technologies, aviation manufacturing
3	SH Chemical Industrial Zone	1996		2012	Petrochemical engineering, advanced material R&D
4	SH Songjiang Economic Zone	1992	1994	2013	Heavy equipment manufacturing, IC design, novel material engineering

Notes: (1) Data is sourced from Shanghai Development Park Statistical Manual, the website of Shanghai Government and the websites of the development zones. (2) No. 1-7 denote state-level development zones, while No. 8-30 represent provincial-level development zones.

Table 10: Effects of zone upgrading on composition

D.V.	DiD		Event Study	
	Star% (1)	Zombie% (2)	Star% (3)	Zombie% (4)
Regulation	0.032**	-0.084**		
	(0.013)	(0.035)		
$k = -2$			0.017	0.043
			(0.031)	(0.089)
$k = 0$			0.046	-0.061
			(0.029)	(0.055)
$k = +1$			0.043*	-0.010
			(0.024)	(0.079)
$k = +2$			0.036	-0.086
			(0.030)	(0.057)
$k = +3$			0.044	-0.116**
			(0.028)	(0.056)
$k = +4$			0.045	-0.115**
			(0.030)	(0.058)
$k = +5$			0.060*	-0.070
			(0.034)	(0.059)
Zone-level controls	YES	YES	YES	YES
Zone FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Obs.	308	308	296	296
R^2	0.724	0.487	0.726	0.471

Notes: (1) All columns report zone-year level regressions. The dependent variables are the share of Little Giant (star) firms and the share of zombie firms within each zone-year. (2) Columns 1–2 report difference-in-differences estimates, where *Regulation* equals one for zone-years after the zone is upgraded to state-level status. (3) Columns 3–4 report event-study estimates with $k = -1$ as the omitted reference period. The sample spans two years before to five years after the upgrade. (4) All specifications include zone fixed effects, year fixed effects, and zone-level controls (natural logarithm of firm count and aggregate R&D expenditures). (5) Standard errors are clustered at the administrative district–year level and reported in parentheses. (6) ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

A Variable Definitions

Table A.1: Variables and definition

Variables	Definition
Patent Measures	
Patent	Patent applications (piece)
Invention	Invention applications (piece)
Model	Utility model applications (piece)
Design	Appearance applications (piece)
Firm Characteristics	
Zone	Registering in Development Zones (0-1)
Emp	Employees (persons)
Emp_RD	R&D employees (persons)
Emp_Edu	Employees with bachelor's degree (persons)
Emp_Exp	Employees with intermediate technical titles (persons)
Age	Firm age (years)
Zombie	Identified as a zombie firm (dummy)
Giant	Certificated as a Little Giant Firm (dummy)
SOE	State-owned enterprise (dummy)
Listed	Listed status by 2018 (dummy)
Financial Measures	
Asset	Total assets (mil RMB)
Debt	Total debt (mil RMB)
RD	R&D expenditure (mil RMB)
DA	Debt-to-assets ratio
ROA	Profit-to-asset ratio
Ex	Export value (mil RMB)
Rev	Total operating revenue (mil RMB)
Profit	Total operating profit (mil RMB)
Government Support	
Gov_Sub	Government R&D subsidy (mil RMB)
Gov_Pro	Government procurement (mil RMB)

Notes: (1) This table presents variable definitions and descriptive statistics for the sample firms. (2) Patent application indicators are obtained from the Incopat patent database. (3) The Zone indicator is constructed by matching firm-level geographic coordinates with development zone boundaries using GIS. (4) Data on R&D personnel, firm age, ownership, financial variables, and government support are obtained from the SSTE database. (5) The listing status is obtained from the CSMAR listed firms database.

B Institutional Background

Table B.1: Catalog of development zones in Shanghai

No.	Development Zone	Est.Year	Pr.Year	St.Year	Leading Industries
1	SH Jinqiao Economic and Technological Zone	1990		2011	New energy vehicles, robotics
2	Zhangjiang Hi-Tech Park	1992		1992	Electronics & information, biopharmaceuticals, opto-mechatronics
3	Caohejing Emerging Technology Zone	1991		1991	Electronics & information, advanced materials, biopharmaceuticals
4	Minhang Economic and Technological Zone	1983		1986	Heavy equipment manufacturing, electromechanical systems, pharmaceuticals
5	SH Zizhu Hi-Tech Zone	2002	2006	2011	Integrated circuits, software development, new energy technologies, aviation manufacturing
6	SH Chemical Industrial Zone	1996		2012	Petrochemical engineering, advanced material R&D
7	SH Songjiang Economic Zone	1992	1994	2013	Heavy equipment manufacturing, IC design, novel material engineering
8	SH Shibei Hi-Tech Service Park	1992	1996		Software solutions, IT services, inspection & testing systems
9	SH Future Island Hi-Tech Industrial Park	2001	2001		Electrical engineering, advanced manufacturing technologies, electronics
10	SH Xinyang Industrial Park	1995	2006		Eco-friendly materials, environmental protection technologies
11	SH Baoshan Industrial Park	2003	2006		Metal products, specialized equipment, electrical machinery components
12	SH Yueyang Industrial Park	2003	2006		Machinery production, automotive parts, steel downstream processing
13	SH Chongming Industrial Park	1994	1996		Non-metallic mineral products, metal fabrication, general-purpose equipment
14	SH Fusheng Economic Development Zone	1994	2006		Optoelectronics, machinery, shipbuilding supporting industries
15	SH Pudong Heqing Industrial Park	1992	2006		Information technologies, equipment manufacturing, advanced materials
16	SH Pudong Airport Industrial Park		2006		Electronics, mechanical systems, aviation logistics
17	SH Jiading Industrial Park	1994	2006		Automotive components, machinery, electronic devices
18	SH Jiading Automotive Industrial Park	1998	2006		Automotive components, machinery, electronic devices
19	Xinzhuang Industrial Zone	1995	2006		Microelectronics, mechanical engineering, novel materials
20	SH Qingpu Industrial Park	1995	2003		Precision machinery, electronics & information, printing technologies
21	SH Xijiao Economic Development Zone	1992	2006		Electronics, automotive/motorcycle parts, machinery
22	SH Songjiang Economic Development Zone	1992	2008		Electronics & information, mechanical systems, building materials
23	SH Pudong Kangqiao Industrial Park	1992	1994		Consumer electronics, automotive parts, medical device manufacturing
24	SH Nanhui Industrial Park	1994	2006		Shipbuilding, automotive industry, new energy solutions
25	SH Xinghuo Industrial Park	1984	1984		Advanced materials, biopharmaceuticals
26	SH Fengxian Economic Development Zone	2001	2006		Power transmission equipment, electronic appliances, mechanical engineering
27	SH Fengcheng Industrial Park	2002	2006		Machinery production, electronics, metal products
28	SH Jinshan Industrial Park	2003	2006		Advanced materials, electromechanical systems, food processing
29	SH Fengjing Industrial Park	1998	2006		New energy vehicles, equipment manufacturing, advanced materials
30	SH Zhujing Industrial Park		2006		Machinery, innovative materials, textile & apparel technologies

Notes: (1) Data is sourced from Shanghai Development Park Statistical Manual, the website of Shanghai Government and the websites of these development zones. (2) No. 1-7 denote state-level development zones, while No. 8-30 represent provincial-level development zones. (3) Est. Year, Pr. Year, and St. Year denote the year in which a development zone was established, upgraded to a provincial-level development zone, and upgraded to a state-level development zone, respectively.

Table B.2: Statistics of state-level and provincial-level development zones

Sample	SDZ	PDZ	Ratio	SDZ	PDZ	Ratio
Period	2018			2014		
Land Area (square kilometer)	6.048	3.033	1.994	5.551	1.776	3.126
Gross Income (bil RMB)	305.415	89.081	3.428	254.330	64.773	3.927
Gross Tax (bil RMB)	20.900	5.471	3.820	12.008	3.205	3.746
Gross Industrial Output (bil RMB)	100.827	45.694	2.307	71.808	37.557	1.912
FDI (bil USD)	3.165	0.217	14.576	0.793	0.190	4.162
R&D Labor (1,000 personnel)	30.696	2.961	10.368	22.561	3.75	6.017
R&D Expenditure (bil RMB)	14.87	0.905	16.426	6.458	0.923	6.995
Inventions in Force (1,000 piece)	8.625	0.901	9.569	3.447	0.542	6.357

Notes: (1) Data is sourced from the Shanghai Development Park Statistical Manual 2014 and 2018, compiled by the Shanghai Economic and Information Technology Commission, Shanghai Bureau of Statistics, and Shanghai Development Park Association. (2) Ratio is defined as the value of the indicator for state-level development zones divided by the corresponding value for provincial-level development zones.

Table B.3: Annual counts of SSTEs

Year	No. of SSTEs counted		
Data source	Shanghai Statistical Yearbook	SSTE database	Ratio
2008	Not disclosed	10,739	.
2009	Not disclosed	14,772	.
2010	18,008	17,947	99.7%
2011	21,117	20,985	99.4%
2012	24,226	24,206	99.9%
2013	13,109	13,033	99.4%
2014	14,147	14,455	102.2%
2015	14,869	14,779	99.4%
2016	15,314	15,306	99.9%
2017	15,459	15,442	99.9%
2018	16,873	16,853	99.9%
Aggregate count	153,122	178,517	99.9%

Notes: The database utilized contains 153,006 observations of SSTEs from 2010 to 2018, compared with 153,122 entities disclosed in official statistical yearbooks for the same period, demonstrating a similarity of 99.9%.

C Robustness Checks

Table C.1: Post-matching balance test

Panel A. PSM results for SDZ firms

Probit	Sample	Mean(T)	Mean(C)	Bias%	BR%	t-stat.	p-value
Emp	U	155.490	114.550	8.4		7.62	0.000
	M	171.520	160.650	2.2	73.4	0.54	0.589
Emp_RD	U	68.251	42.528	12.4		11.54	0.000
	M	73.085	71.602	0.7	94.2	0.13	0.900
Emp_Edu	U	62.806	43.043	10.0		9.17	0.000
	M	71.881	67.973	2.0	80.2	0.49	0.623
Emp_Exp	U	11.931	9.138	3.7		3.49	0.000
	M	0.764	0.829	-0.1	97.7	-0.55	0.583
Age	U	7.990	7.696	4.9		4.32	0.000
	M	8.577	8.201	6.2	-27.9	1.82	0.068
Asset	U	314.110	186.130	4.9		4.67	0.000
	M	546.670	382.080	6.3	-28.6	1.07	0.283
Debt	U	210.140	101.010	1.8		1.80	0.071
	M	235.490	190.690	0.8	58.9	0.72	0.475
RD	U	18.547	8.708	9.5		8.94	0.000
	M	26.624	19.617	6.8	28.8	1.09	0.274
DA	U	0.820	0.678	1.5		1.41	0.158
	M	0.765	0.851	-0.9	39.4	-0.52	0.602
Rev	U	177.850	129.820	4.9		4.46	0.000
	M	236.850	163.860	7.5	-52.0	1.82	0.068
Ex	U	10.209	6.075	3.0		2.70	0.007
	M	5.690	3.714	1.4	52.2	1.38	0.168
Profit	U	23.501	11.590	4.1		3.93	0.000
	M	46.688	19.988	9.1	-124.2	1.64	0.100

Panel B. PSM results for PDZ firms

Probit	Sample	Mean(T)	Mean(C)	Bias%	BR%	t-stat.	p-value
Emp	U	147.070	125.850	4.8		4.54	0.000
	M	155.690	178.220	-5.1	-6.2	-1.43	0.154
Emp_RD	U	40.206	36.145	3.7		3.55	0.000
	M	44.268	47.479	-2.9	20.9	-0.93	0.352
Emp_Edu	U	36.030	34.833	0.9		0.81	0.416
	M	48.000	58.552	-7.5	-780.9	-1.55	0.122
Emp_Exp	U	7.435	7.465	-0.1		-0.07	0.943
	M	0.751	1.099	-0.8	-1064.2	-0.62	0.536
Age	U	9.003	9.141	-2.2		-2.12	0.034
	M	9.805	10.356	-8.8	-298.7	-2.63	0.009
Asset	U	198.980	179.880	1.8		1.69	0.091
	M	279.230	342.040	-5.9	-228.8	-1.39	0.164
Debt	U	99.926	98.030	0.3		0.26	0.795
	M	135.400	186.430	-7.4	-2590.8	-1.74	0.082
RD	U	7.978	7.067	2.6		2.52	0.012
	M	10.761	13.155	-7.0	-162.9	-1.77	0.077
DA	U	0.657	0.719	-0.9		-0.87	0.387
	M	0.997	1.141	-2.1	-132.0	-0.33	0.742
Rev	U	170.820	148.230	2.7		2.51	0.012
	M	210.550	271.220	-7.1	-168.6	-1.77	0.076
Ex	U	8.129	5.323	3.1		2.87	0.004
	M	3.870	3.241	0.7	77.6	0.75	0.454
Profit	U	16.128	11.864	3.9		3.71	0.000
	M	22.622	23.408	-0.7	81.6	-0.21	0.835

Notes: (1) This table reports covariate balance test before (U) and after matching (M) based on propensity scores estimated using a Probit model. (2) Panel A presents the matching results for SDZ firms, while Panel B presents the results for PDZ firms. (3) ”T” and ”C” denote covariate means for the treated and control groups, respectively. (4) ”Bias%” is the standardized mean difference. ”BR%” reports the percentage reduction in absolute bias relative to the unmatched sample. (5) The reported t-statistics and p-values test the equality of covariate means between treated and control groups for each sample.

Table C.2: Effects of development zones on innovation (arsinh measure)

D.V.	arsinh(Patent Applications) in t+1					
	All zones		State-level Zones		Prov.-level Zones	
Est.	OLS	OLS	OLS	PSM	OLS	PSM
	(1)	(2)	(3)	(4)	(5)	(6)
DZ	0.088**					
	(0.037)					
SDZ		0.080	0.121**	0.111		
		(0.051)	(0.053)	(0.083)		
PDZ		0.093*			0.061	0.138*
		(0.048)			(0.052)	(0.082)
Firm-level controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Dist.-Ind.-Year FE	YES	YES	YES	YES	YES	YES
Obs.	88,618	88,618	74,417	23,315	76,227	27,700
R2	0.730	0.730	0.732	0.760	0.730	0.741

Notes: (1) The dependent variable is the arcsine transformation of the number of patent applications filed by the firm in the next year. (2) The key explanatory variable is an indicator for whether the firm is located in a development zone in the previous year. (3) All specifications include firm-level controls (natural logarithm of one plus employees and leverage in the last year), firm fixed effects, and administrative district–industry–year fixed effects. (4) Standard errors are clustered at the administrative district–industry–year level. (5) Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

D Additional Results for Star Firms

Table D.1: Effects of development zones on star firm formation

D.V.	Certificated as a Little Giant Firm (dummy) in $t + 1$					
	All zones		State-level zones		Prov.-level zones	
Est.	OLS	OLS	OLS	PSM	OLS	PSM
	(1)	(2)	(3)	(4)	(5)	(6)
Zone	0.024***					
	(0.009)					
SDZ		0.017*	0.021*	0.019		
		(0.010)	(0.011)	(0.022)		
PDZ		0.030**			0.032**	0.012
		(0.012)			(0.014)	(0.023)
Firm-level controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Dist.-Ind.-Year FE	YES	YES	YES	YES	YES	YES
Obs.	87,903	87,903	75,119	22,394	75,430	26,690
R^2	0.900	0.900	0.892	0.904	0.908	0.930

Notes: (1) The dependent variable is an indicator for whether the firm is certified as a Little Giant firm in year $t + 1$. (2) The key explanatory variable is an indicator for whether the firm is located in a development zone in year t. (3) All specifications include firm-level controls (natural logarithm of one plus employees and leverage in the last year), firm fixed effects, and administrative district–industry–year fixed effects. (4) Standard errors are clustered at the administrative district–industry–year level. (5) Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.2: Spillover effects of star firms

	Dependent Variable		
Sample	All zones (1)	State-level zones (2)	Prov.-level zones (3)
Panel A. ln(R&D Subsidies+1)			
Giant%	-0.051**	-0.113*	-0.024
	(0.025)	(0.063)	(0.026)
Obs.	22,989	10,628	12,223
R2	0.562	0.585	0.524
Panel B. ln(R&D Expenditures+1)			
Giant%	-0.007	0.098	-0.027
	(0.026)	(0.060)	(0.029)
Obs.	22,989	10,628	12,223
R2	0.830	0.830	0.837
Panel C. ln(Patent Applications+1) in t+1			
Giant%	0.001	0.002	0.002
	(0.004)	(0.009)	(0.005)
Obs.	22,989	10,628	12,223
R2	0.729	0.751	0.713
Firm-level controls	YES	YES	YES
zone-level controls	YES	YES	YES
Firm FE	YES	YES	YES
Ind.-Year FE	YES	YES	YES

Notes: (1) Panel A reports the effects on government R&D subsidies, Panel B on R&D expenditures, and Panel C on patent applications in $t + 1$ of non-star firms in development zones. (2) The key explanatory variable is the share of Little Giant firms in the development zone, relative to the total number of firms. (3) The sample is restricted to non-star firms located within development zones. (4) All specifications include firm-level controls (natural logarithm of one plus employees and leverage, both lagged one period), zone-level controls (natural logarithm of firm count and aggregate R&D expenditures), firm fixed effects, and industry–year fixed effects. (5) Standard errors are clustered at the zone–industry–year level. (6) Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.3: Heterogeneous spillover effects of star firms

	Dependent variable		
Sample	All zones (1)	State-level zones (2)	Prov.-level zones (3)
Panel A. ln(R&D Subsidies+1)			
Giant%	-0.114	-0.180	-0.036
	(0.090)	(0.178)	(0.104)
Giant% × lnAsset	0.004	0.004	0.001
	(0.005)	(0.009)	(0.006)
Obs.	22,988	10,628	12,222
R^2	0.562	0.585	0.524
Panel B. ln(R&D Expenditures+1)			
Giant%	0.638***	0.590***	0.717***
	(0.111)	(0.206)	(0.121)
Giant% × lnAsset	-0.036***	-0.027**	-0.042***
	(0.006)	(0.010)	(0.007)
Obs.	22,988	10,628	12,222
R^2	0.832	0.830	0.839
Panel C. ln(Patent Applications+1) in t+1			
Giant%	-0.046***	-0.069***	-0.025
	(0.015)	(0.022)	(0.021)
Giant% × lnAsset	0.003***	0.004***	0.002
	(0.001)	(0.001)	(0.001)
Obs.	22,988	10,628	12,222
R^2	0.729	0.751	0.713
Firm-level controls	YES	YES	YES
zone-level controls	YES	YES	YES
Firm FE	YES	YES	YES
Ind.-Year FE	YES	YES	YES

Notes: (1) Panel A reports the effects on government R&D subsidies, Panel B on R&D expenditures, and Panel C on patent applications in $t+1$ of non-giant firms in development zones. (2) The key explanatory variable is the share of Little Giant Firms in the development zone, relative to the total number of firms. (3) Interaction terms are constructed by interacting the key explanatory variable with the natural logarithm of one plus the firm's lagged total assets. (4) The sample is restricted to non-giant firms located within development zones. (5) All specifications include firm-level controls (natural logarithm of one plus employees and leverage, both lagged one period), zone-level controls (natural logarithm of firm count and aggregate R&D expenditures), firm fixed effects, and industry–year fixed effects. (6) Standard errors are clustered at the zone–industry–year level. (7) Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.