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. A higher local zombie share is also associated with sharp declines in non-zombie R&D and patenting, concentrated among high-productivity 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 examine whether development zones foster innovation and how subsidy allocation within zones shapes the innovation returns to place-based policy. Our analysis moves beyond average treatment effects to show that the composition of firms inside zones, rather than the size of the subsidy pool, determines whether fiscal support translates into innovation.

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 99.9 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.

Yet this support is unevenly distributed, and the unevenness is systematic rather than noise. The average R&D subsidy per recipient firm in state-level development zones (SDZs) is roughly five times that in provincial-level development zones (PDZs). To assess whether this intensity reflects merit-based allocation, we construct a firm-specific benchmark estimated by a high-dimensional LASSO on firms outside zones.

[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).

The distribution of excess support, defined as actual subsidy minus predicted subsidy, has a markedly fatter right tail in SDZs than elsewhere. Most SDZ firms receive less than predicted, while a minority absorb transfers far exceeding what their observable innovation characteristics justify.

We first check whether this concentrated excess translates into stronger innovation. Entry into a development zone raises patenting on average by about 9.4 percent, with the gain concentrated in PDZs: PDZ entry is associated with a 12.7 percent increase, while SDZ entry produces no statistically detectable effect. Because firms with stronger innovation potential may self-select into zones, we address selection using propensity score matching on pre-entry observables. The PDZ gain survives at about 9.5 percent, while the SDZ coefficient remains statistically indistinguishable from zero, even though SDZ firms receive subsidies several times larger than comparable firms in PDZs. The fiscal-intensity gradient and the innovation gradient diverge sharply, and this divergence motivates our analysis of within-zone composition.

To interpret this divergence, we develop a theoretical framework that builds on the knowledge spillovers commonly emphasized in the agglomeration literature and extends Caballero et al. (2008) by introducing a fixed subsidy budget: excess support to one firm reduces what is available to others. Zombie firms harm non-zombies through both channels: they absorb budget that would finance higher-productivity research, and they contribute low-quality R&D while displacing high-quality R&D from the firms they crowd out. The framework yields three implications: zones with larger budgets and weaker governance sustain more zombies; a higher zombie share depresses non-zombie innovation through both channels; and the burden falls disproportionately on high-productivity non-zombies. Building on the excess-support benchmark above, we define zombies empirically as firms whose earnings before interest and taxes would be non-positive absent the excess component of their subsidies. This construction separates subsidy-dependent firms from those temporarily unprofitable because of long-horizon R&D investment, a distinction that matters in technology-intensive industries where standard profit-based definitions can misclassify innovative young firms.

All three implications are supported in the data. First, entry into an SDZ raises the probability that a firm is subsequently classified as a zombie by about 1.3 percentage points, a roughly 4 percent increase over the baseline zombie rate of 35 percent, and the gap survives matching on pre-entry observables. The corresponding effect in PDZs, where subsidies are far less generous, is not robust to selection controls. Second, a 10 percentage point increase in the local zombie share is associated with about 10.7 percent lower R&D expenditure and 3.8 percent fewer patents among non-zombies. Third, these losses fall disproportionately on high-productivity non-zombies, the firms whose marginal R&D project would have generated the largest private return and the strongest contribution to local knowledge spillovers. Intensive zone policies can therefore generate negative externalities when they sustain subsidy-dependent firms that absorb fiscal resources and crowd out the firms with the largest innovation potential.

Finally, we test whether improving governance mitigates these distortions by exploiting staggered upgrades of several Shanghai zones from provincial to state-level status. A staggered difference-in-differences design, complemented by event-study specifications that confirm parallel pre-trends, shows that upgrading reduces zombie prevalence by up to 7.5 percentage points five years after the transition and raises internal R&D expenditure, R&D staffing, and patenting. The fiscal injection that accompanies upgrading is transient: ongoing subsidy flows revert to baseline within a year, while firms' own R&D spending and research staff remain elevated for four years. The pattern is consistent with a governance mechanism operating through improved screening and monitoring rather than a permanent fiscal expansion. These findings speak directly to the design of place-based innovation policies: the binding constraint on zone performance is the quality of subsidy allocation rather than the size of the subsidy pool.

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 contribute to this literature on two fronts. We document a distinct channel of zombie persistence: geographically targeted R&D subsidies inside development zones, a policy-induced survival mechanism that has received limited empirical attention despite its relevance for industrial policy in emerging economies. Methodologically, we construct a subsidy-based zombie measure that isolates excess government support from the component predicted by observable innovation characteristics, addressing the known limitation that profit-based definitions can misclassify innovative young firms whose losses reflect long-horizon R&D rather than nonviability.

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 Special Economic Zones (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 micro-level data to document how subsidy misallocation toward subsidy-dependent firms generates negative externalities for non-zombie innovation.

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) emphasizes the importance of spillovers in shaping the social return to R&D, and Akcigit et al. (2022) show how optimal R&D policy should condition on firm productivity when spillovers are present. Surveys review mixed evidence on tax incentives (Hall and Van Reenen, 2000; Becker, 2015), and for China, Chen et al. (2021) highlights both real and reporting responses to R&D tax incentives. Our theoretical contribution to this literature is to embed a zombie-congestion mechanism within a model that also features agglomeration-style knowledge spillovers: development zones operate under both a fixed subsidy budget and a quality-weighted local knowledge pool, so subsidy misallocation distorts innovation through two channels simultaneously.

Finally, our paper connects with emerging work that emphasizes 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 the advantages of incumbency. Consistent with these insights, our findings show that zone policies reshape the composition of firms operating within them and that the burden of misallocation is highly heterogeneous. The innovation losses from zombie congestion fall almost entirely on high-productivity non-zombies, the firms whose marginal R&D would have generated the largest private return and the strongest contribution to local knowledge spillovers, while low-productivity non-zombies are essentially unaffected. The net effect of place-based subsidies on innovation depends critically on which firms absorb public support and which firms lose access to it.

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, including the LASSO-based excess-support benchmark and the zombie measure. Section 4 presents baseline results on the effects of place-based policies on innovation and introduces the theoretical framework that guides the mechanism analysis. Section 5 tests the three predictions: zombie formation across zone types, within-zone spillovers on non-zombie R&D and patenting, and heterogeneous effects across the productivity distribution. 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 ad-

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

ministratively, 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 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,

[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).

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 Zombie Measure

3.1 Sample Construction and Summary Statistics

Our primary data source is the Shanghai Science and Technology Enterprise (SSTE) Survey, an annual administrative census conducted by the Shanghai Municipal Government from 2008 to 2018. 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 requires 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 report detailed information on 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 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

[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."

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.

Star firms. To identify high-performing firms, we use Shanghai's "Little Giant" enterprise program, a city-level predecessor to the national "Specialized, Refined, Distinctive, and Innovative" (SRDI) system. The program evaluates candidates on R&D intensity, core technological capabilities, intellectual property, and market leadership in specialized segments. Because the designation reflects multi-dimensional assessments of innovative capability rather than short-run profitability, it provides a useful proxy for frontier firms in our setting. We compile annual official directories of certified Little Giant firms and match them to the SSTE database using standardized identifiers. We define a firm-year indicator equal to one from the certification year onward. In the empirical analysis, star firms serve as a source of external capability information to exclude firms from zombie definition.

Development zones. We use a GIS-based approach to identify whether firms are located within development zones. We start from the official list of 30 development zones reported in the 2019 Shanghai Development Zone Statistical Yearbook.[7] 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 sur-

[7] 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.

vey and spatially match firms to development zones based on geographic location.[8] 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.

Other variables. 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.[9] 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. For a complete set of variable definitions and construction details, see Table A.1.

Summary statistics. Table 1 reports summary statistics for the main firm-level variables. 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, but the median is zero across all patent categories, indicating that innovative output is concentrated among a small subset of firms. 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: 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. 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 only 0.05 million RMB, confirming that most subsidy spending is concentrated among a minority of recipients.

[8] 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.

[9] 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.

3.2 Subsidy Allocation Patterns

We first document allocation patterns that motivate the zombie classification introduced in Section 3.3. To assess whether subsidy allocation deviates from observable merit, we predict each firm's expected R&D subsidy using an adaptive LASSO trained on firms outside development zones. The LASSO estimates what a firm would receive under a merit-based system that rewards demonstrated R&D capacity. We then examine the residual, actual subsidy minus predicted subsidy, as a continuous measure of excess support that does not require any firm-level classification.

Table 2 shows that SDZs channel substantially more R&D support than other zones along both the extensive and intensive margins. The share of firms receiving any subsidy is 20.3 percent in SDZs, 12.7 percent in PDZs, and 10.2 percent outside zones. Conditional on receipt, the mean subsidy is 7.4 million RMB in SDZs against 1.5 million in PDZs and 4.4 million outside zones. Kolmogorov–Smirnov tests reject equality of the SDZ distribution against both the PDZ and outside-zone distributions at the 1 percent level. The ranking survives scaling by firm size and by internal R&D expenditure as well.

Figure 2 shows that this excess support is concentrated rather than uniform. The SDZ distribution has a markedly fatter right tail than elsewhere, while most of its mass lies below zero. The share of firm-years above the merit-based benchmark is 14.4 percent in SDZs, 9.2 percent in PDZs, and 7.3 percent outside zones. The coexistence of a negative center and a positive tail is consistent with a fixed-budget allocation in which excess support absorbed by a minority reduces what remains for the rest. PDZs show a compressed distribution centered slightly below zero, consistent with a smaller budget envelope and less scope for distortion on either margin.

A large positive residual alone, however, does not imply nonviability. A high-growth firm may receive outsized support and still be innovation-productive. We therefore combine the residual with profitability information to separate subsidy-dependent survival from merit-based support.

3.3 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. In the influential study of Japan's lost decade, Caballero et al. (2008) showed that banks sustained insolvent borrowers through subsidized lending, and that the resulting zombie congestion depressed investment, employment, and productivity among healthy firms. Traditional approaches to identifying zombies include the credit subsidy method (Caballero et al., 2008) and the excessive borrowing method (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 government transfers. 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 refine this approach by separating *excess* support from *merit-based* support. Excess support is the component beyond what a firm's observable innovation characteristics would predict. Merit-based support is the component that reflects the firm's demonstrated R&D capacity.

Predicting merit-based subsidies. We estimate theoretical subsidy values using a hurdle LASSO procedure. Stage 1 is a linear probability model of $\mathbf{1}\{Gov\_RD_{it} > 0\}$, predicting whether the firm receives any subsidy. Stage 2 is a linear regression of $\ln(Gov\_RD_{it})$ conditional on positive receipt. The two stages are combined through Duan's smearing correction to yield a predicted subsidy level. We use 14 firm-level covariates and their pairwise interactions as candidate predictors, giving approximately 105 candidates in total. Covariates include invention patents, total patents, design patents, utility model patents, internal R&D expenditure, R&D personnel, employment, revenue, assets, debt, leverage, firm age, and high-tech industry classification. Industry, administrative district, and year fixed effects are partialled out.

Two methodological choices shape the benchmark. First, predictors are measured at the current period rather than lagged. This choice reflects a sample-comparability concern rather than an informational one. Lagged predictors would restrict the sample to firms observed at $t-1$, differentially excluding young and newly entering firms. These excluded firms are disproportionately loss-making during startup phases and therefore more likely to be classified as zombies under the SC and FK definitions, which rely on profitability alone. Lagged predictors would compress the apparent gap between the benchmark and the alternatives by dropping firms that the alternatives would otherwise flag. Current-year predictors keep the same underlying sample across the three measures and support a cleaner comparison.[10] Second, we restrict the

[10] Current-year predictors raise the usual concern about simultaneity between subsidy receipt and contemporaneous R&D inputs. The LASSO benchmark is descriptive rather than causal, so the sample-comparability priority dominates.

training sample to firms located outside development zones. Outside-zone firms are not subject to the zone-level allocation distortions we seek to measure, so the LASSO learns the relationship between firm characteristics and subsidies in an environment free of zone-specific policy discretion. The resulting predictions represent a plausible counterfactual: the subsidy a firm would receive if allocated purely according to observable merit.[11]

Appendix Table C.2 reports variable selection results. The Stage 1 pseudo-R^2 is 0.104 and the Stage 2 R^2 is 0.399. The moderate 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 characteristics predict. The selected variables are stable across training samples. R&D personnel is the strongest main-effect predictor, with coefficients above 0.28 in every training sample. Internal R&D expenditure, total assets, and invention patents are selected across all specifications. The core relationship between firm characteristics and subsidy receipt is consistent across environments.

Defining zombie firms. Let Gov_RD_{it} denote actual R&D subsidies received by firm i in year t, and $\widehat{Gov\_RD}_{it}$ the hurdle-LASSO predicted value. Excess support is $Gov\_RD_{it} - \widehat{Gov\_RD}_{it}$, the subsidy component that cannot be explained by observable innovation characteristics. We classify a firm as a zombie if its earnings before interest and taxes (EBIT) net of excess support are nonpositive:

$$Zombie_{it} = \begin{cases} 1 & \text{if } EBIT_{it} - (Gov\_RD_{it} - \widehat{Gov\_RD}_{it}) \leq 0 \text{ and } Star_{it} = 0, \\ 0 & \text{otherwise,} \end{cases} \tag{1}$$

The intuition is straightforward. A firm with positive EBIT may appear profitable only because it receives subsidies far exceeding what its characteristics would predict. If removing this excess renders the firm unprofitable, its continued operation depends on policy-driven transfers rather than on its own fundamentals. Such firms are zombies in the sense of Caballero et al. (2008). Their survival is sustained by external support that would not flow to them under a merit-based system. $Star_{it}$ indicates whether firm i has been certified as a Little Giant by year t. The benchmark incorporates external capability information through this exclusion. Using it as a hard exclusion rule ensures that firms independently recognized as frontier performers cannot be flagged as zombies even in years of negative EBIT.

The definition has two desirable properties. First, it distinguishes subsidy-dependent

[11] Training on the full sample, which includes SDZ firms, would contaminate the predicted subsidy with SDZ-specific allocation patterns, biasing the excess support measure toward zero precisely for the firms where distortion is most likely.

firms from those that are temporarily loss-making due to long-horizon R&D investment. A young firm investing heavily in R&D may record negative EBIT. If its subsidy receipt is commensurate with its observable innovation inputs so that excess support is near zero, the firm is not classified as a zombie. Second, the measure is a firm-specific benchmark. Each firm's subsidy is compared to what its own observable characteristics would predict, not to an absolute threshold. A large firm can receive millions in subsidies without being flagged if its innovation inputs justify the support, while a smaller firm receiving far less can still be flagged if its support is disproportionate to its observables.

According to Table 3, zombie prevalence varies systematically by zone type. 36.3 percent of firms in SDZs are classified as zombies, compared with 30.3 percent in PDZs. The 6-percent gap between SDZs and PDZs is the comparison that isolates the zone policy environment. Both are zones that receive R&D subsidies, so the difference reflects the environment rather than sample composition. The gap maps directly to the excess subsidy pattern documented in Section 3.2. Firms receiving support far beyond what their characteristics predict are disproportionately those whose profitability depends on that excess. We also examine the persistence of the classification. Panel B of Table 3 reports one-year transition probabilities. A firm classified as a zombie at t has a 65.4 percent probability of being classified again at $t+1$. Persistence is similar across zones. The finding speaks to two concerns. It validates the measure against year-to-year noise, since zombie status is a durable property of firms rather than a transient label. It also separates the zone effect into an incidence margin, which differs meaningfully across SDZs and PDZs, and a retention margin, which does not. Zones differ in how many firms become zombies, not in how long zombies persist once classified.

The benchmark is robust to specification choices. The primary classification uses hurdle LASSO with EBIC penalty selection. To verify that the classification is not driven by the choice of LASSO procedure, we also estimate a single-stage LASSO with cross-validation on the same underlying sample and vary this alternative across six specifications: two levels of cross-validation folds, two random seeds, two restricted covariate sets, and two estimation methods (LASSO versus OLS) as reported in Appendix Table C.3. Pairwise correlations with the primary specification range from 0.91 to 1.00, and firm-level agreement rates range from 95.5 to 99.9 percent. Under the main LASSO variants, classifications agree with the benchmark in more than 99 percent of observations. Stability extends to the choice of training sample. Using PDZ firms or the full sample to train the LASSO produces classifications with correlations of 0.98 and 0.99 relative to the outside-zone baseline.

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

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

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

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

Panel A of Table 3 compares prevalence across the three definitions. The SC and FK rules classify 42.4 and 44.2 percent of observations as zombies. The benchmark rate is 35.0 percent. The aggregate gap is modest. The classifications differ more substantively in which firms they flag. SC and FK classify on profitability alone. They capture many technology firms undergoing temporary losses from long-horizon R&D investment, regardless of whether these firms receive outsized public support. The benchmark classifies on profitability net of excess subsidies and flags a firm only when its apparent viability depends on support that its observable characteristics do not justify.

Composition of firms, innovation, and subsidies. Table 4 decomposes firm-years into three mutually exclusive groups: star firms, zombie firms, and middle firms. For each group we report the share of firms, invention patents, total patents, internal R&D expenditures, and government R&D subsidies. The mismatch index at the bottom of each panel equals the zombie subsidy share divided by the zombie invention patent share. A value above one indicates that zombies absorb disproportionate public support relative to innovation output.

Panel A applies the benchmark definition. In SDZs, zombies are 35.6 percent of firms and produce 23.8 percent of invention patents, yet absorb 62.1 percent of R&D subsidies. Star firms show the mirror pattern. They are 13.1 percent of firms and produce 22.1 percent of invention patents, yet receive only 16.1 percent of subsidies. The mismatch index is 2.61. PDZs show the same pattern in a muted form. The mismatch index is 1.80, and PDZ stars receive a share of subsidies close to their share of innovation output. The benchmark identifies a systematic reallocation of public support from high-output stars to subsidy-dependent zombies, and the reallocation is more severe in the high-budget, looser-governance environment of SDZs.

Panels B and C apply the SC and FK definitions. The contrast with the benchmark is informative. SC-classified zombies in SDZs absorb 13.1 percent of subsidies against a 19.9 percent invention patent share. The SC mismatch index is 0.66. SC flags loss-making firms without reference to subsidy allocation and therefore captures technology firms investing through R&D losses rather than firms dependent on excess support. FK subtracts all subsidies and captures a mix of merit-based and excess recipients. Its SDZ mismatch index of 2.43 is close to the benchmark. The benchmark refines FK by flagging only the excess component and isolates firms whose survival depends on allocation distortion rather than on absolute support. These patterns confirm that the three definitions identify different populations of firms, and that the benchmark captures the population most consistent with the concept of subsidy-dependent survival.

Firm-level averages in Appendix Table C.1 confirm the composition pattern at the per-firm level. Under the benchmark, zombies receive 0.78 million RMB in subsidies on average against 0.25 million for non-zombies. The pattern inverts under the SC definition. SC-classified zombies receive 0.25 million RMB against 0.55 million for non-zombies. SC flags firms that are loss-making but not subsidy-dependent. The benchmark flags firms whose survival depends on outsized support. Benchmark zombies are also smaller, younger, less R&D-intensive, and more leveraged than non-zombies.

4 Empirical Findings

4.1 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.

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

Here, $\text{Patent}_{i,t+1}$ denotes the number of patent applications filed by firm i in year $t+1$, and $\text{Zone}_{i,t-1}$ is an indicator for whether the firm is located in a development zone in year $t-1$. Zone status is lagged to $t-1$ because patent applications in $t+1$ reflect R&D effort undertaken earlier in the innovation pipeline. The relevant zone exposure is therefore the one that shaped the firm's R&D environment during the earlier period rather than the year the application is filed. Using a lagged zone indicator also breaks any contemporaneous correlation between zone membership and year-t shocks that could bias the coefficient. The vector $X_{i,t-1}$ includes lagged firm size and leverage. The specifications include firm fixed effects μ_i and 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. Standard errors are two-way clustered by firm and by administrative district $\times$ industry $\times$ year.

A natural concern is that firms with stronger innovation potential may self-select into development zones. We therefore combine OLS with propensity score matching (PSM) based on pre-entry characteristics, matching treated firms (those in SDZs or PDZs) to control firms outside development zones using 1:2 nearest-neighbor matching with replacement. Matching covariates include employment, workforce composition, balance sheet characteristics, firm age, leverage, revenue, export status, and profitability. Table D.1 shows that matching substantially reduces covariate differences across treatment and control groups. Firm age retains a small residual imbalance, which is absorbed either by firm fixed effects or by direct inclusion of firm age as a control in the regressions below.[12]

Despite large differences in subsidy intensity, innovation outcomes do not follow the same ranking. Table 5 reports the results. Entry into a development zone is associated with approximately a 9.4 percent increase in patent applications. The average hides a stark divergence across zone types. The SDZ coefficient is statistically indistinguishable from zero in every specification. The joint regression that includes both SDZ and PDZ indicators yields an SDZ coefficient of 0.051. The OLS restricted to SDZ firms and outside-zone firms yields 0.068. Propensity score matching on pre-entry observables yields 0.055. None of the three is statistically significant. The substantial public resources flowing to SDZs do not translate into measurable patenting gains once the comparison group is chosen carefully.

PDZs show the opposite pattern. Every specification returns a positive and significant coefficient. In the joint regression, PDZs generate roughly a 12.7 percent increase in patent applications, significant at the 1 percent level. The OLS restricted to PDZ firms and outside-zone firms yields 9.2 percent, significant at the 5 percent level. Propensity score matching yields 9.5 percent, significant at the 10 percent level. The three estimates are tightly clustered and describe a robust effect on innovation output. PDZs deliver a measurable increase in patenting despite receiving only a fraction of the subsidies that flow to SDZs.

Our findings speak to a broader debate over whether development zones primar-

[12] After discarding unmatched observations, the matched sample contains 82,515 firm-year observations. We restrict the estimation sample to firms that enter zones during the sample period and never exit (treated) and firms that remain outside throughout (control), yielding 37,159 firm-year observations for the main matched-sample analysis.

ily *select* productive firms or *foster* productivity after entry. Several studies emphasize selection (Fontagné et al., 2013; Yu and Wan, 2022), while others find fostering effects (Brandt et al., 2012; Criscuolo et al., 2019). Our results suggest that both mechanisms operate. PDZs exhibit fostering effects once observable selection is accounted for, whereas the higher SDZ innovation outcomes largely reflect pre-existing differences across firms.

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 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 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 high-performing and subsidy-dependent firms affects subsidy allocation and innovation inside zones.

4.2 Conceptual Framework and Predictions

We develop a simple model to organize the key mechanisms and guide the empirical analysis to explain the puzzle. The framework adapts Caballero et al. (2008) to a development zone setting where congestion operates through the subsidy budget, and adds a knowledge spillover channel.[13]

Setup

Consider a development zone z with a unit mass of firms. Each firm i has innovation productivity θ_i drawn from a zone-specific distribution $F_z(\theta)$ on $[0,1]$, and produces R&D output

$$y_i = \theta_i \cdot r_i^{\alpha} \cdot S_z^{\beta}, \qquad \alpha \in (0,1),\ \beta \geq 0, \tag{5}$$

[13]Our model is deliberately simple. We do not attempt to characterize optimal policy, as in Akcigit et al. (2022), or to quantify aggregate productivity losses, as in Gao (2025). The goal is to generate testable predictions about the consequences of zombie congestion under the existing allocation regime within development zones.

where $r_i = \theta_i w + s_i$ is total R&D investment (own resources $\theta_i w$ plus government subsidy s_i), and

$$S_z = \int_0^1 \theta_j \, r_j \, dj$$

is the quality-weighted R&D activity in the zone, capturing knowledge spillovers among co-located firms. The zone serves as both the *budget unit*: each zone administrator allocates a fixed subsidy budget B_z, and the *spillover boundary*: co-location and shared infrastructure concentrate knowledge flows within the zone.[14] When $\beta = 0$, spillovers are shut down and the model reduces to a pure budget-congestion framework.

The administrator observes a noisy signal $\sigma_i = \theta_i + \eta_i$ of each firm's productivity and allocates subsidies proportionally to the signal:

$$s_i^* = \frac{\sigma_i}{\int_0^1 \sigma_j \, dj} \cdot B_z.$$

This merit-based benchmark corresponds to our LASSO-predicted subsidy in Section 3.3. A fraction λ_z of firms are *zombies*: low-productivity firms ($\theta_i < \bar{\theta}$) that receive excess support $e > 0$ beyond the formula due to screening errors. Because the budget is fixed, excess support to zombies crowds out non-zombie allocations:

$$s_i^{nz} = s_i^* - \frac{\lambda_z \, e}{1 - \lambda_z}. \tag{6}$$

The second term is the per-capita crowding-out: each non-zombie firm's subsidy is reduced by the total excess absorbed by zombies, $\lambda_z e$, spread across the $1 - \lambda_z$ non-zombie firms.

Congestion: Two Reinforcing Channels

Substituting (6) into (5), a non-zombie firm's innovation output is $y_i^{nz} = \theta_i \left(r_i^{nz}\right)^\alpha \cdot S_z(\lambda_z)^\beta$. Taking the total derivative with respect to the zombie share:

$$\frac{d\, y_i^{nz}}{d\, \lambda_z} = \underbrace{\alpha \, \theta_i \, (r_i^{nz})^{\alpha-1} \, S_z^\beta \cdot \left(- \frac{e}{(1-\lambda_z)^2} \right)}_{\text{Channel 1: budget congestion } (<0)} + \underbrace{\beta \, \theta_i \, (r_i^{nz})^\alpha \, S_z^{\beta-1} \cdot \frac{dS_z}{d\lambda_z}}_{\text{Channel 2: spillover degradation } (<0)} < 0. \tag{7}$$

Channel 1 is the direct budget effect: zombies absorb subsidies, reducing non-zombie R&D investment. Channel 2 is indirect: zombies contribute low-quality R&D to the

[14] The agglomeration rationale for development zones implies that co-located firms benefit from each other's R&D activities. The quality weighting in S_z reflects the insight from the optimal R&D policy literature (Akcigit et al., 2022) that the social return to innovation depends on firm productivity: high-productivity firms generate richer spillovers per unit of R&D investment.

spillover pool (θ^z is low even though r^z is inflated by excess support) while crowding out high-quality R&D from productive firms, degrading S_z.[15] Both channels are negative and reinforce each other, yielding three predictions.

Testable Implications

P1 (Composition). The zombie share λ_z is increasing in the subsidy budget B_z and decreasing in governance quality, which determines both the screening error rate and the excess support e per misclassified firm. Zones with larger budgets can sustain more low-θ firms at any given screening accuracy, and zones with weaker oversight both misclassify more firms and extend e for each one. We map this to the data by treating state-designated zones as the high-B_z, looser-governance regime and province-designated zones as the low-B_z, tighter-governance regime, predicting $\lambda_{SDZ} > \lambda_{PDZ}$. This mapping yields two testable implications: the gap should survive matching on pre-entry firm observables, since it is driven by the policy environment rather than by $F_z(\theta)$, and exogenous tightening of governance within a zone should reduce λ_z.

P2 (Scrambling). Non-zombie innovation is strictly decreasing in the zombie share: $dy_i^{nz}/d\lambda_z < 0$. Two channels reinforce each other. Through the budget channel, zombies absorb excess support $\lambda_z e$ from a fixed pool and reduce the subsidy available to each non-zombie by $\lambda_z e/(1-\lambda_z)$. Through the spillover channel, zombies contribute low-quality R&D to the quality-weighted pool S_z while displacing the high-quality R&D of the non-zombies they crowd out. Both channels lower non-zombie innovation output, and neither can reverse sign under the model's assumptions.

P3 (Heterogeneous congestion). The congestion effect is larger for more productive non-zombies. Under merit-based allocation $s_i^* = \sigma_i / \int \sigma_j \, dj \cdot B_z$, high-$\theta$ firms receive larger subsidies because their signals are higher on average. When zombies absorb excess support $\lambda_z e$ from the fixed budget, the allocations that are displaced would have gone disproportionately to high-θ firms. These are also the firms whose marginal R&D projects have the largest private returns and contribute the most to the spillover pool S_z. The innovation loss from zombie congestion therefore falls on firms with the largest stake in the subsidy they lose and the largest contribution to the knowledge pool they degrade.

[15] The result follows because the quality-weighted R&D contribution of a zombie ($\theta^z \cdot r^z$, with $\theta^z < \bar{\theta}$) is less than that of the non-zombie it displaces, and the remaining non-zombies each contribute less due to increased crowding out.

Discussion

Our framework relates to several literatures. The congestion structure follows Caballero et al. (2008), but operates through a *fixed subsidy budget* rather than factor market competition and adds a spillover channel specific to the development-zone setting. The spillover channel draws on insights from the optimal R&D policy literature. Akcigit et al. (2022) show that the optimal R&D subsidy is nonlinear, because R&D generates non-internalized spillovers and high-productivity firms already have high private returns. In our setting, zone administrators use a roughly linear allocation formula, which is already suboptimal relative to their benchmark. Zombies exacerbate the distortion by absorbing budget that a well-designed scheme would direct toward high-productivity, high-spillover firms.

5 Firm Composition and Spillovers inside Development Zones

This section examines whether the policy environment in development zones systematically shapes the composition of firms the zones host. Section 5.1 tests the first prediction of the framework directly: whether SDZs sustain more zombie firms than PDZs, and whether the gap survives matching on pre-entry firm observables. Section 5.2 then tests the second and third predictions, which concern how zombie prevalence within a zone affects the innovation outcomes of non-zombie firms.

5.1 Firm Composition: Zombie Formation

We test the composition prediction directly by examining whether zone-location affects the probability that a firm is classified as a zombie in the current year. Under P1, SDZs should sustain more zombies than PDZs, and the gap should survive matching on pre-entry firm observables because it is driven by the policy environment rather than by the distribution of firms the zone draws from.

Table 6 reports the results. Firms located in any development zone at $t-1$ are 1.3 percentage points more likely to be classified as zombies in year t, significant at the 1 percent level. The pooled effect masks a sharp divergence between the two zone types. In SDZs, the OLS coefficient is 2.4 percentage points and significant at the 1 percent level. Restricting the sample to SDZ versus outside-zone firm-years yields a similar estimate of 2.2 percentage points. After propensity score matching on pre-entry observables, the coefficient falls to 1.4 percentage points and remains significant at the 5 percent level. The reduction under matching is substantial. Roughly 40 percent of the raw SDZ-zombie correlation reflects selection on firm observables. Against a baseline zombie rate of 35 percent, the 1.4 percentage point environment effect translates to a roughly 4 percent relative increase in zombie probability attributable to the SDZ environment.

PDZs show a contrasting pattern. The OLS coefficient is only 0.4 to 0.5 percentage points and statistically indistinguishable from zero in every specification, whether in the joint regression, the PDZ-versus-outside subsample, or under propensity score matching. Firms in PDZs are no more likely to become zombies than firms outside development zones once the policy comparison is drawn cleanly. In contrast to SDZs, PDZ membership does not raise the probability of becoming a zombie.

The asymmetry between SDZs and PDZs is the central test of P1. Both zone types draw firms from the same underlying population of Shanghai technology enterprises, yet only SDZs generate a detectable environment effect on zombie formation. The pattern maps to the model's primitives. SDZs combine larger subsidy budgets with weaker oversight, so both the screening-error rate and the excess support per misclassified firm are higher. The LASSO benchmark captures this by flagging firms whose subsidies exceed what their observable innovation characteristics would predict, and the PSM exercise shows that the SDZ effect survives after firms with comparable pre-entry characteristics are matched. PDZs, with smaller budgets and tighter oversight, do not generate zombies beyond what their firm mix already implies.

5.2 Spillovers within Development Zones

Section 3.3 showed that zombies absorb a disproportionate share of public support. We now test P2. If this allocation distortion has real consequences, non-zombie innovation should decline when the local zombie share rises. We follow Caballero et al. (2008) in testing this prediction through firm-level regressions that interact non-zombie status with the local zombie share.

We regress a firm's innovation outcome on a *NonZombie* indicator, the lagged zombie share in the firm's zone-district $\times$ broad industry cell, and their interaction. The zombie share is constructed leave-one-out so that firm i's own classification does not enter the cell share it faces. All specifications absorb zone-district fixed effects and 3-digit industry $\times$ year fixed effects. Standard errors are two-way clustered by firm and by zone-district $\times$ year.

The interaction coefficient is the test of P2 and the only coefficient we interpret directly. The level terms on *NonZombie* and *ZombieShare* capture a mix of sample composition and the direct effect of zombie absorption on zombies themselves. Zombies receive outsized subsidies by construction, so their R&D and patent outcomes may be mechanically elevated in some specifications. This makes the main effects difficult to sign ex ante. The interaction is free of this concern. A negative interaction says that non-zombie innovation falls more steeply with the local zombie share than zombie innovation does, which is the differential response predicted by the crowd-out mechanism.

A natural alternative interpretation is that a high zombie share proxies for unobserved cell-level conditions that depress innovation generally. If that were the full story, zombies and non-zombies should respond similarly to the zombie share, and the interaction coefficient should be near zero. A significantly negative interaction indicates that non-zombies respond differently from zombies in the same cell, which is the signature of congestion rather than a common cell-level shock.

Panel A of Table 7 reports the pooled in-zone results. A 10-percentage-point increase in the cell zombie share is associated with approximately 10.7 percent lower R&D expenditure, 3.8 percent fewer patent applications, and 1.5 percent smaller R&D staff for non-zombies relative to zombies. The magnitudes rank intuitively. Discretionary R&D spending responds most strongly because it is the margin firms adjust first when facing fiscal tightening. Patent applications respond about a quarter as much, reflecting the lag between reduced R&D inputs and measurable innovation output. R&D personnel show the smallest response because headcount adjusts slowly. All three coefficients are statistically significant and consistent with P2. The pattern survives progressively more demanding fixed-effect structures that absorb zone conditions and industry-year shocks, reported in Appendix Table D.2.

Panels B and C test whether the pattern differs across zone types. The SDZ congestion effect is about 2.5 times the PDZ effect on R&D expenditure and about 1.6 times on patents. A 10-percentage-point increase in the cell zombie share is associated with 14.9 percent lower R&D expenditure and 4.6 percent fewer patents for SDZ non-zombies. The corresponding effects in PDZs are 5.9 percent lower R&D expenditure and 2.8 percent fewer patents. The severity ranking maps directly to the severity of the underlying allocation distortion documented in Section 3.3. SDZs have both a larger zombie share and a larger mismatch index, so the fiscal pressure on non-zombies is more intense. The R&D staff interaction is not significantly different from zero in either zone-split panel, consistent with the small pooled coefficient being undetectable in reduced sample sizes.

The sample-mean cell zombie share is 35 percent. For a non-zombie firm in a cell at the sample mean, the pooled estimates imply roughly 38 percent lower R&D expenditure and 13 percent fewer patents than a counterfactual firm in a zombie-free cell. In SDZs specifically, the same non-zombie would have 52 percent lower R&D expenditure and 16 percent fewer patents. The innovation footprint of zombie congestion is first-order, and it is concentrated on firms that the measure classifies as viable. These magnitudes are equilibrium correlations within zones rather than causal spillovers, but the differential response between zombies and non-zombies, together with the stability across specifications in Appendix Table D.2, makes alternative interpretations difficult to sustain.

5.3 Heterogeneous Spillover Effects by Firm Productivity

The spillover results in Section 5.2 established that non-zombie innovation falls with the local zombie share. P3 predicts that this congestion effect falls disproportionately on high-productivity non-zombies because they are the firms merit-based allocation would have funded. When zombies absorb excess support from the fixed budget, the displaced allocation would have flowed mostly to firms at the top of the productivity distribution. These are the firms whose marginal R&D projects have the largest private returns, and these are the firms that contribute most to the local knowledge pool. The crowd-out from zombie congestion should therefore land on them.

We estimate the spillover regression with a triple interaction, $HighTFP_{it}$ equals one for non-zombie firms above the median TFP in their 3-digit industry-year cell. TFP is the residual from a regression of log total revenue on log total assets and log employment. The coefficient on the triple interaction is the test of P3. A negative coefficient indicates that high-TFP non-zombies bear more of the congestion cost than low-TFP non-zombies. The fixed-effect and clustering structure matches Table 7.

Table 8 reports the results. The double interaction $NonZombie \times ZombieShare$, which measures the spillover effect for low-TFP non-zombies, is essentially zero on all three outcomes: 0.189 on R&D expenditure, 0.003 on patents, and 0.020 on R&D staff. None is statistically distinguishable from zero. The triple interaction is sharply negative and significant on two of the three outcomes: -2.856 on R&D expenditure and -0.835 on patents, both at the 5 percent level. The staff triple is -0.596 and not statistically distinguishable from zero, consistent with headcount being the slowest-adjusting margin as in Section 5.2.

The aggregate spillover effects reported in Section 5.2 therefore mask sharp heterogeneity. A 10 percentage point increase in the local zombie share leaves low-TFP non-zombies essentially unchanged. The same 10 percentage point increase reduces high-TFP non-zombies' R&D expenditure by roughly 27 percent and their patent applications by roughly 8 percent. The burden of zombie congestion falls almost entirely on the upper half of the productivity distribution.

The full coefficient pattern reinforces a redistribution interpretation. The coefficient on $ZombieShare \times HighTFP$ is positive and significant on R&D expenditure (2.010) and patents (0.733). This is the effect of zombie share on high-TFP zombies. High-productivity zombies increase their R&D and patent output when the local zombie share rises, which is consistent with them absorbing a growing share of the excess subsidy flow. Combined with the negative triple, the table describes a reallocation: when zombie share rises, resources flow from high-TFP non-zombies to high-TFP zombies. Low-productivity firms on both sides are largely unaffected. The subsidy budget is redistributed across the productive half of the firm distribution, not evenly across all firms.

P3 is supported for innovation outcomes where the firm has active adjustment margin. R&D expenditure and patents respond strongly to the triple. R&D staff, which adjusts on a slower timescale, does not. More importantly, the concentration of the congestion effect on high-TFP non-zombies sharpens the welfare implication of zombie persistence. The firms displaced are precisely the ones whose marginal R&D dollar would have generated the largest private returns and the strongest contribution to local spillovers. Zombie congestion is not a uniform tax on non-zombie innovation. It is a selective redistribution that removes resources from the most productive firms in each zone, magnifying the misallocation documented in Section 3.3.

For completeness, Appendix Table D.3 reports the same specification with firm size (log total assets) replacing TFP. Size-based heterogeneity is weaker on innovation outcomes, where baseline R&D activity differs systematically across the size distribution and produces margin-of-adjustment differences rather than a single directional effect. Size-based heterogeneity does appear on real-economy outcomes, reported in Appendix Table D.4: small firms bear larger crowd-out on asset growth and employment growth, while large firms show no comparable response. The contrast suggests that different firms absorb the congestion cost on different margins. Productive firms adjust R&D and small firms adjust scale. The redistribution documented in Table 8 operates on the innovation margin.

6 Policy Upgrading and the Governance Channel

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 within a zone can mitigate zombie misallocation, improve within-zone spillovers, and raise the innovation returns to place-based policy.

6.1 Background and Scope of the Experiment

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. 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. SDZ status comes with stronger regulatory authority, including more frequent audits, stricter monitoring of firms receiving public support, and tighter screening of new entrants. Upgrading can also change how fiscal and administrative resources are allocated within the zone by strengthening oversight and shifting support toward firms with higher innovation potential. If governance frictions are a key source of zombie persistence, upgrading should reduce zombie prevalence, reallocate resources toward higher-return firms, and improve innovation outcomes.

The upgrading experiment is complementary to the cross-sectional evidence of Section 5 rather than a substitute for it. The cross-sectional SDZ sample used in earlier sections includes zones at widely different maturities: several are state-level since the 1980s or early 1990s, and their current operation reflects decades of accumulated policy history. The composition and spillover tests in Section 5 characterize this full population. The upgrading experiment, by contrast, exploits within-zone variation from a specific governance shock applied to a subset of PDZs during our sample period. As we document below, the fiscal injection that accompanies upgrading is transient: ongoing subsidy flows to upgraded zones do not remain elevated beyond the transition year. This feature is an advantage for identification. It allows us to isolate the governance channel of P1 from the budget channel, observing what happens when regulatory scrutiny tightens without a corresponding permanent expansion of fiscal support.

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.

Zone-level composition. We first ask whether upgrading reshapes the zone's mix of firms. We estimate the difference-in-differences specification

$$Y_{zt} = \alpha + \beta \,\text{Regulation}_{zt} + X'_{zt}\theta + \lambda_z + \delta_t + \varepsilon_{zt}, \tag{8}$$

where Y_{zt} is the within-zone zombie share and Regulation_{zt} equals one for zone-years after zone z is upgraded to state-level status. The specification includes zone fixed effects, year fixed effects, and zone-level controls. We complement the DiD with an event-study specification:

$$Y_{zt} = \alpha + \sum_{k \neq -1} \beta_k \mathbf{1}\{t - T_z = k\} + \lambda_z + \delta_t + \varepsilon_{zt}, \tag{9}$$

where T_z is the upgrade year for zone z and $k = -1$ is the omitted reference period.

Table 10 reports the results. Column (1) shows the zone-level event study on the zombie share. The pre-upgrade coefficient at $k = -2$ is -0.010 and statistically insignificant, supporting parallel trends. Post-upgrade coefficients are negative at every horizon and grow over time. The effect reaches -5.7 percentage points at year 3 and -7.5 percentage points at year 5, the latter significant at the 5 percent level. It is consistent with a process in which tighter screening and oversight progressively reduce the survival margin for subsidy-dependent firms.

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

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

where X_{izt} contains the same firm-level controls as the baseline. The specification includes firm fixed effects, zone fixed effects, and industry-year fixed effects, absorbing time-invariant firm heterogeneity, permanent differences across zones, and common industry-year shocks. We again complement this with an event-study analogue. Standard errors are clustered at the zone level.

The four firm-level outcomes respond to strikingly different time paths. R&D subsidies jump sharply in the upgrade year with a coefficient of 1.31, significant at the 5 percent level. The magnitude indicates a large one-time fiscal injection tied to the administrative transition itself. The coefficient reverts to baseline in every subsequent year. Upgraded zones do not maintain elevated subsidy flows beyond the upgrade event. Internal R&D expenditure, by contrast, jumps at $k = 0$ with a coefficient of 1.67

and remains elevated at 0.73 to 0.76 through year 4, a sustained increase of roughly 100 percent above the pre-upgrade baseline. R&D personnel shows a parallel shape: a jump of 0.71 at the upgrade year and a persistent elevation of 0.16 to 0.21 in years 2 through 4, or roughly 15 to 20 percent above baseline. Patent applications respond more slowly. Only the year-3 coefficient of 0.174 reaches conventional significance, implying approximately a 19 percent increase in patent applications three years after upgrading. The lag is consistent with the typical delay between R&D investment and patentable output.

The contrast between the subsidy response and the private R&D response is central to interpreting the experiment. If upgrading operated through a permanent expansion of fiscal support, every firm-level outcome would remain elevated throughout the post-upgrade period. The subsidy coefficient instead dies at $k = 1$, while firms sustain their own R&D spending and research staffing for four years without any ongoing top-up from the zone. Firms respond to the governance change by investing more of their private resources in research rather than by absorbing more public support. Innovation output follows the input response with the typical lag between R&D spending and patentable output.

By year 5, all four firm-level coefficients fade while the zone-level zombie share reaches its largest reduction. The pattern does not mean the upgrade effect unwinds. Firms complete their year-over-year adjustment to the new policy environment within four years, reaching a steady state at which treated and control groups no longer diverge in annual changes. The stock of zombies continues to decline because the flow of new zombie classifications in upgraded zones remains below the control-zone flow throughout the post-upgrade period. The zone-level accumulation effect and the firm-level transition effect describe two sides of the same adjustment.

The upgrading results isolate the governance channel of P1. Because the subsidy injection is transient, the experiment is not a test of what happens when a zone receives permanently larger fiscal support. It is a test of what happens when regulatory scrutiny tightens. Under this regime, zombie prevalence declines progressively, non-zombie firms raise their private R&D spending by roughly 100 percent, research staffing rises 15 to 20 percent, and patent output rises modestly with the expected delay. These gains occur without corresponding expansions of public subsidy flow. Combined with the cross-sectional evidence in Section 5, where mature SDZs with both high budgets and comparatively loose governance sustain more zombies than PDZs, the two analyses point to a consistent conclusion. The binding constraint on development-zone performance is the quality of subsidy allocation, not the size of the subsidy pool.

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 detectable causal effect on patenting at the firm level. The PDZ effect on patenting is robust across specifications at 9 to 13 percent, while the SDZ coefficient is statistically indistinguishable from zero in every specification we estimate. 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. The SDZ-zombie relationship survives matching on pre-entry firm observables, indicating an environment effect rather than selection alone.

Second, zombie prevalence within a zone has first-order consequences for non-zombie innovation. A 10 percentage point increase in local zombie share is associated with 10.7 percent lower R&D expenditure and 3.8 percent fewer patents among non-zombies. The congestion effect is concentrated on the productive half of the firm distribution. High-productivity non-zombies bear nearly the entire crowd-out on innovation inputs and patenting, while low-productivity non-zombies are essentially unaffected. The pattern is consistent with zombies absorbing budget that merit-based allocation would have directed to the firms with the largest private returns to R&D and the strongest contributions to local knowledge spillovers.

Third, the upgrading experiment isolates the governance channel of this distortion. Upgrading raises regulatory scrutiny without providing sustained increases in subsidy flow: the fiscal injection at the transition year is a one-time event, not a permanent expansion. Under this regime, zombie prevalence declines progressively over time, reaching a reduction of 7.5 percentage points five years after upgrading. Firms in upgraded zones roughly double their private R&D spending and expand research staffing by 15 to 20 percent for four consecutive years, without ongoing subsidy top-ups. Patent output rises more slowly, consistent with the typical lag between R&D investment and measurable innovation.

Taken together, the results imply that the binding constraint on development-zone performance is the quality of subsidy allocation, not the size of the subsidy pool. Mature SDZs pair high budgets with comparatively loose governance and sustain more zombies as a result. The upgrading experiment shows that tightening governance without raising budgets to SDZ levels is sufficient to reduce zombies and induce firms to invest more of their own resources in innovation. Place-based industrial 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 public R&D spending.

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Main Figures

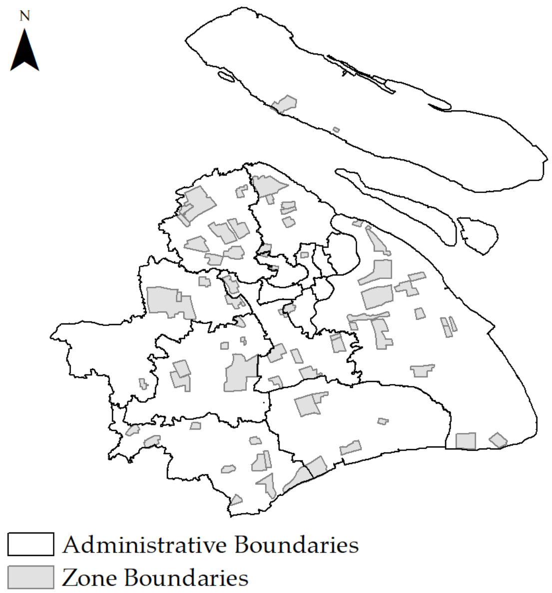

Figure 1: Development zones in Shanghai

Notes: This figure shows the geographic distribution of state-designated zones (SDZs, dark shading) and province-designated zones (PDZs, light shading) in Shanghai. Zone boundaries are obtained from official GIS shapefiles.

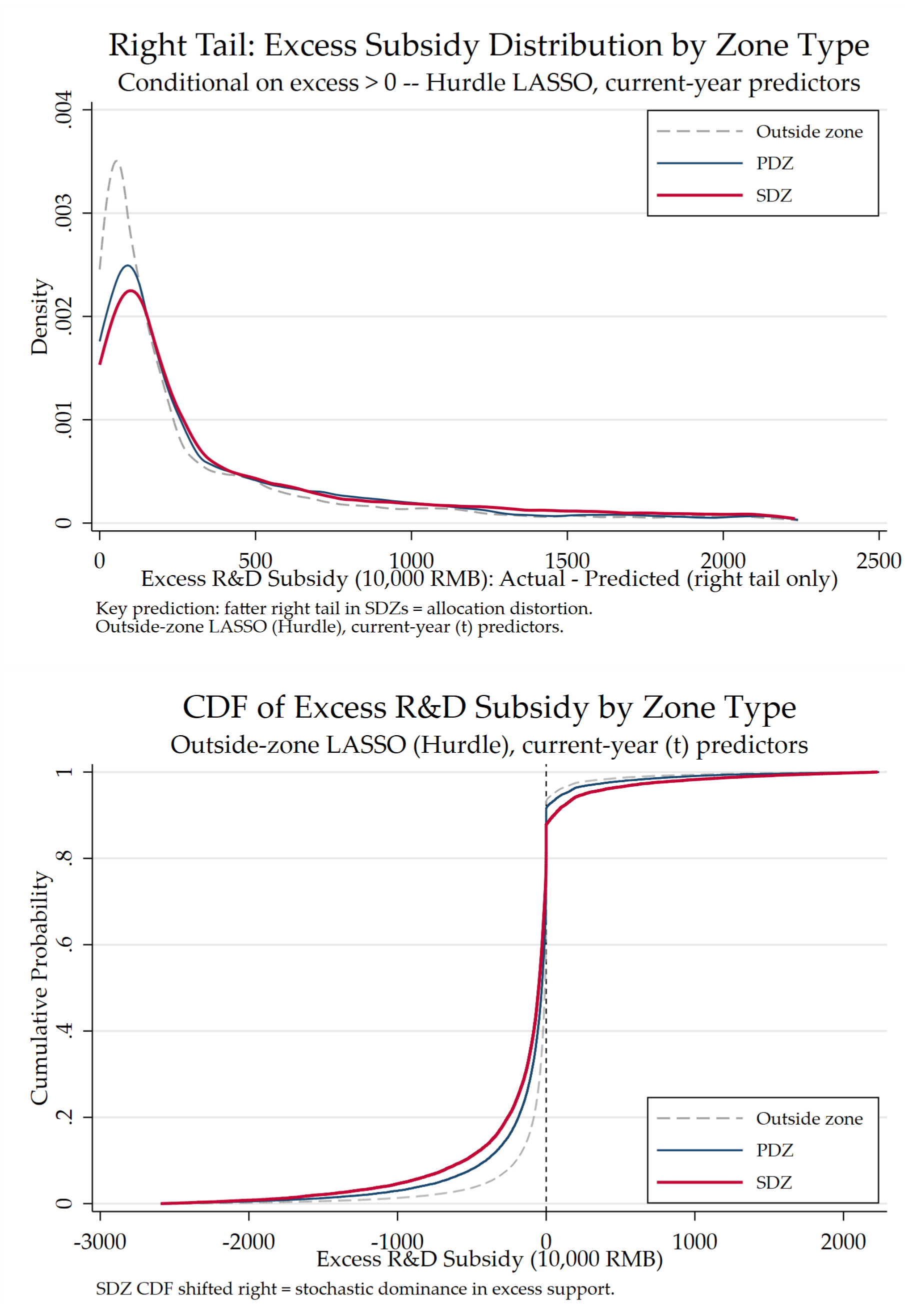

Figure 2: Distribution of excess R&D subsidies by zone type

Notes: This figure plots the distribution of excess R&D subsidies (actual minus LASSO predicted, in 10,000 RMB) by zone type. The LASSO is trained on outside-zone firms using current-year (t) predictors under the hurdle benchmark (two-stage LASSO with Duan smearing correction). Panel A shows kernel densities conditional on positive excess; Panel B shows empirical CDFs. The SDZ distribution has a markedly fatter right tail: at the 95th percentile, excess support reaches 787.9 in SDZs versus 171.1 in PDZs and 74.4 in outside zones, and 4.5% of SDZ firm-years exceed a subsidy of 1,000 (10,000 RMB) above the merit-based benchmark versus 1.8% in PDZs and 1.3% outside. Kolmogorov–Smirnov tests reject equality of distributions for SDZ vs. PDZ ($D = 0.085$) and SDZ vs. outside ($D = 0.230$), both with $p < 0.001$.

Main Tables

Table 1: Variables and summary statistics

Variables	Obs.	Mean	S.D.	P10	P50	P90
Patent Measures						
Patent	178,510	2.023	15.634	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
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
Gov_Sub	178,517	0.533	18.372	0.000	0.000	0.050
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

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 an 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: R&D subsidy allocation by zone type

Panel A. Policy intensity across zones	Obs.	Mean	S.D.	P10	P50	P90
Government R&D subsidy (mil RMB)						
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	13,071	4.379	56.771	0.020	0.200	2.450
Effective 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	113,279	0.056	0.087	0.000	0.034	0.117

Panel B. Subsidies relative to firm R&D	Obs.	Mean	P50	P75	P90
R&D subsidy / R&D expenditure ratio					
SDZs	17,248	0.080	0.000	0.000	0.167
PDZs	19,287	0.055	0.000	0.000	0.077
Outside	76,358	0.066	0.000	0.000	0.088
R&D subsidies >0 while R&D expenditures $=0$					
SDZs	21,741	2.10%			
PDZs	28,275	1.33%			
Outside	128,501	0.69%			

Panel C. Excess R&D subsidy distribution	Obs.	Mean	P25	P50	P75	P90
Excess subsidy (mil RMB)†						
SDZs	20,816	0.632	−0.203	−0.050	−0.002	0.129
PDZs	26,015	−0.108	−0.141	−0.030	−0.001	0.000
Outside	119,154	0.090	−0.060	−0.009	−0.000	0.000
% of firms with excess subsidy >0						
SDZs	20,816	14.4%				
PDZs	26,015	9.2%				
Outside	119,154	7.3%				

Notes: (1) Panel A reports the distribution of government R&D subsidies conditional on receipt, by zone type. The share of firms receiving subsidies is 20.3% in SDZs, 12.7% in PDZs, and 10.2% outside zones. The effective tax rate row is computed on the full SSTE sample of firms with positive revenue; tax rate is defined as total taxes paid divided by total revenue. (2) Panel B reports the ratio of R&D subsidies to internal R&D expenditure, conditional on positive R&D (winsorized at the 0.1% level); the second sub-block reports the share of firms receiving subsidies while reporting zero R&D expenditure. (3) Panel C reports the distribution of excess R&D subsidies, defined as the difference between actual R&D subsidy receipt and its LASSO-predicted value. The LASSO is estimated on outside-zone firms using current-year predictors under the hurdle specification described in Section 3.3. (4) All monetary values are in millions of RMB. Panel A and B statistics are computed on the full sample (N = 178,517 firm-years); Panel C is computed on the LASSO prediction sample (N = 169,696 firm-years, partitioned by zone in the table).

Table 3: Zombie classification: prevalence and persistence across definitions

	Benchmark	SC	FK
Panel A. Zombie prevalence (%)			
All zones	35.0	42.4	44.2
SDZ	36.3	44.5	47.4
PDZ	30.3	36.6	38.1
SDZ − PDZ gap	+6.0	+7.9	+9.3
Panel B. Zombie persistence (%)			
One-year: $P(\text{zombie}_{t+1} \mid \text{zombie}_t)$			
All zones	65.4	70.0	70.3
SDZ	66.6	68.6	69.7
PDZ	65.0	68.2	68.6
SDZ − PDZ gap	+1.6	+0.4	+1.1

Notes: (1) This table compares zombie prevalence and persistence across three definitions of zombie firms. (2) The Benchmark definition classifies a firm as a zombie if its pre-tax profit (EBIT) minus the LASSO-predicted excess R&D subsidy is non-positive (Equation 1), using the hurdle-LASSO specification. (3) Panel A reports zombie prevalence, defined as the share of firm-year observations classified as zombies, within the LASSO prediction sample (N = 169,696). (4) Panel B reports one-year transition probabilities, defined as the probability that a zombie at t is also a zombie at t+1, estimated on the sub-sample of firms observed in both t and t+1. Firm-years without a t+1 observation are excluded because non-appearance at t+1 may reflect survey coverage rather than firm exit. (5) Restricting the sample to zone-stable firm-years (zone unchanged from t to t+1) changes all reported persistence rates by less than 0.2 percentage points.

Table 4: Composition of firms, innovation, and subsidies by zone type

	SDZ			PDZ		
	Stars	Zombie	Middle	Stars	Zombie	Middle
Panel A. Benchmark zombie definition						
% of firms	13.1	35.6	49.3	11.2	29.7	57.2
% inv. patents	22.1	23.8	53.7	28.6	20.5	49.8
% total patents	22.8	22.9	53.8	25.5	16.8	57.0
% R&D expend.	14.5	14.4	70.7	23.2	10.6	65.9
% subsidies	16.1	62.1	21.6	34.0	37.0	28.7
Mismatch index		2.61			1.80	
N	2,784	7,561	10,473	2,962	7,870	15,185
Panel B. SC zombie definition						
% of firms	13.1	41.7	45.2	11.2	35.1	53.8
% inv. patents	22.1	19.9	58.0	28.6	21.1	50.3
% total patents	22.8	20.1	57.1	25.5	17.5	57.0
% R&D expend.	14.5	13.5	72.0	23.2	12.3	64.5
% subsidies	16.1	13.1	70.8	34.0	20.7	45.4
Mismatch index		0.66			0.98	
N	2,784	8,871	9,603	2,962	9,303	14,260
Panel C. FK zombie definition						
% of firms	13.1	44.0	42.9	11.2	36.4	52.4
% inv. patents	22.1	26.4	51.5	28.6	23.0	48.4
% total patents	22.8	25.5	51.7	25.5	18.8	55.7
% R&D expend.	14.5	16.1	69.4	23.2	13.1	63.7
% subsidies	16.1	64.2	19.7	34.0	38.2	27.8
Mismatch index		2.43			1.66	
N	2,784	9,346	9,128	2,962	9,665	13,898

Notes: (1) This table decomposes firms, patents, R&D expenditures, and subsidies into three mutually exclusive firm types, separately for SDZs and PDZs and for each of three zombie definitions. (2) Stars are firms ever certified as "Little Giants" by the Shanghai Municipal Government. Zombies in Panel A follow the benchmark definition (Equation 1); in Panel B they follow the SC definition (Equation 2); in Panel C they follow the FK definition (Equation 3). In Panels B and C, a firm satisfying both the Little Giant criterion and the zombie criterion is classified as a Star, so Stars and Zombies remain mutually exclusive within the table. Middle firms are the remainder. (3) Each cell reports the share (in percent) of the zone's firm-years, invention patent applications, total patent applications, internal R&D expenditures, or government R&D subsidies, summed over the 2008–2018 sample period. Total patent applications is the sum of invention, utility model, and design patent applications. Rows sum to 100% within each zone $\times$ panel block (small rounding residuals apply). (4) The mismatch index equals the Zombie subsidy share divided by the Zombie invention patent share; values above one indicate that zombies absorb a disproportionate share of subsidies relative to their share of invention output. (5) All panels use the LASSO prediction sample (N = 169,696 firm-years); approximately 2% of firm-years in Panel A are further excluded due to missing benchmark-zombie classification.

Table 5: Effects of development zones on innovation

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_{t-1}	0.094**					
	(0.037)					
SDZ_{t-1}		0.051	0.068	0.055		
		(0.053)	(0.056)	(0.064)		
PDZ_{t-1}		0.127***			0.092**	0.095*
		(0.045)			(0.046)	(0.057)
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	73,505	22,394	75,430	26,690
R^2	0.707	0.707	0.711	0.744	0.714	0.741

Notes: (1) The dependent variable is the inverse hyperbolic sine of the number of patent applications filed by the firm in year $t+1$. (2) DZ_{t-1} is an indicator equal to one if the firm is located in any development zone in year $t-1$; SDZ_{t-1} and PDZ_{t-1} are analogously defined for state-level and province-level zones. (3) Columns 1–2 use the full sample; columns 3–4 restrict to SDZ versus outside-zone firm-years (excluding PDZs); columns 5–6 restrict to PDZ versus outside-zone firm-years (excluding SDZs). Columns 4 and 6 apply PSM weights estimated on firm-level covariates. (4) All specifications include firm-level controls (lagged log employment and debt-to-assets ratio), firm fixed effects, and administrative district $\times$ industry $\times$ year fixed effects. (5) Standard errors are two-way clustered by firm and by administrative district $\times$ industry $\times$ year. (6) Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 6: Effects of development zones on zombie formation

D.V.	Identified as zombie in year t					
	All zones		State-level Zones		Prov.-level Zones	
Est.	OLS	OLS	OLS	PSM	OLS	PSM
	(1)	(2)	(3)	(4)	(5)	(6)
DZ_{t-1}	0.013***					
	(0.004)					
SDZ_{t-1}		0.024***	0.022***	0.014**		
		(0.005)	(0.005)	(0.006)		
PDZ_{t-1}		0.004			0.005	0.004
		(0.005)			(0.005)	(0.006)
Firm-level controls	YES	YES	YES	YES	YES	YES
District FE	YES	YES	YES	YES	YES	YES
Ind. $\times$ Year FE	YES	YES	YES	YES	YES	YES
Obs.	99,724	99,724	83,959	32,346	86,391	37,626
R^2	0.106	0.106	0.101	0.112	0.104	0.117

Notes: (1) The dependent variable is an indicator equal to one if the firm is classified as a benchmark zombie in year t, defined as pre-tax profit minus the LASSO-predicted excess R&D subsidy being non-positive, with Little Giant firms assigned as non-zombies by construction. (2) DZ_{t-1} is an indicator equal to one if the firm is located in any development zone in year $t-1$; SDZ_{t-1} and PDZ_{t-1} are analogously defined for state-level and province-level zones. (3) Columns 1–2 use the full sample; columns 3–4 restrict to SDZ versus outside-zone firm-years (excluding PDZs); columns 5–6 restrict to PDZ versus outside-zone firm-years (excluding SDZs). Columns 4 and 6 apply PSM weights estimated on firm-level covariates. (4) All specifications include firm-level controls (lagged log employment, debt-to-assets ratio, and current firm age), administrative district fixed effects, and industry $\times$ year fixed effects. The specification does not include firm fixed effects because P1 predicts cross-firm variation in zombie propensity rather than within-firm changes. (5) Standard errors are clustered at the administrative district $\times$ industry $\times$ year level. (6) Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 7: Impact of zombie firms on the innovation input and output of non-zombies

D.V.	R&D Exp.	R&D Staff	Patent
Panel A. Pooled in-zone sample			
$NonZombie_{i,t}$	0.565***	0.196***	0.216***
	(0.111)	(0.029)	(0.034)
$ZombieShare_{z,t-1}$	0.381	0.068	0.143*
	(0.327)	(0.071)	(0.081)
$NonZombie \times ZombieShare$	−1.074***	−0.152**	−0.376***
	(0.355)	(0.069)	(0.089)
Obs.	27,698	27,698	27,698
R^2	0.741	0.830	0.461
Panel B. SDZs only			
$NonZombie_{i,t}$	0.674***	0.203***	0.243***
	(0.196)	(0.059)	(0.055)
$ZombieShare_{z,t-1}$	0.616*	0.114	0.247*
	(0.363)	(0.145)	(0.148)
$NonZombie \times ZombieShare$	−1.489**	−0.187	−0.457***
	(0.602)	(0.135)	(0.142)
Obs.	12,770	12,770	12,770
R^2	0.721	0.821	0.492
Panel C. PDZs only			
$NonZombie_{i,t}$	0.478***	0.165***	0.191***
	(0.105)	(0.032)	(0.042)
$ZombieShare_{z,t-1}$	0.031	−0.029	0.039
	(0.367)	(0.082)	(0.098)
$NonZombie \times ZombieShare$	−0.589*	−0.035	−0.279**
	(0.333)	(0.083)	(0.114)
Obs.	14,836	14,836	14,836
R^2	0.763	0.841	0.451
Firm-level controls	YES	YES	YES
Zone-level controls	YES	YES	YES
Zone FE	YES	YES	YES
Ind. × Year FE	YES	YES	YES

Notes: (1) Dependent variables in year t are the inverse hyperbolic sine of firm R&D expenditure, R&D personnel, and total patent applications. (2) $NonZombie_{i,t}$ equals one if firm i is not classified as a benchmark zombie in year t(Equation 1). $ZombieShare_{z,t-1}$ is the leave-one-out share of benchmark zombies in cell z (zone-district × broad industry) in year $t-1$. (3) All specifications include firm-level controls (lagged firm age, log employment, debt-to-assets ratio, R&D expenditures, R&D staff, invention applications), zone-level controls (log firm count, log total R&D), zone-district fixed effects, and 3-digit industry × year fixed effects. (4) Standard errors two-way clustered by firm and by zone-district × year.

Table 8: Heterogeneous spillover effects by firm productivity

	R&D Exp. (1)	Patent (2)	R&D Staff (3)
$NonZombie_{i,t}$	0.180	0.024	0.047
	(0.240)	(0.108)	(0.083)
$HighTFP_{i,t}$	−1.277***	−0.081	−0.307
	(0.464)	(0.144)	(0.194)
$ZombieShare_{z,t-1}$	−0.025	−0.091	0.027
	(0.626)	(0.249)	(0.193)
$NonZombie \times HighTFP$	1.598***	0.188	0.376*
	(0.476)	(0.150)	(0.194)
$ZombieShare \times HighTFP$	2.010*	0.733**	0.445
	(1.194)	(0.367)	(0.454)
$NonZombie \times ZombieShare$	0.189	0.003	0.020
	(0.620)	(0.256)	(0.200)
$NonZombie \times ZombieShare \times HighTFP$	−2.856**	−0.835**	−0.596
	(1.226)	(0.384)	(0.452)
Firm-level controls	YES	YES	YES
Zone-level controls	YES	YES	YES
Zone FE	YES	YES	YES
Ind. × Year FE	YES	YES	YES
Obs.	18,918	18,918	18,918
R^2	0.783	0.481	0.840

Notes: (1) Dependent variables in year t are the inverse hyperbolic sine of firm R&D expenditure (column 1), total patent applications (column 2), and R&D personnel (column 3). The sample is the pooled in-zone sample. (2) $NonZombie_{i,t}$ equals one if firm i is not classified as a benchmark zombie in year t. $ZombieShare_{z,t-1}$ is the leave-one-out share of benchmark zombies in cell z (zone-district × broad industry) in year $t-1$. $HighTFP_{i,t}$ equals one if firm i has above-median TFP in its 3-digit industry–year cell, where TFP is the residual from a regression of log total revenue on log total assets and log employment. (3) The coefficient on $NonZombie \times ZombieShare \times HighTFP$ is the test of P3. A negative coefficient indicates that the congestion effect from a higher local zombie share falls disproportionately on high-productivity non-zombies. (3) All specifications include firm-level controls (lagged firm age, log employment, debt-to-assets ratio, R&D expenditures, R&D staff, invention applications), zone-level controls (log firm count, log total R&D), zone-district fixed effects, and 3-digit industry × year fixed effects. (5) Standard errors are two-way clustered by firm and by zone-district × year. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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 zombie share and firm innovation

	Zone-level	Firm-level			
	Zombie Share	R&D Sub.	R&D Exp.	Patent	R&D Staff
	(1)	(2)	(3)	(4)	(5)
$\mathbf{1}\{k=-2\}$	-0.010	-0.068	-0.258	-0.036	-0.111
	(0.059)	(0.122)	(0.243)	(0.034)	(0.084)
$\mathbf{1}\{k=0\}$	-0.029	1.306**	1.673***	0.011	0.705***
	(0.038)	(0.635)	(0.521)	(0.078)	(0.262)
$\mathbf{1}\{k=1\}$	-0.059	-0.052	0.633	-0.051	0.209
	(0.057)	(0.230)	(0.410)	(0.076)	(0.142)
$\mathbf{1}\{k=2\}$	-0.037	-0.102	0.761**	-0.011	0.211**
	(0.032)	(0.225)	(0.329)	(0.072)	(0.096)
$\mathbf{1}\{k=3\}$	-0.057*	-0.028	0.748**	0.174**	0.160*
	(0.030)	(0.304)	(0.322)	(0.072)	(0.086)
$\mathbf{1}\{k=4\}$	-0.054	-0.027	0.729**	0.083	0.161*
	(0.042)	(0.220)	(0.340)	(0.072)	(0.082)
$\mathbf{1}\{k=5\}$	-0.075**	0.160	0.207	0.083	0.129
	(0.033)	(0.228)	(0.302)	(0.065)	(0.079)
Zone-level controls	YES				
Firm-level controls		YES	YES	YES	YES
Zone FE	YES	YES	YES	YES	YES
Year FE	YES				
Firm FE		YES	YES	YES	YES
Ind. $\times$ Year FE		YES	YES	YES	YES
Obs.	341	26,040	26,040	26,040	26,040
R^2	0.540	0.581	0.845	0.710	0.891

Notes: (1) Column (1) estimates Equation (9) at the zone-year level. The dependent variable is the within-zone zombie share computed under the benchmark definition. Columns (2)–(5) estimate the firm-level event study analogue. Dependent variables are the inverse hyperbolic sine of firm-level government R&D subsidies, internal R&D expenditure, total patent applications, and R&D personnel, all measured in year t. (2) $\mathbf{1}\{k=j\}$ equals one for observations j years relative to the zone's upgrade year. $k=-1$ is the omitted reference period. (3) The control group consists of zones (column 1) or firms (columns 2–5) in PDZs that were never upgraded during the sample period. (4) Zone-level controls are the log number of firms in the zone, log aggregate firm R&D expenditure, and log aggregate R&D subsidies. Firm-level controls are the one-period lag of firm age, log employment, debt-to-assets ratio, log R&D expenditure, log R&D personnel, and log invention patent applications. (5) Standard errors are clustered at the administrative-district $\times$ year level in column (1) and at the zone level in columns (2)–(5). *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

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	Zombie firm indicator (dummy)
Giant	Little Giant certification indicator (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)
Gov_Sub	Government R&D subsidy (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)

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 Zombie Checks

Table C.1: Statistics of zombies and healthy firms

	Benchmark		SC		FK	
	Non-Z	Zombie	Non-Z	Zombie	Non-Z	Zombie
Patent measures						
Patent	2.572	1.155	2.769	1.056	2.725	1.182
Invention	1.121	0.612	1.207	0.548	1.152	0.644
Model	1.190	0.449	1.283	0.415	1.289	0.444
Design	0.261	0.095	0.279	0.092	0.284	0.095
Firm characteristics						
Zone	0.291	0.266	0.293	0.267	0.292	0.269
Emp	112.0	37.4	121.0	35.0	122.4	36.7
Emp_RD	34.7	13.4	37.3	12.5	37.2	13.7
Emp_Edu	35.6	14.0	38.2	13.3	38.5	13.9
Emp_Exp	7.4	2.7	8.1	2.4	8.1	2.7
Gov_Sub	0.245	0.783	0.553	0.249	0.221	0.681
Age	9.0	6.1	9.4	5.9	9.4	6.0
Financial measures						
Asset	199.4	54.4	218.3	47.8	221.1	51.4
Debt	111.5	35.4	122.0	31.0	123.8	32.6
RD	7.12	2.42	7.76	2.15	7.69	2.47
DA	0.641	1.739	0.579	1.674	0.583	1.623
ROA	0.273	−1.167	0.313	−1.041	0.322	−0.996
Ex	5.08	1.24	5.54	1.10	5.67	1.12
Rev	148.6	26.9	163.2	23.6	166.6	25.1
Profit	15.67	−4.34	17.63	−3.95	18.15	−3.71
Obs.	107,886	58,099	97,810	71,886	94,686	75,010

Notes: (1) This table presents mean values for zombie and non-zombie firms under three zombie definitions. (2) The Benchmark definition (Equation 1) classifies a firm as a zombie if its pre-tax profit (EBIT) minus the LASSO-predicted excess R&D subsidy is non-positive, with Little Giant firms assigned as non-zombies by construction. The SC definition (Equation 2) classifies a firm as a zombie if its pre-tax profit (EBIT) is non-positive. The FK definition (Equation 3) classifies a firm as a zombie if its pre-tax profit (EBIT) minus all government R&D subsidies is non-positive. Under SC and FK, Little Giants are assigned based on the financial criterion alone and may appear in either column. (3) All three definitions are computed on the LASSO prediction sample (N = 169,696 firm-years); column sample sizes reflect firm-years with non-missing zombie classification. (4) *Zone* is the share of firm-years located in any zone. Patent variables are in native counts. (5) Other variables are defined according to Appendix A.

Table C.2: LASSO variable selection for predicted R&D subsidy

	Training sample		
Predictor	Outside	PDZ	Full
Panel A. Main effects			
R&D personnel (ln)	0.330	0.329	0.286
Internal R&D expenditure (ln)	0.214	0.043	0.194
Total assets (ln)	0.211	0.184	0.224
Invention patent applications (ln)	0.147	0.065	0.161
Invention patents granted (ln)	0.066		0.010
Total patents (ln)	0.043	0.008	0.060
Employment (ln)	0.009		0.010
Main business income (ln)	0.006	0.008	0.007
Total income (ln)	0.004		0.009
Firm age	−0.002		−0.002
Design patents (ln)			−0.008
Utility model patents (ln)			0.033
Total debt (ln)		0.001	0.011
Panel B. Interaction terms (top 20 by total $\|coef\|$)			
Design patents × leverage	0.033		0.053
Inv. patents × inv. patents granted	0.022	0.012	0.048
Inv. patents granted × design patents	−0.015		−0.044
Inv. patents granted × leverage	−0.004	0.040	−0.004
Total patents × inv. patents	−0.014	0.014	−0.021
Inv. patents × R&D personnel	0.014		0.015
Internal R&D × employment	−0.010	−0.001	−0.012
Employment × R&D personnel	−0.009		−0.013
Inv. patents × utility patents	0.003	−0.007	0.011
Design patents × utility patents	0.010		0.010
Total patents × utility patents	−0.003	−0.003	−0.008
Inv. patents × debt	0.004	0.006	0.001
Utility patents × internal R&D	−0.009	−0.001	−0.002
Total patents × employment	−0.008		−0.002
Inv. patents granted × debt	0.003		0.008
Inv. patents granted × total income	−0.005		−0.005
R&D personnel × assets	0.003		0.007
Design patents × R&D personnel	−0.005		−0.004
Utility patents × main income			−0.009
Inv. patents granted × utility patents	0.002		0.006
Training N (Stage 1)	121,913	26,525	169,696
Training N (Stage 2)	12,907	3,554	20,816
R^2 (Stage 1)	0.104	0.069	0.095
R^2 (Stage 2)	0.399	0.268	0.396
Variables selected (union)	64	21	74
Smearing factor (Stage 2)	3.02	2.48	3.09

Notes: (1) This table reports variable selection results from hurdle LASSO regressions predicting government R&D subsidies. Let S_{it} denote the R&D subsidy received by firm i in year t. Stage 1 is a linear probability model of $\mathbf{1}\{S_{it} > 0\}$; Stage 2 is a linear regression of $\ln S_{it}$ conditional on $S_{it} > 0$. (2) Candidate predictors are 14 current-year firm-level variables and their pairwise interactions (approximately 105 candidates in total). Industry, administrative-district, and year fixed effects are partialled out. (3) The primary specification (column 1) trains on firms outside development zones. Columns 2 and 3 report robustness checks using PDZ-only and full-sample training sets. The smaller PDZ training sample yields fewer selected variables and a lower Stage 2 R^2. (4) Coefficients shown are the maximum absolute value across Stage 1 and Stage 2 within each training sample; this captures the strongest contribution of each predictor regardless of the stage in which it is selected. Blank cells indicate the variable was not selected in either stage for that specification. Panel B reports the top 20 interaction terms ranked by the sum of absolute coefficients across the three training samples. (5) Lambda values selected by EBIC: Stage 1 / Stage 2 – Outside: 38.75 / 253.93; PDZ: 91.84 / 372.61; Full: 30.30 / 260.93. (6) "Variables selected (union)" reports the count of unique variables selected in either stage for each training sample.

Table C.3: Robustness of LASSO zombie classification

Specification	Vars	CV R^2	All	Zombie share (%) SDZ	PDZ	Out	Corr.	Agree (%)
Panel A. LASSO specification variants								
Primary (10-fold, seed=401)	95	0.167	38.7	40.4	33.1	39.6	1.000	—
5-fold CV	90	0.167	38.7	40.3	33.1	39.6	0.998	99.9
10-fold, seed=12345	90	0.168	38.7	40.3	33.1	39.6	0.998	99.9
Drop R&D expenditure	44	0.136	36.8	39.5	32.3	37.3	0.950	97.6
Drop invention patents	48	0.164	38.7	40.3	33.2	39.7	0.991	99.6
OLS, top 5 vars	5	0.098	34.3	38.9	31.0	34.2	0.908	95.5
OLS, all 15 main vars	14	0.155	39.0	40.2	33.3	40.0	0.967	98.4
Panel B. Training sample variants								
Outside-zone (Primary)	95	0.167	38.7	40.4	33.1	39.6	1.000	—
PDZ training sample	51	0.100					0.982	99.1
Full-sample training	91	0.163					0.991	99.6

Notes: (1) This robustness check uses truncation LASSO with cross-validation rather than the hurdle LASSO with EBIC penalty selection used as the primary benchmark; the two approaches yield classifications with firm-level agreement above 99 percent under the main specification variants. (2) "Vars" is the number of non-zero coefficients selected by LASSO (or the number of regressors for OLS rows). "CV R^2" is the out-of-sample R^2 at the cross-validated λ (in-sample R^2 for OLS rows). "Corr." is the pairwise correlation of zombie indicators with the primary specification (all $p < 0.001$). "Agree" is the overall firm-level agreement rate with the primary classification. Panel B varies the training sample; zombie shares by zone type are not directly comparable across training samples and are therefore omitted.

D Robustness Checks

Table D.1: Post-matching balance test

Probit	Sample	Mean(T)	Mean(C)	Bias%	BR%	t-stat.	p-value
Panel A. PSM results for SDZ firms							
Emp	U	155.487	83.701	15.6		15.37	0.000
	M	155.487	154.039	0.3	98.3	0.24	0.812
Emp_RD	U	68.251	25.260	22.6		19.68	0.000
	M	68.251	64.461	1.5	93.5	1.31	0.189
Emp_Edu	U	62.806	27.037	19.2		17.97	0.000
	M	62.806	62.597	0.1	99.5	0.08	0.935
Emp_Exp	U	11.931	7.043	6.6		5.97	0.000
	M	11.931	12.526	-0.7	88.9	-0.63	0.526
Age	U	7.990	8.313	-5.4		-5.70	0.000
	M	7.990	7.513	7.9	-47.6	7.06	0.000
Asset	U	314.113	138.979	6.5		5.89	0.000
	M	314.113	272.159	1.5	76.8	1.30	0.194
Debt	U	210.142	81.768	2.1		1.77	0.077
	M	210.142	139.855	1.2	45.3	0.97	0.335
RD	U	18.547	5.305	13.6		11.74	0.000
	M	18.547	16.266	1.7	87.8	1.50	0.135
DA	U	0.820	0.800	0.1		0.16	0.870
	M	0.820	0.690	1.4	–	1.13	0.259
Rev	U	177.852	104.339	7.0		7.61	0.000
	M	177.852	175.014	0.3	96.1	0.24	0.807
Ex	U	10.209	3.274	5.9		5.33	0.000
	M	10.209	8.670	1.1	81.9	0.95	0.340
Profit	U	23.501	7.038	5.7		4.78	0.000
	M	23.501	17.042	2.1	62.5	1.79	0.073
Panel B. PSM results for PDZ firms							
Probit	Sample	Mean(T)	Mean(C)	Bias%	BR%	t-stat.	p-value
Emp	U	147.073	83.701	16.6		19.65	0.000
	M	147.073	157.554	-2.2	86.7	-2.21	0.027
Emp_RD	U	40.206	25.260	13.8		15.28	0.000
	M	40.206	43.741	-3.0	78.3	-2.92	0.004
Emp_Edu	U	36.030	27.037	6.6		7.81	0.000
	M	36.030	40.746	-3.1	52.6	-3.11	0.002
Emp_Exp	U	7.435	7.043	0.8		0.99	0.324
	M	7.435	8.266	-2.0	–	-1.87	0.061
Age	U	9.003	8.313	11.5		13.27	0.000
	M	9.003	9.553	-8.7	24.8	-8.49	0.000
Asset	U	198.980	138.979	4.4		6.51	0.000
	M	198.980	228.244	-2.6	41.9	-2.58	0.010
Debt	U	99.926	81.768	2.2		3.10	0.002
	M	99.926	119.583	-2.8	-27.4	-2.79	0.005
RD	U	7.978	5.305	6.5		8.74	0.000
	M	7.978	8.873	-2.4	62.6	-2.41	0.016
DA	U	0.657	0.800	-1.2		-1.96	0.050
	M	0.657	0.693	-0.6	–	-0.56	0.575
Rev	U	170.819	104.339	7.3		9.57	0.000
	M	170.819	189.967	-2.1	71.1	-2.11	0.035
Ex	U	8.128	3.274	6.7		7.97	0.000
	M	8.128	6.665	1.7	74.5	1.71	0.087
Profit	U	16.128	7.038	9.6		11.30	0.000
	M	16.128	16.309	-0.1	98.5	-0.15	0.882

Notes: (1) This table reports covariate balance before (U) and after matching (M) based on propensity scores estimated using a Probit model. Matching is performed separately within each year from 2009 to 2018 using nearest-neighbor matching with two neighbors, and the yearly matched samples are then pooled. (2) Panel A presents the matching results for SDZ firms (N = 32,988), while Panel B presents the results for PDZ firms (N = 38,568). (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, and is suppressed (–) for covariates with $|\text{Bias\%}| < 2$ in the unmatched sample, for which the ratio is uninformative. (5) The reported t-statistics and p-values test the equality of covariate means between treated and control groups for each sample, based on Welch's test allowing for unequal variances. (6) All monetary variables (Asset, Debt, RD, Rev, Ex, Profit) are reported in millions. (7) All post-matching standardized biases fall below the 10% threshold; firm age exhibits the largest residual imbalance (7.9% in Panel A; -8.7% in Panel B) and is included as a control in all outcome regressions.

Table D.2: Zombie congestion and in-zone non-zombie innovation: fixed-effect specification ladder

	(1)	(2)	(3)	(4)
Panel A. R&D Expenditure				
$NonZombie_{i,t}$	0.502***	0.546***	0.565***	0.535***
	(0.133)	(0.112)	(0.111)	(0.131)
$ZombieShare_{z,t-1}$	0.801*	0.416	0.381	0.978**
	(0.426)	(0.311)	(0.327)	(0.459)
$NonZombie \times ZombieShare$	−0.906**	−1.024***	−1.074***	−0.986**
	(0.422)	(0.357)	(0.355)	(0.426)
R^2	0.717	0.739	0.741	0.734
Panel B. R&D Staff				
$NonZombie_{i,t}$	0.193***	0.190***	0.196***	0.199***
	(0.029)	(0.030)	(0.029)	(0.029)
$ZombieShare_{z,t-1}$	0.079	0.087	0.068	0.088
	(0.070)	(0.069)	(0.071)	(0.071)
$NonZombie \times ZombieShare$	−0.154**	−0.145**	−0.152**	−0.159**
	(0.070)	(0.070)	(0.069)	(0.070)
R^2	0.825	0.829	0.830	0.834
Panel C. Patent				
$NonZombie_{i,t}$	0.209***	0.223***	0.216***	0.210***
	(0.034)	(0.034)	(0.034)	(0.034)
$ZombieShare_{z,t-1}$	0.047	0.139*	0.143*	0.048
	(0.083)	(0.082)	(0.081)	(0.085)
$NonZombie \times ZombieShare$	−0.350***	−0.394***	−0.376***	−0.352***
	(0.090)	(0.089)	(0.089)	(0.089)
R^2	0.448	0.459	0.461	0.458
Industry FE	YES			YES
Year FE	YES			
Industry × Year FE		YES	YES	
Zone FE			YES	
Zone × Year FE				YES
Obs.	27,779	27,698	27,698	27,774

Notes: (1) Each column within each panel is a separate regression on the pooled in-zone sample. Dependent variables in year t are the inverse hyperbolic sine of firm R&D expenditure (Panel A), R&D personnel (Panel B), and total patent applications (Panel C). (2) $NonZombie_{i,t}$ equals one if firm i is not classified as a benchmark zombie in year t (Equation 1). $ZombieShare_{z,t-1}$ is the leave-one-out share of benchmark zombies in cell z (zone-district × broad industry) in year $t-1$. Column (3) corresponds to the main-text specification of Table 7. (3) All specifications include firm-level controls (lagged firm age, log employment, debt-to-assets ratio, R&D expenditures, R&D staff, invention applications) and zone-level controls (log firm count, log total R&D). (4) Standard errors are two-way clustered by firm and by zone-district × year. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.3: Heterogeneous spillover effects by firm size

	R&D Exp. (1)	Patent (2)	R&D Staff (3)
Panel A. Large firms (above-median assets)			
$NonZombie_{i,t}$	0.560***	0.219***	0.174***
	(0.102)	(0.050)	(0.044)
$ZombieShare_{z,t-1}$	0.667**	0.039	−0.153
	(0.322)	(0.137)	(0.119)
$NonZombie \times ZombieShare$	−1.172***	−0.283**	0.057
	(0.333)	(0.138)	(0.121)
Obs.	16,706	16,706	16,706
R^2	0.831	0.463	0.791
Panel B. Small firms (below-median assets)			
$NonZombie_{i,t}$	0.319***	0.126***	0.163***
	(0.116)	(0.046)	(0.038)
$ZombieShare_{z,t-1}$	−0.093	0.002	0.142*
	(0.314)	(0.089)	(0.084)
$NonZombie \times ZombieShare$	−0.143	−0.190*	−0.146
	(0.289)	(0.115)	(0.089)
Obs.	10,902	10,902	10,902
R^2	0.658	0.258	0.767
Firm-level controls	YES	YES	YES
Zone-level controls	YES	YES	YES
Zone FE	YES	YES	YES
Ind. × Year FE	YES	YES	YES

Notes: (1) Dependent variables in year t are the inverse hyperbolic sine of firm R&D expenditure (column 1), total patent applications (column 2), and R&D personnel (column 3). Panels A and B split the pooled in-zone sample by firm size, where size is defined as above or below the median of log total assets in the firm's 3-digit industry-year cell. (2) $NonZombie_{i,t}$ equals one if firm i is not classified as a benchmark zombie in year t. $ZombieShare_{z,t-1}$ is the leave-one-out share of benchmark zombies in cell z (zone-district × broad industry) in year $t-1$. (3) The coefficient on $NonZombie \times ZombieShare$ is the spillover test within each size group. The patterns across panels are not consistent with a uniform P3 on firm size: large firms bear the R&D expenditure crowd-out, while small firms show a stronger patent response and a marginal R&D staff response. (4) All specifications include firm-level controls (lagged firm age, log employment, debt-to-assets ratio, R&D expenditures, R&D staff, invention applications), zone-level controls (log firm count, log total R&D), zone-district fixed effects, and 3-digit industry × year fixed effects. (5) Standard errors are two-way clustered by firm and by zone-district × year. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.4: Heterogeneous real-activity spillovers by firm size

	$\Delta \ln L$	$\Delta \ln A$	$\Delta \ln \text{Rev}$
	(1)	(2)	(3)
Panel A. Large firms (above-median assets)			
$NonZombie_{i,t}$	0.081***	0.299***	0.775***
	(0.017)	(0.049)	(0.291)
$ZombieShare_{z,t-1}$	−0.041	0.290*	−0.587
	(0.054)	(0.168)	(0.881)
$NonZombie \times ZombieShare$	0.059	−0.209	0.616
	(0.053)	(0.178)	(0.900)
Obs.	16,502	16,636	11,591
R^2	0.064	0.068	0.071
Panel B. Small firms (below-median assets)			
$NonZombie_{i,t}$	0.129***	0.686***	1.249***
	(0.024)	(0.117)	(0.268)
$ZombieShare_{z,t-1}$	0.052	0.747***	0.146
	(0.055)	(0.271)	(0.570)
$NonZombie \times ZombieShare$	−0.126**	−0.977***	−0.087
	(0.056)	(0.288)	(0.599)
Obs.	10,748	10,722	4,105
R^2	0.060	0.098	0.116
Firm-level controls	YES	YES	YES
Zone-level controls	YES	YES	YES
Zone FE	YES	YES	YES
Ind. × Year FE	YES	YES	YES

Notes: (1) Dependent variables are real-economy growth outcomes in year t: log employment growth (column 1), log asset growth (column 2), and log revenue growth (column 3). Panels A and B split the pooled in-zone sample by firm size, where size is defined as above or below the median of log total assets in the firm's 3-digit industry-year cell. (2) $NonZombie_{i,t}$ equals one if firm i is not classified as a benchmark zombie in year t. $ZombieShare_{z,t-1}$ is the leave-one-out share of benchmark zombies in cell z (zone-district × broad industry) in year $t-1$. (3) The coefficient on $NonZombie \times ZombieShare$ is the spillover test within each size group. Small firms bear substantial crowd-out on employment growth (−0.126) and asset growth (−0.977), while large firms show no comparable response on either margin. Revenue growth is noisier and not statistically distinguishable from zero in either panel. (4) Firm-level controls are the one-period lags of firm age, debt-to-assets ratio, and log R&D expenditure, together with lagged scale controls adapted to each outcome: column (1) includes lagged log assets, column (2) includes lagged log employment, and column (3) includes both lagged log employment and lagged log assets. The lagged level of each column's outcome variable is excluded to avoid redundancy with the growth outcome on the left-hand side. All specifications also include zone-level controls (log firm count, log total R&D), zone-district fixed effects, and 3-digit industry × year fixed effects. (5) Standard errors are two-way clustered by firm and by zone-district × year. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.