Agglomeration disruption, firm innovation, and export resilience: Evidence from China's national zone reform

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Abstract

This paper leverages China's 2003-2004 national reform of economic development zones (EDZs) as a quasi-experimental setting to estimate the effects of zone closures on firm innovation. Relative to firms that remain in continuing zones, closures reduce innovation performance–especially citation-weighted patent quality; these losses are only partially offset by gains at new zones opened under the reform. Two mechanisms are implicated: withdrawal of state subsidies, which heightens financial constraints, and disruption of agglomeration economies and local supply chains, which erodes place-based externalities. Firms with stronger innovation capabilities are more resilient, mitigating downstream export losses and sustaining international competitiveness. These findings underscore that abrupt withdrawal of place-based support is disruptive even when zones are deemed inefficient, highlighting the importance of building internal innovation capabilities and preserving access to external finance and knowledge networks during policy transitions.

Keywords: Place-based Policy; Agglomeration; Innovation; Export Resilience; China

1 Introduction

Economic development zones (EDZs) and other place-based policies are among the most widely deployed instruments for shaping regional economies (Duranton and Venables, 2018). EDZs help relax firm frictions–through infrastructure investment, streamlined land-use and regulatory procedures, and targeted finance–thereby attracting new firms, suppliers, and services into close proximity. Agglomeration economies, in turn, lower search and coordination costs, thicken input and labor markets, and accelerate knowledge spillovers through dense co-location networks (Rosenthal and Strange, 2004).

Despite their global reach, place-based policies remain contested on efficiency grounds (Fajgelbaum and Gaubert, 2025), and policymakers may consider phasing out support earlier than expected. Yet the implications of withdrawing place-based support for local market conditions and firm competitiveness remain largely unknown. In principle, if an EDZ has fostered self-sustaining agglomeration, removing incentives need not materially undermine firm performance, given remaining infrastructure and established networks.

In practice, however, EDZ closures may undermine firm performance through two complementary channels. First, firm-internal adjustments–loss of subsidies and precautionary cuts to R&D–constrain the inputs that sustain inventive effort (Hall and Lerner, 2010; Cong and Howell, 2021). Second, firm-external agglomeration disruptions–erosion of horizontal (diversity/specialization) and vertical (buyer–supplier) production networks–reduce access to tacit production-process and component-specific know-how that underpins performance-enhancing externalities (Henderson, 1997).

While empirical work documents varied innovation and development benefits attributed to EDZs (Tian and Xu, 2022; Chen and Qiu, 2021; Wang, 2013), most studies analyze settings where spatial-targeting incentives remain active. This makes it difficult to distinguish transitory policy-induced gains from effects that outlast support. A small body of evidence finds economic benefits that persist after program cessation–attributed in part to sustained agglomeration (Kline and Moretti, 2014; Ehrlich and Seidel, 2018)–though these contexts involve predictable phase-outs rather than abrupt withdrawal.

Exploiting a national reform that led to the mass closure of EDZs in China, I examine

the firm-level consequences of an abrupt withdrawal of place-based support. The paper addresses three interrelated questions for regional policy and firm strategy: (i) what are the effects of EDZ closures on firms' innovation performance and export competitiveness; (ii) through which mechanisms these effects operate; and (iii) to what extent do built-up innovation capabilities mitigate adverse closure effects and promote export resilience?

The reform policy of interest is China's national EDZ reform, which led to the closure of more than 70 percent of EDZs–mainly in coastal China during 2003-2004–prompted by government concerns about zone inefficiency and regional inequality (Zhang, 2011). The zone reform aimed to: (i) curb the unchecked proliferation of poorly governed and inefficient zones established during the 1990s "zone fever"; and (ii) rebalance development by relocating activity from closed coastal EDZs to inland areas (Wei, 2015).

Treating the EDZ reform as a quasi-natural experiment, I use a difference-in-differences (DiD) design to estimate the effects of EDZ closures on firms' innovation performance and to assess the role of built-up innovation capabilities in export resilience. Treatment assignment is at the district level using geolocated firm EDZ status, cross-checked against official zone boundaries. Administrative firm- and patent-level data, combined with a commercial patent-citation database, are used to construct a firm–patent linked dataset.

The main sample is a balanced panel of more than 45,000 privately-owned, above-scale industrial firms (annual sales $\geq$ 5 million RMB) operating in coastal China during 2001–2007; all of which operated in a coastal EDZ catchment-area defined at the district level prior to the reform. Following the reform, 28.9 percent of firms remained in a district with an active EDZ while 71.1 percent were exposed to a zone closure. Additional samples are used to: (i) isolate direct effects on firms located inside EDZs; (ii) incorporate compositional changes due to firm dynamics when estimating total effects; and (iii) examine inland EDZ firms to benchmark potential offsets from new zone openings.

Well-known empirical challenges are inherent in evaluating place-based policies (Neumark and Simpson, 2015). Although closures were mandated top-down–reducing worries that local authorities tailored treatment to unobservables–the central government did not target EDZs at random: the reform sought to revoke designation for inefficient, locally

operated EDZs (Zhang, 2011). Other empirical challenges include contemporaneous policy reforms (e.g., land policies) that may confound estimates, and potential spillovers that raise SUTVA risks if firms or workers in closed EDZs relocate into continuing EDZs.

Several considerations help mitigate–though not eliminate–these concerns. First, the main comparison contrasts firms in closed versus continuing EDZs–both initially selected into an EDZ–limiting residual selection bias relative to comparisons with never-zone firms. Second, the design employs inverse-propensity weighting (IPW) alongside a rich set of fixed effects and covariate trends to absorb local market dynamics and accommodate divergent trends by firm, zone, and district characteristics. Third, SUTVA checks show that continuing EDZs exhibit stable innovation and employment trends around the timing of closures, suggesting limited reallocation from closed to continuing EDZs.

The results show that EDZ closures led to modest declines in patent counts but comparatively larger declines in citation-weighted quality. This asymmetry is consistent with lower-value invention, proxied by counts, being relatively easier to sustain amid China's mid-2000s patenting surge (Hu and Jefferson, 2009), whereas citation-weighted patents reflect higher-quality, cumulative invention that depends more on sustained R&D investment and thick external knowledge networks (Hall and Harhoff, 2012). As a first explanation, I document that firms in closed EDZs receive fewer state subsidies and reduce R&D intensity, consistent with tighter financing constraints that raise the fixed and working-capital costs of innovation.

As a second explanation, I build agglomeration-disruption indices–covering diversity (Jacobs), within-industry specialization (MAR), and vertical supplier–buyer links–and use shift-share Bartik-style instruments to purge post-treatment endogeneity. Larger instrumented disruption in these channels is associated with larger declines in innovation, especially patent quality. This pattern is consistent with the erosion of transaction-mediated knowledge flows along local production networks—flows that would otherwise diffuse tacit know-how, support problem-solving, and open commercialization pathways.

Not all firms are harmed equally by closure, however. Firms that became more successful innovators while the EDZ was active are better positioned to withstand the adverse

effects of closures–exhibiting higher export resilience–whereas firms with less innovation success fare notably worse in international markets. Taken together with the mechanism evidence, these patterns suggest that better-endowed firms substitute internal know-how for lost nonmarket supports as local externalities dissipate.

To better assess the reform's net innovation effects, I implement a counterfactual exercise that benchmarks coastal losses against inland gains from newly designated EDZs in inland areas: I first estimate opening effects in a balanced inland panel, then construct a no-reform counterfactual in which coastal closure losses scale with measured disruption intensity and inland opening gains scale with entry-driven agglomeration formation. Comparing observed outcomes to these counterfactuals shows that despite generating innovation gains in new inland zones, they only partially offset the losses from coastal zone closures, yielding a net negative short-run effect on firms' innovation performance.

This study makes three contributions. First, it provides empirical evidence on the consequences of abruptly withdrawing place-based support, extending our understanding of how policy shocks and uncertainty shape firms' innovation performance (Cong and Howell, 2021). Second, it develops and applies a suite of agglomeration–disruption indices instrumented with shift-share Bartik-like counterparts to quantify the how zone closure effects scale with increasing disruptions linked to specific externality types. Third, it bridges resource- and place-based perspectives, showing that innovation capabilities function as resilience assets that sustain international competitiveness even amid policy-induced disruptions to firms' internal and external operating environment.

2 Empirical Framework

2.1 Institutional Context

China's zone policy evolved rapidly from the early 1980s. EDZs were first established in select coastal cities to attract FDI and promote export-led growth; their success spurred the wider rollout of economic and technological development zones and high-tech parks at multiple administrative levels. EDZs typically offered tax relief, subsidies, streamlined

regulation, serviced industrial land, and infrastructure, with these nonmarket supports intended to catalyze agglomeration forces and accelerate local industrial upgrading, innovation, and competitiveness.

By the early 2000s, however, the proliferation of locally approved EDZs raised mounting concerns, often described as `zone" or`project" fever. Many jurisdictions created EDZs to compete for capital without adequate planning or oversight, leading to fragmentation, idle or prematurely converted land, and weak governance (Zeng, 2011). The unchecked expansion was associated with low-quality projects, rent seeking, corruption, and wasteful development (Wei, 2015).

In response, the central government suspended new approvals, audited existing parks, and ordered widespread closures, mergers, and boundary reductions. The stated objectives were twofold: (i) curb the 1990s "zone fever," marked by unchecked proliferation, land misuse, corruption, and waste; and (ii) rebalance development by closing or consolidating substandard parks and redirecting activity toward higher-quality, better-governed inland EDZs. The total number of EDZs fell from 6,866 to 1,568 between 2003 and 2006, and planned area contracted by about 74 percent (Zhang, 2011).

2.2 Data Sources and Variable Construction

The main data source is the Annual Survey of Industrial Firms (ASIF) from China's National Bureau of Statistics. ASIF covers the universe of above-scale industrial firms with annual sales $\geq$ 5 million RMB–including state-owned enterprises (SOEs), foreign-invested enterprises (FIEs), and privately owned enterprises (POEs)–and accounts for roughly 90 percent of national industrial output (Brandt et al., 2012). ASIF reports firm identifiers, industry and location codes, R&D investments, new product and process sales, export sales, and other detailed financial and operational variables (e.g., sales, employment, subsidies, intermediate inputs and material costs, fixed assets).

2.2.1 Firm Innovation Performance

Patent outcomes. Patent quantity is measured as the number of granted invention patents from the China National Intellectual Property Administration (CNIPA). To capture patent quality, I augment CNIPA with forward-citation metadata from IncoPat and compute three-year forward citations from the application year, normalized by application year and technology field. Citation data are observed through 2010, yielding a consistent window for the 2001–2007 cohort. Utility-model and design patents are excluded because they are weaker proxies for substantive technological advance and are often acquired for non-innovation motives (Hu et al., 2017).

Patent–firm linkage. CNIPA assignees are linked to the ASIF database by first extracting stem names from both patent-assignee and firm names and removing corporate designators (e.g., jituan). Next, exact and partial stem-name matching are used to recover true positives, with ambiguous pairs manually checked using address cues (e.g., province, city, district). Approximately 50 percent of CNIPA invention patents are linked to the ASIF database, and all patent–firm aggregates are time-stamped by the patent's application year. Prior work validates the patent–citation–ASIF record linking, and documents a positive association between R&D expenditures and citation-weighted patents, and between citation-weighted patents and firm productivity (Wu et al., 2022).

Commercialization outcome. Patents are an informative, albeit noisy, proxy for innovation–many innovations are not patentable or are not patented (Griliches, 1998). As an alternative innovation output measure, I define new-innovation sales intensity to capture commercialization success, calculated as the firm's new-product and new-process sales divided by its total sales. During the study period, this variable primarily reflects products and processes that are new to the firm (often sourced externally) rather than new to the market, capturing the firm's ability to bring in or adapt existing technologies.

2.3 EDZ Closure: Treatment Assignment

Firm-level EDZ status. I classify firms and their operating districts into one of three mutually exclusive groups–closed, continuing, or never-zone–using an address-based tag-

ging procedure cross-checked against official zone records. Because ASIF address fields can be incomplete, I first merge ASIF with the Chinese Firm Registration Data (National Enterprise Credit Information Publicity System) on firm name and legal-person code to recover historical addresses and geocodes. Following Chen et al. (2019); Howell (2019), I then search ASIF firm-name and sub-address fields each year (e.g., town; street name/number; sub-district office; neighborhood committee; address; street) for 17 zone-related keywords (e.g., yuanqu, gongyeyuan) to identify firm-level EDZ participation.

Validation. Tagged firms are cross-checked against the China Development Zones Audit Announcement Directory (2006) issued by the Ministry of Natural Resources: firms whose geocoded locations fall within surviving-EDZ districts are classified as continuing, while firms tagged as EDZ participants in 2001–2002 but located outside surviving districts are classified as closed. The keyword-based tagging accurately assigns more than 95 percent of continuing-zone assignments to the 2006 directory of surviving EDZs.

Spillovers and classification concerns. Two considerations motivate defining treatment at the district level. First, EDZ closures are expected to affect not only firms inside formal boundaries but also nearby firms in the zone's catchment area (Zheng et al., 2017), creating district-wide spillovers. Second, while continuing status can be validated against surviving districts, a key identification risk is misclassification of closed EDZ status at the firm level–for example, a firm in an EDZ in 2002 that is closed in 2003 or 2004 but lacks zone keywords in its name/address would be excluded from the treated group.

EDZ closure exposure. To address these concerns, I aggregate firm tags to a district-level EDZ closure-exposure indicator: firms operating in the same district as verified closed zones are treated as exposed, ensuring that firms affected by closures but missed by name/address tagging are nonetheless captured within the closure catchment. This reduces idiosyncratic exclusion errors since zone boundaries do not span administrative boundaries, while aligning the exposure definition with expected spatial spillovers.

District classification. I aggregate firm-level status indicators to classify continuing-zone districts, closed-zone districts, and never-zone districts in mutually exclusive groups.

For continuing districts, tagged firms must fall within the Directory's street-level surviving-EDZ districts. A district is classified as closed if it hosted tagged firms in 2001–2002 but contains no surviving polygon in the 2006 Directory; the district's closure year is assigned as 2003 or 2004 based on the first year in which tagged firms in the district lose the tag. Districts with no EDZ-tagged firms at any time are classified as never-zone.

2.4 Main Comparison Group and Sample

To assess whether firms in continuing EDZ districts are a suitable counterfactual for treated firms (i.e., what would have happened had EDZs not closed), Figure S2 reports average mean values for the main patenting outcomes. Compared with a common alternative that uses never-zone firms, continuing EDZ districts provide a much closer match: never-zone firms have lower average patenting and substantially larger pre-treatment gaps than the differences between continuing and closed EDZ districts. To reduce concerns about residual selection into treatment, I exclude never-zone districts from the empirical analysis and retain only firms located in previously operational (later closed) or continuing EDZ districts in coastal China.

A second concern is that firm dynamics (entry, exit, spin-offs) may correlate with treatment status, conflating treatment effects with compositional change. To address this, I use a balanced panel of firms operating throughout 2001–2007, fixing firm composition across pre- and post-policy periods so estimated effects reflect within-firm changes. A semi-balanced panel is used as a robustness check against survivorship bias.

The sample is further restricted to privately owned enterprises (POEs), excluding SOEs and FIEs, for two reasons. First, POEs are more exposed to local externalities and market-based finance, making their innovation outcomes more sensitive to EDZ support, whereas SOEs face distinct budget constraints and policy mandates (Lin and Tan, 1999). Second, FIEs have global financing, supply-chain, and IP strategies that weaken the link between local zone conditions and observed innovation outcomes.

After these exclusions, the main sample comprises 46,840 firms across 827 districts. Roughly two-thirds of these districts (66%) lost their designation, which is in line with

official statistics. At the firm level, 71.1 percent of firms are in EDZs that lost designation (treated), while 28.9 percent are in EDZs that retained it (comparison). Among treated firms, 68.1 percent were exposed to an EDZ closure in 2003 and 31.9 percent in 2004, yielding two staggered cohorts.

Figure S1 presents a spatial visualization of closed EDZs overlaid with the comparison group of continuing districts. Because closures are concentrated in coastal areas, the comparison group is restricted to continuing districts drawn from the same prefectures that experienced closures. This spatial overlap reduces bias from unobserved geographic heterogeneity (e.g., infrastructure, local institutions) and strengthens pretrends assumptions by aligning treated and comparison firms within the same local markets. A concern that arises, however, is that firms and workers exposed to EDZ closures may relocate to nearby continuing EDZ locations, requiring additional checks for potential SUTVA violations.

2.5 Estimation Strategy

To estimate the average effect of EDZ closures on firm outcomes, I use a two-way fixed effects (TWFE) specification that absorbs firm-invariant heterogeneity and rich time shocks:

$$Y_{it} = \beta\, D_{it}^{\text{close}} + \alpha_i + \delta_{p(i),t} + \Gamma_{h(i),t} + \sum_{\tau} \boldsymbol{\theta}_{\tau}^{\top} X_i^{\text{base}}\, \mathbf{1}\{t = \tau\} + \varepsilon_{it}, \tag{1}$$

where $z(i)$ the district-level zone catchment area of firm i, $p(i)$ its prefecture (city-level jurisdiction), and $h(i)$ its 4-digit industry. Define the zone closure treatment as

$$D_{it}^{\text{close}} \equiv \mathbf{1}\big\{\text{Close}_{z(i)} = 1 \text{ and } t \geq g_{z(i)}\big\},$$

with $g_z \in \{2003, 2004\}$ the district's first closure year; for continuing districts, set $\text{Close}_z = 0$ (equivalently, $g_z = +\infty$). α_i are firm fixed effects; $\delta_{p(i),t}$ are city–year fixed effects; $\Gamma_{h(i),t}$ are industry–year fixed effects.

To address potential divergent trends, pre-treatment firm and zone characteristics are

interacted with year dummies, $\sum_\tau \boldsymbol{\theta}_\tau^\top X_i^{\text{base}} \mathbf{1}\{t = \tau\}$. The main characteristics included are firms' age, size, and productivity, and for zones' administrative level, classification type, and distance to port. This allows firms with different initial characteristics (e.g., size, age, and EDZ classification) to follow distinct time paths, ensuring that the estimated treatment effect is not biased by pre-existing differences in trends.

Firm productivity refers to total factor productivity (TFP), constructed using the Levinsohn–Petrin approach (Levinsohn and Petrin, 2003). Including TFP, along with age and size, is relied on to directly address efficiency–related selection into closure, while zone characteristics account for EDZs selected for closure tending to be administered by less efficient zones governed by lower–level government and with less potential international market access.

Eq. (1) is estimated with robust standard errors two-way clustered by firm and district. The coefficient β captures the average treatment effect under standard DiD assumptions, but two issues warrant additional considerations. First, firms in EDZs that eventually close differ pre–treatment from firms in continuing EDZs (Table S2). To improve covariate balance, I estimate IPW–TWFE models that reweight firms by pre–treatment characteristics.

Second, closures occur in 2003 and 2004, generating staggered exposure and potential heterogeneity in group–time effects; in such settings, conventional TWFE can suffer from implicit negative weighting. To accommodate staggered timing and recover group–time and aggregate effects, I complement IPW–TWFE with the doubly robust estimator of Callaway and Sant'Anna (2021) (CS–DR), which combines IPW with outcome regression to identify $\text{ATT}_{g,t}$ under weaker conditions than TWFE.

Specifically, I estimate:

$$ATT_{g,t} = \mathbb{E}[Y_{it}(1) - Y_{it}(0) \mid G_i = g, T = t], \tag{2}$$

where G_i indexes the group of firms first treated in year $g \in \{2003, 2004\}$, and $T = t$ denotes calendar year. This framework allows me to present both dynamic event-study plots, which assess the plausibility of parallel pre-trends and identify the timing and

persistence of treatment effects.

2.6 State Subsidy Withdrawal and Financial Constraints

Subsidies tied to EDZ designation commonly target innovation and productivity upgrading, relaxing financing frictions that make R&D lumpy and cash-intensive (Hall and Lerner, 2010). When EDZ status is withdrawn, spatial targeting and direct fiscal support diminish. This increases firms' external finance premia and raises the fixed and working-capital costs of R&D investment. To examine this explanation, I estimate the treatment effects of EDZ closures on subsidy intensity (subsidies divided by sales) and on own R&D intensity (R&D expenditures divided by sales).

2.7 Agglomeration Disruption, Index Construction, and Bartik-Style Instruments

Agglomeration advantages hinge on the thickness of the local production environment—dense co-location that lowers search and coordination costs and fosters matching, learning, and sharing (Rosenthal and Strange, 2004). Two classic horizontal channels are (i) diversity-based (Jacobs/urbanization) externalities (Glaeser et al., 1992) and (ii) specialization-based (MAR/localization) externalities (Henderson, 1997). A related vertical channel operates through buyer–supplier production networks that transmit tacit process and component knowledge along input–output links (Delgado et al., 2016).

While new EDZs aim to foster co-location and thicken local production, EDZ closures may conversely erode production networks and generate ecosystem losses. To explore this explanation, I construct four agglomeration–disruption indices (M_{im}) from pre-treatment district–industry composition (2001–2002) and, for vertical links, 2002 input–output weights (Appendix A): Jacobs (diversity), MAR (localization), Supplier (upstream), and Buyer (downstream). The indices combine baseline composition with exit rates observed during each district's closure window to translate the policy shock into ecosystem losses along these channels.

Because realized exit (thinning) is a post-treatment outcome, I estimate heterogeneous

effects by 2SLS, instrumenting $D_{it}^{close} \times M_{im}^{\text{real}}$ with a Bartik-style instrument of predicted exposure $D_{it}^{close} \times M_{im}^{\text{pred}}$ for each agglomeration source. Predicted exposure M_{im}^{pred} is built from national 4-digit industry shocks over 1998–2002 interacted with 2001–2002 district–industry shares and, for vertical channels, 2002 IO weights. National shifts are computed adopting a leave-one-prefecture-out strategy so that the shift component is orthogonal to local shocks (Appendix B).

3 Results

3.1 Zone Closures and Firm Innovation Performance

Table 1 reports IPW–TWFE estimates of EDZ-closure effects on patenting. Relative to otherwise similar firms in continuing EDZ districts, closures reduce both patent counts and citation-weighted quality, with comparatively larger losses for quality. Estimates are stable across increasingly flexible specifications that absorb sectoral cycles, local market shocks, and differential trends by pre-treatment firm and zone characteristics.

In Column (4), the preferred specification, closures are associated with a 1.8% decline in patent quantity $[-2.2\%, -1.4\%]$ and a 2.3% decline in citation-weighted patent quality $[-3.3\%, -1.4\%]$. These estimates are robust to the use of a Poisson Pseudo–MLE TWFE estimator, which yields similar magnitudes (Table S3), validating our interpretation of the effects as approximate percentage changes and reducing concerns about functional form and zero inflation (Chen and Roth, 2024). CS–DR event studies show that losses emerge 1–2 years post-closure and persist (Figure 1).

The pattern of results—muted effects on counts, larger effects on quality—is consistent with both the China context and the nature of innovation. First, higher-value invention (proxied by citation-weighted quality) relies more on sustained R&D effort and dense external knowledge flows, which are more sensitive to closure-induced disruptions; firms respond by scaling back lumpy, knowledge-intensive projects (Hall and Lerner, 2010). Second, lower-value patenting in China surged in the mid-2000s, partly due to administrative incentives, making filing volume easier to sustain (Hu and Jefferson, 2009).

[Insert Table 1 about here.]

[Insert Figure 1 about here.]

3.2 Identifying Assumptions and Robustness Checks

The CS-DR group-time average treatment effects, as displayed in Figure 2, provide evidence that the key DID assumptions are met. The analysis shows that the pre-treatment trends are flat with no anticipation. The post-closure effects for the two treatment cohorts evolve largely in parallel, suggesting that timing of the closures was not influenced by unobserved factors or a systematic trend that would caused cohorts to behave differently.

[Insert Figure 2 about here.]

Appendix C reports a set of sensitivity tests and checks for robustness against for potential threats to identification. Two falsification (placebo) tests are conducted that reduce concerns about unobserved residual selection and policy confounders: (i) randomized treatment year among treated firms (Figure S3); and (ii) randomized treated-unit assignment (Figure S4).

Results are robust to outcome modeling and sample composition, covariate extension to IPW and trends, spillovers that could violate SUTVA, and an alternative measure of innovation outcome. First, allowing post-treatment exit in a semi-balanced panel (Table S4) yields somewhat larger negative effects, consistent with exit being part of the closure response (a check against survivorship bias). Second, restricting to firms directly identified as EDZ participants (Table S5) produces larger adverse effects, as expected for firms most directly exposed to the policy shock.

In addition, extending IPW covariates and baseline trends to include pre-treatment district composition (shares of SOEs, FIEs, and high-tech firms) and supplier-buyer linkages to inland areas does not materially change the estimates (Table S6). This suggests that latent local composition and potential coastal-inland pull do not drive the main results. Finally, patenting outcomes and employment in continuing zones are typically insensitive to the cumulative share of nearby closures (Table S7), suggesting limited re-

allocation from closed to continuing EDZs. One exception is a negative prefecture-level spillover on patent quality, which may attenuate the main DiD estimates, since the comparison group is mildly harmed.

The main results on patenting quality are insensitive to the citation window: using one-, three-, or five-year forward citations yields very similar estimates (Table S8). Using an alternative innovation outcome—the commercialization of new products and processes—yields similar patterns (Table S9). Closures reduce the probability of reporting a new product or process and lower the intensive margin of innovation sales.

3.3 Explanations

Internal Firm Disruptions

The results in Table 2 show irrespective of specification, that EDZ closure results in reductions in the subsidies that firms receive and in own-investment in R&D. For subsidies, Column (4) reports an estimate of -0.018 corresponding to about a 9 percent decline relative to the 0.195 pre-treatment mean. For R&D intensity, the effect of -0.0012 represents about a 6 percent decline relative to the 0.019 pre-treatment mean. These patterns are consistent with a financing-constraint channel: when zones close, direct support falls and firms scale back cash-intensive knowledge investment first.

[Insert Table 2 about here.]

3.3.1 External Agglomeration Disruptions

To quantify how closure effects scale with ecosystem losses, I instrument the endogenous interaction Closure $\times$ Disruption with a Bartik-style predicted disruption index (national 1998–2002 industry shocks crossed with 2001–2002 local composition; 2002 IO weights for vertical links). First-stage diagnostics are strong, and reported in Table S10. The second stage IV results are reported in Table 3.

Moving from a district with average disruption to one that is one standard deviation more disrupted makes patent counts fall by an additional -0.1% to -0.3% on top of the

average −1.8% decline, implying a total loss of −1.9% to −2.1%. For citation-weighted quality, the incremental loss is −0.4% to −0.8%, which, when combined with the average −2.3%, implies a total reduction of about −2.7% to −3.1%. The largest amplifications arise through supplier (upstream) and within-industry specialization (MAR) channels, although differences across channels are not statistically distinguishable. The same pattern appears for commercialization outcomes: disruption lowers the probability of introducing a new product/process and reduces innovation sales intensity (Table S11).

[Insert Table 3 about here.]

3.4 Closures, Innovation Capabilities, and Export Resilience

Innovation capabilities underpin export competitiveness, and negative shocks can directly—or indirectly via weakened innovation—spill over to trade performance (Lileeva and Trefler, 2010). I examine firm heterogeneity along innovation dimensions to assess the downstream implications of closures for international competitiveness and resilience. Grounded in the resource-based view (Barney, 1991), firms with deeper innovation capabilities—internal knowledge, problem-solving routines, and commercialization know-how—are expected to be better positioned to withstand closure-induced disruptions.

In Table S12 I first report the average effect of EDZ closures on export performance using the same specifications as for innovation. Treatment effects are stable across specifications. In Column (4), closures reduce the likelihood of becoming a new exporter by 0.5 percentage points (3.6 percent of the 0.138 control mean) and lower export intensity by 1.4 percentage points (5.2 percent of the 0.269 control mean).

Exploring heterogeneous treatment effects by firms' pre-treatment innovation capabilities, I form groups along three dimensions: innovation type (imitation vs. genuine innovation), invention quality (lower vs. higher citations), and commercialization success (below- vs. above-median innovation-sales share). Table 4 reports heterogeneous effects estimated with the fully saturated IPW–TWFE model.

Across all subgroupings, effects are attenuated for firms with stronger innovation capabilities and often statistically insignificant on the extensive export margin. Adverse

exporting effects are larger for weaker-capability firms, and equality tests reject homogeneity within each panel ($p < 0.01$), indicating statistically meaningful differences across capability groups. Overall, the results suggest that firms with stronger innovation capabilities more readily substitute internal know-how for lost external supports as local externalities dissipate.

[Insert Table 4 about here.]

3.5 Net Innovation Effects of EDZ Reform

EDZ closures harmed firm innovation performance in coastal areas, particularly among firms with fewer internal capabilities. Because the reform simultaneously created new inland EDZs, a natural question is how far inland gains offset or exceed coastal losses. Mirroring the coastal analysis, I construct a balanced inland panel of 9,106 POE firms and estimate average opening effects using an IPW–TWFE design that compares firms in districts receiving a new zone during the reform with firms in districts that already operated a zone prior to the reform period (Appendix D).

I then allow opening effects to scale with local agglomeration formation in a way that mirrors the closure-side disruption analysis (Appendix E). Specifically, I instrument the interaction $D_{it}^{\text{open}} \times M_{im}^{\text{real,formation}}$ with Bartik-style instruments $D_{it}^{\text{open}} \times M_{im}^{\text{pred,formation}}$ constructed from 1998–2002 national 4-digit industry employment shocks crossed with 2001–2002 district composition and 2002 input–output weights (leave-one-prefecture-out).

In the inland sample, new EDZ openings raise patent quantity by about 1.7% and citation-weighted patent quality by about 1.3% (imprecisely estimated), and CS–DR group–time effects show flat pretrends with gains that persist over time (Table S13; Figure S5). Agglomeration formation modestly amplifies these gains: a one-standard-deviation increase in instrumented formation adds +0.15% to +0.32% for counts and +0.18% to +0.37% for quality (Table S14).

Next I build a no-reform counterfactual on both sides of the policy that explicitly accounts for heterogeneous treatment intensity (Appendix F): for coastal firms, EDZ-closure losses scale with instrumented agglomeration-disruption exposure; for inland

firms, EDZ-opening gains scale with instrumented agglomeration-formation exposure. I then aggregate firm-level effects over 2003–2007 for the treated coastal and inland samples and obtain uncertainty via a district-cluster bootstrap with 1,000 replications.

In the short run, coastal losses outweigh inland gains, yielding a small negative net impact concentrated in quality: the reform is associated with a \$-\$0.2% net change in patent counts (not statistically different from zero) and a \$-\$1.0% net change in citation-weighted quality (statistically significant) (Table 5). A back-of-the-envelope calculation implies roughly 2 fewer patents per 1,000 baseline patents among treated firms and 10 fewer forward citations per 1,000 baseline citations. While informative about short-run firm-level responses, this benchmarking exercise does not model general-equilibrium feedbacks (prices, wages, relocation) and should be interpreted as partial-equilibrium net effects.

[Insert Table 5 about here.]

4 Conclusion

This paper provides firm-level evidence on the consequences of withdrawing place-based policy support at scale. Exploiting China's national zone reform as a quasi-natural experiment, I show that closures depress innovation primarily on quality, while leaving patent volume only modestly affected–consistent with higher-value invention's reliance on steady R&D and dense knowledge flows. These losses are only partially offset by modest innovation gains at newly opened inland EDZs attributable to the reform's relocation mandate.

Two complementary channels help explain these findings. Internally, financing frictions tighten after closure: subsidy intensity and R&D intensity decline, raising the option value of waiting and prompting firms to prune knowledge-intensive projects. Externally, agglomeration disruptions weaken knowledge flows and market connectivity: losses are amplified where upstream supplier ties and within-industry specialization erode. Export performance also deteriorates (especially on the intensive margin), but firms with deeper innovation capabilities are more resilient–consistent with the resource-based view.

Two empirical implications follow from these findings. First, the abrupt withdrawal of

place-based support can disrupt firms' internal financing and external networks, eroding the agglomeration and innovation gains created while the program was active. Second, in settings where withdrawal is justified on efficiency grounds, measures that maintain near-term access to R&D finance and preserve supplier–buyer connections may attenuate transitional losses, particularly for less resilient firms most vulnerable to the shock.

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5 Figures

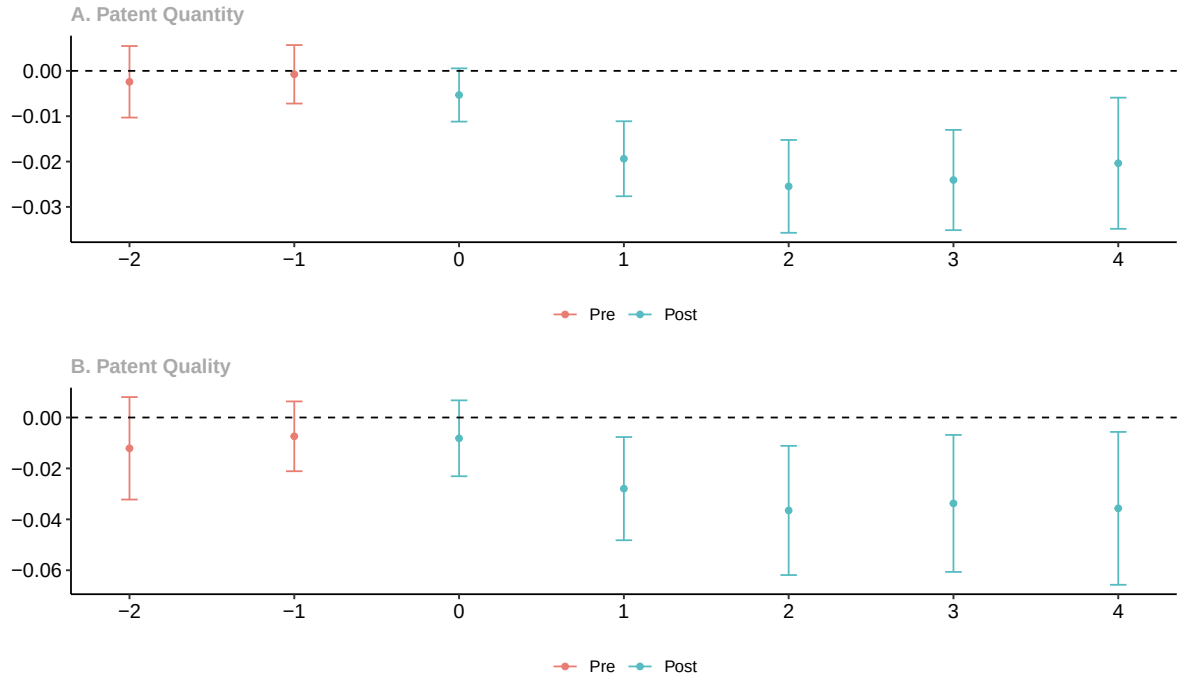


Figure 1: CS-DR Dynamic Treatment Effects on Firm Patenting Outcomes

Notes: Figure plots dynamic CS-DR treatment effects (Callaway and Sant'Anna, 2021). Outcomes are patent quantity $\ln(1 + \#$ patents) and patent quality ($\ln(1 + \#$3-year forward citations)).

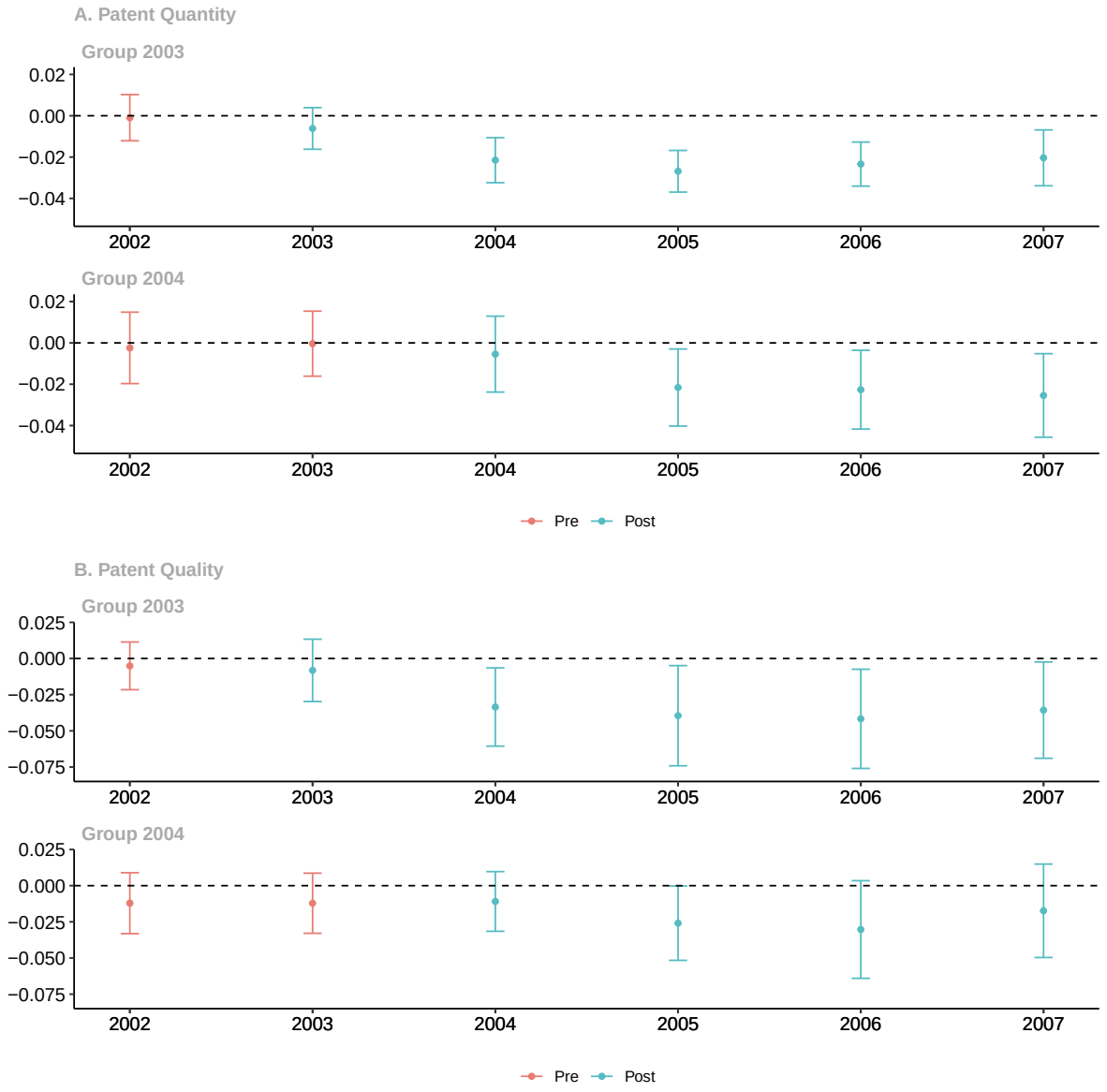


Figure 2: EDZ Closure Time-Varying Treatment Effects on Firm Patenting Outcomes

Notes: Figure plots group–time average treatment effects, $\text{ATT}_{g,t}$ (Callaway and Sant'Anna, 2021). Outcomes are patent quantity $\ln(1 + \#\text{ patents})$ and patent quality ($\ln(1 + \#\text{3-year forward citations})$).

6 Tables

Table 1: Effects of EDZ Closure on Firm Patenting

	(1)	(2)	(3)	(4)
A. Patent quantity				
Closure	−0.016*	−0.017*	−0.018*	−0.018*
	[-0.020, -0.012]	[-0.021, -0.013]	[-0.022, -0.014]	[-0.022, -0.014]
B. Patent quality				
Closure	−0.020*	−0.023*	−0.023*	−0.023*
	[-0.030, -0.011]	[-0.032, -0.013]	[-0.033, -0.013]	[-0.033, -0.014]
Firms (#)	46,840	46,840	46,840	46,840
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	—	—	—
Industry-Year FE	No	Yes	Yes	Yes
City-Year FE	No	No	Yes	Yes
Covariate Trends	No	No	No	Yes

Notes: * indicates the null value lies outside the 95 percent confidence interval (reported in brackets). Robust standard errors are two-way clustered by firm and district. Outcomes are patent quantity ln(1+# patents) and patent quality (ln(1+#3-year forward citations)). Column (1) includes year FE; Columns (2)–(3) replace year FE with industry-year and city-year FE; Column (4) adds interactions between pre-treatment firm/zone characteristics and year dummies.

Table 2: Effects of Zone Closure on State Support and Firm R&D Investment

	(1)	(2)	(3)	(4)
A. Subsidy intensity				
Closure	−0.022*	−0.021*	−0.020*	−0.018*
	[−0.029, −0.015]	[−0.026, −0.016]	[−0.023, −0.017]	[−0.022, −0.014]
B. R&D intensity				
Closure	−0.0015*	−0.0014*	−0.0013*	−0.0012*
	[−0.0020, −0.0010]	[−0.0017, −0.0010]	[−0.0016, −0.0010]	[−0.0015, −0.0009]
Firms (#)	46,840	46,840	46,840	46,840
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	—	—	—
Industry-Year FE	No	Yes	Yes	Yes
City-Year FE	No	No	Yes	Yes
Covariate Trends	No	No	No	Yes

Notes: * indicates the null lies outside the 95 percent confidence interval (reported in brackets). Robust standard errors are two-way clustered by firm and district. Outcomes are subsidy intensity (subsidies divided by firm sales) and R&D intensity (R&D expenditures divided by firm sales). Column (1) includes year FE; Column (2) adds industry-year FE; Column (3) additionally includes city-year FE; Column (4) further adds interactions between pre-treatment firm/zone characteristics and year dummies.

Table 3: EDZ Closures, Agglomeration Disruptions, and Patenting

	Disruption Index:			
	Diversity	Specialization	Supplier	Buyer
	(1)	(2)	(3)	(4)
A. Patent quantity				
Closure × Disruption (IV)	-0.001^{*}	-0.002^{*}	-0.003^{*}	-0.001
	$[-0.002, -0.001]$	$[-0.003, -0.001]$	$[-0.004, -0.002]$	$[-0.002, 0.000]$
B. Patent quality				
Closure × Disruption (IV)	-0.004^{*}	-0.007^{*}	-0.008^{*}	-0.005^{*}
	$[-0.006, -0.002]$	$[-0.009, -0.004]$	$[-0.011, -0.005]$	$[-0.007, -0.003]$
Firms (#)	46,840	46,840	46,840	46,840
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes
Covariate Trends	Yes	Yes	Yes	Yes

Notes: * indicates the null lies outside the 95 percent confidence interval (reported in brackets). Robust standard errors are two-way clustered by firm and district. Outcomes are patent quantity ln(1 + # patents) and patent quality (ln(1 + #3-year forward citations)). Entries report 2SLS estimates of Closure × Disruption Index for each channel (Diversity, Specialization, Supplier, Buyer). The endogenous interaction is instrumented with Closure × Predicted Disruption, where the predicted index interacts 2001–2002 local composition with national 1998–2002 industry employment shocks; Supplier/Buyer use 2002 input–output weights (Appendix A). First-stage results and diagnostics are reported in Table S10. Specifications include firm FE, industry–year FE, city–year FE, interactions of pre-treatment covariates with year dummies, and all lower-order terms implied by the interaction.

Table 4: Zone Closures, Innovation Capabilities, and Export Resilience

	Innovation Strategy		Invention Quality		Commercialization Success	
	New exporter (1=yes)	Export Intensity (share)	New exporter (1=yes)	Export Intensity (share)	New exporter (1=yes)	Export Intensity (share)
A. Type						
Imitator	−0.008*	−0.020*	...	...	...	...
	[−0.012,	[−0.024,	...	...	...	...
	−0.004]	−0.016]	...	...	...	...
Genuine innovator	−0.003	−0.011*	...	...	...	...
	[−0.006,	[−0.015,	...	...	...	...
	0.000]	−0.007]	...	...	...	...
B. Citations						
Lower	...	...	−0.007*	−0.018*	...	...
	...	...	[−0.011,	[−0.022,	...	...
	...	...	−0.003]	−0.014]	...	...
Higher	...	...	−0.003	−0.012*	...	...
	...	...	[−0.006,	[−0.016,	...	...
	...	...	0.000]	−0.008]	...	...
C. Commercialization						
Lower	...	...	...	...	−0.006*	−0.019*
	...	...	...	...	[−0.010,	[−0.023,
	...	...	...	...	−0.002]	−0.015]
Higher	...	...	...	...	−0.002	−0.011*
	...	...	...	...	[−0.006,	[−0.015,
	...	...	...	...	0.002]	−0.007]
Equiv. Test (p-value)	0.00	0.00	0.00	0.00	0.00	0.00
Firms (#)	46,840	46,840	46,840	46,840	46,840	46,840
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Trends	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * indicates the null value lies outside the 95 percent confidence interval (reported in brackets). Robust standard errors are two-way clustered by firm and district. Outcomes are new exporter (indicator = 1 if the firm exports for the first time, and 0 otherwise) and export intensity (export sales divided by total sales). Subgroups are defined using pre-treatment characteristics: Strategy–non-innovators omitted; Imitator (no R&D and no patents, positive innovation sales) vs. Genuine innovator (positive R&D and either non-zero patents or innovation sales). Invention quality–firms with no pre-treatment patents omitted; split by median 3-year forward citations. Commercialization success–firms with no pre-treatment innovation sales omitted; split by median share of sales from new products/processes. P-values from a within-panel joint F-test of equality reject equal effects across subgroups. Specifications include firm FE, industry-year FE, city-year FE, and firm/zone trends.

Table 5: Net Effect of EDZ Reform

	Patent Quantity	Patent Quality
Coastal loss Δ^{coast}	-1.9 $[-2.7, -1.1]$	-2.3 $[-3.3, -1.3]$
Inland gain Δ^{inland}	$+1.7$ $[+0.8, +2.6]$	$+1.3$ $[-0.2, +2.8]$
Net (gain + loss) per firm	-0.2 $[-0.7, +0.3]$	-1.0 $[-2.0, -0.1]$

Notes: The table compares observed innovation outcomes with a counterfactual scenario of no EDZ reform. Outcomes are patent quantity ln(1 + # patents) and patent quality (ln(1 + #3-year forward citations)). Values are approximate percent changes relative to the treated-group counterfactual mean under no reform. Net effects aggregate firm-level EDZ closure effects in the coastal sample and EDZ opening effects in the inland sample over 2003-2007. Heterogeneous effects for agglomeration disruption intensity in coastal sample and heterogeneous agglomeration creation inland sample are estimated by 2SLS (Appendix F), instrumenting the interaction terms with pre-determined, Bartik-style indices constructed from national 1998-2002 industry shocks and 2001-2002 local composition (and 2002 IO weights). Bootstrap confidence intervals (reported in brackets) use 1,000 district-cluster replications.

7 Supplementary Information (SI)

A Agglomeration Disruption Indices

Setup. Let i index firms, $h(i)$ the 4-digit industry, and $z(i)$ the district-level zone catchment area. For each district z, let $t_z^\star \in \{2003, 2004\}$ be the zone-specific closure year; for continuing zone districts set $t_z^\star = 2004$ to align post windows. Baseline district–industry employment and shares are the 2001–2002 averages, $E_{kz,0}$ and $s_{kz,0} \equiv E_{kz,0} / \sum_j E_{jz,0}$. Define the closure-window thinning (exit) rate

$$\Delta\text{Exit}_{kz} \;\equiv\; \frac{E_{kz,0} - E_{kz,t_z^\star}}{E_{kz,0}}.$$

Using the 2002 input–output (IO) table, let A_{uk} be Leontief input coefficients and G_{ku} gross-output allocation shares. Normalize to obtain convex upstream/downstream weights that sum to one:

$$\omega^{\text{up}}_{h(i)k} \equiv \frac{A_{k\,h(i)}}{\sum_r A_{r\,h(i)}}, \quad \omega^{\text{down}}_{k\,h(i)} \equiv \frac{G_{h(i)\,k}}{\sum_r G_{h(i)\,r}}.$$

Horizontal (Jacobs) disruption. Losses from cross-industry agglomeration (urbanization/diversity externalities) equal baseline agglomeration formation outside the firm's own industry, weighted by subsequent agglomeration disruption, expressed as

$$M_{iz}^{\text{Jacobs}} = \sum_{k \neq h(i)} s_{kz,0}\, \Delta\text{Exit}_{kz} = \big(1 - s_{h(i)z,0}\big) \cdot \overline{\Delta\text{Exit}}_{-h,z}.$$

Here baseline agglomeration formation (thickness) refers to the supply of agglomeration economies available outside the firm's own industry leading up to the reform. Subsequent agglomeration disruption refers to the share of firm exits within the district that occur during the treatment window that occur outside of the firm's own industry.

Localization (MAR) disruption. Losses from within-industry localization (specialization/MAR externalities) equal baseline own-industry thickness times its thinning:

$$M_{iz}^{\text{MAR}} = s_{h(i)z,0} \cdot \Delta\text{Exit}_{h(i)z}.$$

Vertical production-network disruption. Supplier- and buyer-side losses weight local thinning by the relevance of upstream inputs and downstream sales for $h(i)$:

$$M_{iz}^{\text{Supplier}} = \sum_k \omega_{h(i)k}^{\text{up}}\, s_{kz,0}\, \Delta\text{Exit}_{kz}, \qquad M_{iz}^{\text{Buyer}} = \sum_k \omega_{k\,h(i)}^{\text{down}}\, s_{kz,0}\, \Delta\text{Exit}_{kz}.$$

Here $s_{kz,0}\,\Delta\text{Exit}_{kz}$ is the *district-local* share-weighted thinning of industry k; the IO weights map those local losses into the subset of upstream/downstream industries most important for $h(i)$, yielding a convex, relevance-weighted average.

Each index is standardized. Table S15 reports treatment–control differences in exposure by channel. Average value for each index is larger in closed EDZ districts than in continuing EDZ ones, consistent with the idea that treated districts experienced larger zone closure-induced disruptions to each considered externality type.

[Insert Table S15 about here.]

B Agglomeration Disruption with Bartik-Style Instruments

Motivation. When interacted with the EDZ closure indicator, the four constructed indices capture how treatment effects scale with disruption intensity for each agglomeration channel where closures occur, expressed as

$$Y_{it} = \beta\, D_{it}^{\text{close}} + \boldsymbol{\vartheta}^{\top}\big(D_{it}^{\text{close}}\, \mathbf{M}_i^{\text{disrupt}}\big) + \alpha_i + \delta_{p(i),t} + \Gamma_{h(i),t} + \sum_{\tau} \boldsymbol{\theta}_{\tau}^{\top} X_i^{\text{base}}\, \mathbf{1}\{t=\tau\} + \varepsilon_{it}, \quad (3)$$

where $\mathbf{M}_i^{\text{disrupt}} = \big(M_{iz}^{\text{Jacobs}},\, M_{iz}^{\text{MAR}},\, M_{iz}^{\text{Supplier}},\, M_{iz}^{\text{Buyer}}\big)'$, constructed from baseline 2001-2002 composition and exit-induced thinning described in Appendix A, which includes all lower-order components implied by the triple interaction (i.e., $\mathbf{M}_i^{\text{disrupt}}$, $\mathbf{M}_i^{\text{disrupt}} \times \mathbf{1}\{t \geq g_{z(i)}\}$, and $\mathbf{M}_i^{\text{disrupt}} \times \mathbf{1}\{z(i) \text{ closes}\}$). The coefficient vector $\boldsymbol{\vartheta}$ traces heterogeneous effects: the ATT at exposure $\mathbf{M}_i^{\text{disrupt}}$ equals $\beta + \boldsymbol{\vartheta}^{\top}\mathbf{M}_i^{\text{disrupt}}$. The disruption vector $\mathbf{M}_i^{\text{disrupt}}$ uses *realized* exit, which is post-treatment and thus potentially endogenous. The

endogenous interaction $D_{it}^{\text{close}} M_i^{m,\text{real}}$ is therefore instrumented with a pre-determined, shift-share (Bartik) interaction $D_{it}^{\text{close}} M_i^{m,\text{pred}}$.

National shocks and leave-one-out. National shocks $\Delta E_{k,98\text{–}02}^{nat}$ are computed from 1998 and 2002 industry employment. In the calculation, the firm's own prefecture is excluded when forming the national aggregates (leave-one-out), $\Delta E_{k,98\text{–}02}^{\text{nat},-p(i)}$. This ensures that the shock used for prediction is not mechanically correlated with local shocks in the outcome equation.

Bartik-style predicted disruption indices. For firm i in district $z(i)$ and industry $h(i)$, the predicted (pre-period) exposure for channel m is obtained by replacing realized local exit rates with national shocks in the substantive definitions of Section A. Denote $\Delta E_k^{\text{nat}} \equiv \Delta E_{k,98\text{–}02}^{\text{nat},-p(i)}$ for brevity.

Horizontal (Jacobs/urbanization): outside the firm's own industry

$$M_{iz}^{\text{Jacobs,pred}} \;=\; \sum_{k \neq h(i)} s_{kz,0}\, \Delta E_k^{\text{nat}} \;=\; \big(1 - s_{h(i)z,0}\big) \cdot \underbrace{\left(\sum_{k \neq h(i)} \frac{s_{kz,0}}{1 - s_{h(i)z,0}}\, \Delta E_k^{\text{nat}} \right)}_{\text{baseline-share–weighted average outside } h(i)} .$$

Horizontal (MAR/localization): own industry

$$M_{iz}^{\text{MAR,pred}} \;=\; s_{h(i)z,0}\, \Delta E_{h(i)}^{\text{nat}}.$$

Vertical (upstream suppliers): industries that supply $h(i)$ nationally, weighted by their local presence

$$M_{iz}^{\text{Supplier,pred}} \;=\; \sum_{k} \omega_{h(i)k}^{\text{up}}\, s_{kz,0}\, \Delta E_k^{\text{nat}}.$$

Vertical (downstream buyers): industries that buy from $h(i)$ nationally, weighted by their local presence

$$M_{iz}^{\text{Buyer,pred}} \;=\; \sum_{k} \omega_{k\,h(i)}^{\text{down}}\, s_{kz,0}\, \Delta E_k^{\text{nat}}.$$

Bartik-style IV with interaction. Define the closure exposure $D_{it}^{\text{close}} \equiv \mathbf{1}\{z(i) \text{ closes}\} \cdot \mathbf{1}\{t \geq g_{z(i)}\}$, where $g_{z(i)} \in \{2003, 2004\}$ is the district's first closure year. For channel $m \in \{\text{Jacobs}, \text{MAR}, \text{Supplier}, \text{Buyer}\}$, let $M_i^{m,\text{pred}}$ denote the *predetermined* (leave-one-prefecture-out) Bartik exposure constructed from 1998–2002 national shocks crossed with 2001–2002 local composition and, for vertical links, 2002 IO weights. The endogenous regressor is the realized interaction

$$W_{im} \;\equiv\; D_{it}^{\text{close}}\, M_i^{m,\text{real}},$$

and the excluded instrument is the Bartik interaction

$$Z_{im} \;\equiv\; D_{it}^{\text{close}}\, M_i^{m,\text{pred}}.$$

First stage.

$$W_{im} \;=\; \pi_m\, Z_{im} \;+\; \lambda_1\, D_{it}^{\text{close}} \;+\; \lambda_2 \left(M_i^{m,\text{pred}} \times \mathbf{1}\{t \geq g_{z(i)}\} \right) \;+\; \text{FE} \;+\; v_{it}. \tag{4}$$

Second stage.

$$y_{it} = \theta_m\, \widehat{W}_{im} + \beta\, D_{it}^{\text{close}} + \eta \left(M_i^{m,\text{pred}} \times \mathbf{1}\{t \geq g_{z(i)}\} \right) + \text{FE} + \varepsilon_{it}. \tag{5}$$

where $y_{it} = log(Y_{it} + 1)$ and FE comprises firm fixed effects (α_i), prefecture×year fixed effects ($\delta_{p(i),t}$), industry×year fixed effects ($\Gamma_{h(i),t}$), and interactions of pre-treatment covariates with year dummies $\left(\sum_\tau \boldsymbol{\theta}_\tau^\top X_i^{\text{base}}\, \mathbf{1}\{t = \tau\} \right)$. The specification includes all lower-order terms (e.g. $M_i^{m,\text{pred}} \times \mathbf{1}\{t \geq g_{z(i)}\}$, the time-varying step based on the district's cohort). Estimation uses two-stage least squares with robust standard errors two-way clustered by firm and district.

Exclusion and relevance. The "share" $s_{kz,0}$ and IO weights $(\omega^{\text{up}}, \omega^{\text{down}})$ are pre-determined, and the "shift" ΔE_k^{nat} is computed from pre-period national data with leave-one-out, so $M_{iz}^{m,\text{pred}}$ is predetermined with respect to post-closure outcomes. Relevance is assessed

via the Kleibergen-Paap F-statistic and partial R^2 (Table S10). Exclusion assumes that, conditional on FE and controls, the leave-one-out national shock affects y_{it} only through its prediction of within-district agglomeration disruption intensity in channel m.

C Additional Robustness Checks

Falsification (placebo) tests

To probe for unobserved confounding and timing selection, I implement two randomization-inference placebos.

Timing placebo. Within prefecture×industry strata, I randomly permute the first-treatment year among treated firms, reconstruct the treatment (preserving the 2003 vs. 2004 cohort shares), and re-estimate the Column (4) IPW–TWFE specification (Table 1) for each draw (B=1,000). Controls remain never treated. Placebo coefficients form the distributions in Figure S3. The observed estimates (red lines) lie in the extreme tails with small two-sided empirical p-values, indicating that the estimated effects are not driven by arbitrary cohort timing.

[Insert Figure S3 about here.]

Assignment placebo. Within the same strata, I also randomly reassign treated firms while preserving the number of 2003 and 2004 treated per stratum, and re-estimate the Column (4) model (Table 1) for each draw (B=1,000). Figure S4 shows placebo distributions that center near zero–as expected under a sharp null of no effect–while the observed estimates again fall in the extreme tails with small empirical p-values.

[Insert Figure S4 about here.]

Alternative estimator and sample composition

Table S3 shows that Poisson Pseudo–MLE results closely track the OLS results for counts of grants and three-year forward citations across all specifications. This alignment is consistent with PPML's robustness to heteroskedasticity and the prevalence of zeros, as well as the inclusion of high-dimensional fixed effects. Tables S4–S5 further document that (i) effects are larger in a strict firm-tagging subsample that isolates direct participation in closed zones, and (ii) effects are larger when allowing post-treatment exit in a semi-balanced panel (no new entrants), consistent with innovative firms disproportionately

exiting closed-zone districts. Taken together, these checks suggest that the main results are not driven by specification choice and that both exposure and composition (exit) channels contribute to the observed declines.

[Insert Table S3 about here.]

[Insert Table S4 about here.]

[Insert Table S5 about here.]

SUTVA risks

A main concern is relocation from closed EDZs into continuing coastal EDZs, which could induce spillovers and bias the DiD. To test for such spillovers, I restrict the sample to continuing districts and regress outcomes on the cumulative prefecture- (Panel A) or province-level (Panel B) share of closures by year, with firm fixed effects and industry-year fixed effects. As shown in Table S7, the effects on patenting outcomes and employment are small and statistically weak, indicating limited spillover-induced SUTVA violations. This pattern is consistent with the reform's stated goal of redirecting economic activity from coastal to inland areas to address regional imbalances.

[Insert Table S7 about here.]

Residual selection and coastal–inland linkages

Table S6 addresses residual selection by enriching both reweighting (IPW) and controls with pre-treatment district characteristics. Column (1) adds district shares of SOEs, FIEs, and high-tech firms to the IPW propensity score. Column (2) includes district-year controls for these baseline shares to absorb differential local trends.

A separate concern is an inland "pull" during reform: if some firms or workers in continuing coastal EDZs were also encouraged to relocate inland, comparison-group outcomes could change, affecting estimated closure effects. Coastal firms with stronger inland ties may also respond differently to closure. To proxy pre-treatment inland connections, I con-

struct a district–industry IO-based linkage using the 2002 IO table and inland pre-2003 industry composition:

$$L^{\text{IO}}_{z(i),h(i)} \;=\; \sum_{k} \left(\omega^{\text{down}}_{k\,h(i)} + \omega^{\text{up}}_{h(i)k} \right) s^{\text{inland}}_{k,2002},$$

where ω^{down} and ω^{up} are normalized IO shares and $s^{\text{inland}}_{k,2003}$ is the inland employment share in industry k pre-2003. Column (3) adds L^{IO} to the IPW; Column (4) interacts L^{IO} with year dummies to allow inland-linked firms to follow distinct paths. Closure coefficients are stable across Columns (1)–(4), suggesting that latent district composition and inland pull are unlikely to drive the main DiD results.

[Insert Table S6 about here.]

Alternative citation window and innovation outcome

Table S8 reports treatment effects on patent quality using 1- and 5-year citation windows, and the pattern of results remain the same as for the 3-year window. Table S9 reports treatment effects realted to the introduction and commercialization of new innovations. Closures reduce the probability of reporting a new product or process by about -0.006, which is roughly a 7 percent decline relative to the 0.091 pre-treatment mean. Innovation sales intensity falls by about -0.003, a 10 percent decline relative to the 0.034 pre-treatment mean. The direction and stability mirror the patent results, with intensive-margin commercialization bearing a meaningful share of the adjustment.

[Insert Table S8 about here.]

[Insert Table S9 about here.]

D Inland Firm Sample and Analysis: EDZ Openings

Sample. The inland benchmark uses a balanced panel of POE firms located in inland districts with either (i) an EDZ first opened in 2003-2005 (treated) or (ii) a continuing EDZ operating prior to 2003 (comparison), observed from 2001 to 2007. The total inland sample comprises 9,106 firms, of which 4,659 are in districts that receive a new EDZ (Table S16); the remainder are in inland districts with pre-existing EDZs that stay active throughout the period. Fewer than 5 percent of treated firms are in districts that became operational in 2005, which are retained to accommodate late approvals tied to the zone reform wave.

Descriptives. Pre-treatment means (Table S17) indicate that, relative to firms located in districts with a pre-existing EDZ prior to the reform period, firms in new-EDZ districts exhibit similar innovation and export performance and similar TFP prior to opening; differences on other observables are small. While this does not rule out unobserved selection into treatment, the descriptive suggest that firms in continuing inland EDZs provide a suitable comparison group for the counterfactual of no new EDZ establishment under the reform, and this choice mirrors the comparison used in the coastal analysis.

[Insert Table S17 about here.]

Specification: EDZ openings (inland) Let $g_d \in \{2003, 2004, 2005\}$ denote the district's new zone opening cohort and define $D_{it}^{\text{open}} \equiv \mathbf{1}\{t \geq g_{z(i)}\}$. The specification for the new zone opening TWFE is the analogue of Eq.(1), expressed as

$$Y_{it} = \beta^{\text{open}} D_{it}^{\text{open}} + \alpha_i + \delta_{p(i),t} + \Gamma_{h(i),t} + \sum_{\tau} \boldsymbol{\theta}_{\tau}^{\top} X_i^{\text{base}} \mathbf{1}\{t = \tau\} + \varepsilon_{it}, \tag{6}$$

estimated by IPW-TWFE with robust standard errors clustered by firm and district.

E Agglomeration Formation with Bartik-Style Instruments

Setup. For new-EDZ inland districts, let $t_z^\star \in \{2003, 2004, 2005\}$ denote the opening cohort and define

$$\Delta\text{Entry}_{kz} \equiv \frac{E_{kz,t_z^\star} - E_{kz,0}}{E_{kz,0}}, \qquad E_{kz,0} \equiv \overline{E}_{kz,2001\text{–}2002}, \quad s_{kz,0} \equiv \frac{E_{kz,0}}{\sum_j E_{jz,0}}.$$

Replace ΔExit_{kz} with ΔEntry_{kz} in the four definitions of Section A (with the same ω^{up} and ω^{down}) to obtain

$$\mathbf{M}_i^{\text{formation}} = \big(M_{iz}^{\text{Jacobs,form}},\, M_{iz}^{\text{MAR,form}},\, M_{iz}^{\text{Supplier,form}},\, M_{iz}^{\text{Buyer,form}}\big)',$$

standardized (mean 0, s.d. 1) in the inland sample. Table S18 summarizes treatment–control differences. Average value for each index is larger in new EDZ opening districts than in districts with a pre-existing EDZ, consistent with the idea that treated districts experienced larger zone opening-induced agglomeration formation.

[Insert Table S18 about here.]

Bartik-style predicted formation indices. Construct $\mathbf{M}_i^{\text{pred,formation}}$ by substituting the same leave-one-out national shocks $\Delta E_{k,98\text{–}02}^{\text{nat},-p(i)}$ for ΔEntry_{kz} in each channel's definition, crossed with inland $s_{kz,0}$ and 2002 IO weights

$$M_{iz}^{\text{Jacobs,pred,form}} = \sum_{k \neq h(i)} s_{kz,0}\, \Delta E_k^{\text{nat}}, \qquad M_{iz}^{\text{MAR,pred,form}} = s_{h(i)z,0}\, \Delta E_{h(i)}^{\text{nat}},$$

$$M_{iz}^{\text{Supplier,pred,form}} = \sum_k \omega_{h(i)k}^{\text{up}}\, s_{kz,0}\, \Delta E_k^{\text{nat}}, \qquad M_{iz}^{\text{Buyer,pred,form}} = \sum_k \omega_{k\,h(i)}^{\text{down}}\, s_{kz,0}\, \Delta E_k^{\text{nat}}.$$

Bartik-style IV with interaction. Mirroring Eq. 3, one could interact the observed entry-induced agglomeration formation with the DiD term,

$$Y_{it} = \beta^{\text{open}} D_{it}^{\text{open}} + \boldsymbol{\varphi}^\top\big(D_{it}^{\text{open}}\, \mathbf{M}_i^{\text{formation}}\big) + \alpha_i + \delta_{p(i),t} + \Gamma_{h(i),t} + \sum_\tau \boldsymbol{\theta}_\tau^\top X_i^{\text{base}}\, \mathbf{1}\{t = \tau\} + \varepsilon_{it},$$

however the formation vector $\mathbf{M}_i^{\text{formation}}$ uses *realized* entry, which is post-treatment and thus potentially endogenous. To avoid conditioning on post-opening outcomes, instrument $D_{it}^{\text{open}}\mathbf{M}_i^{\text{formation}}$ with $D_{it}^{\text{open}}\mathbf{M}_i^{\text{pred,formation}}$, where $\mathbf{M}_i^{\text{pred,formation}}$ replaces ΔEntry_{kz} by the same pre-period national shocks $\Delta E_{k,98\text{–}02}^{\text{nat}}$ crossed with *inland* baseline composition and 2002 IO weights (leave-one-prefecture-out when forming ΔE^{nat}). First- and second-stage equations mirror (4)–(5). Relevance is assessed via the Kleibergen-Paap F-statistic and partial R^2 (Table S14). Exclusion assumes that, conditional on FE and controls, the leave-one-out national shock affects y_{it} only through its prediction of within-district agglomeration formation intensity in channel m.

Results. New inland EDZ openings are associated with modest gains in innovation. Column (4) of Table S13 indicates that treated firms increase patent quantity by 1.7 percent. The effect on patent quality implies a 1.3 percent increase but is imprecisely estimated. When the opening indicator is interacted with the instrumented agglomeration formation indices, effects are larger in new zones more conducive to fostering agglomeration economies, with the most pronounced amplification in supplier linkages and within-industry specialization (Table S14, Panel B). The pattern mirrors the coastal results in sign and channels: closures reduce both quantity and quality, while openings raise quantity and, where agglomeration formation is strong, can also bolster quality.

[Insert Table S13 about here.]

[Insert Table S14 about here.]

F Counterfactual Estimation Procedure

Setup. Let $y_{it} = log(Y_{it} + 1)$. For coastal closures, the per-firm treatment effect for treated firm i is

$$\widehat{\Delta}_i^{\text{close}} \;=\; \widehat{\beta}_{\text{close}} \;+\; \sum_m \widehat{\theta}_m \, M_i^{m,\text{disruption}},$$

where M_i^m are the standardized disruption indices (Jacobs diversity, MAR specialization, supplier, buyer) constructed from baseline 2001-2002 composition and closure-window thinning. For inland openings, the per-firm effect allows gains to scale with agglomeration formation:

$$\widehat{\Delta}_i^{\text{open}} \;=\; \widehat{\beta}_{\text{open}} \;+\; \sum_m \widehat{\theta}_m \, M_i^{m,\text{formation}},$$

where $M_i^{m,\text{formation}}$ are the entry-based mirrors of the four agglomeration indices (baseline 2001-2002 composition interacted with opening-window entry rates).

Instrumented heterogeneity. For closures,

$$\widehat{\Delta}_i^{close} = \widehat{\beta}_{close} + \sum_m \widehat{\theta}_m \, X_{im}^{close},$$

and for openings,

$$\widehat{\Delta}_i^{open} = \widehat{\beta}_{open} + \sum_m \widehat{\varphi}_m \, X_{im}^{open}.$$

Here $X_{im}^{\cdot}$ denotes the first-stage projected exposure as described in Appendix B (closure-induced agglomeration disruptions) and Appendix E (opening-induced agglomeration formation).

Counterfactuals. With $y_{it} = log(Y_{it} + 1)$, the treated-firm counterfactual in the no-reform scenario is

$$y_{it}^{\text{no-close}} = y_{it}^{\text{obs}} - \widehat{\Delta}_i^{\text{close}} \quad \text{for closures,} \qquad y_{it}^{\text{no-open}} = y_{it}^{\text{obs}} - \widehat{\Delta}_i^{\text{open}} \quad \text{for openings.}$$

Average closure losses (inland gains) are the means of $\widehat{\Delta}_i^{\text{close}}$ ($\widehat{\Delta}_i^{\text{open}}$) across treated firms and post years 2003-2007.

Uncertainty. Inference is based on a district-cluster bootstrap (B=1,000). At each replication: (i) coastal and inland districts are resampled with replacement; (ii) models are re-estimated for closures (with disruption interactions) and openings (with agglomeration formation interactions); (iii) firm-level counterfactuals are recomputed; and (iv) coastal loss Δ_b^{coast}, inland gain Δ_b^{inland}, and the net $\Delta_b^{\text{coast}} + \Delta_b^{\text{inland}}$ are recorded. Percentile 2.5/97.5 bounds are reported as 95 percent confidence intervals.

A SI Figures

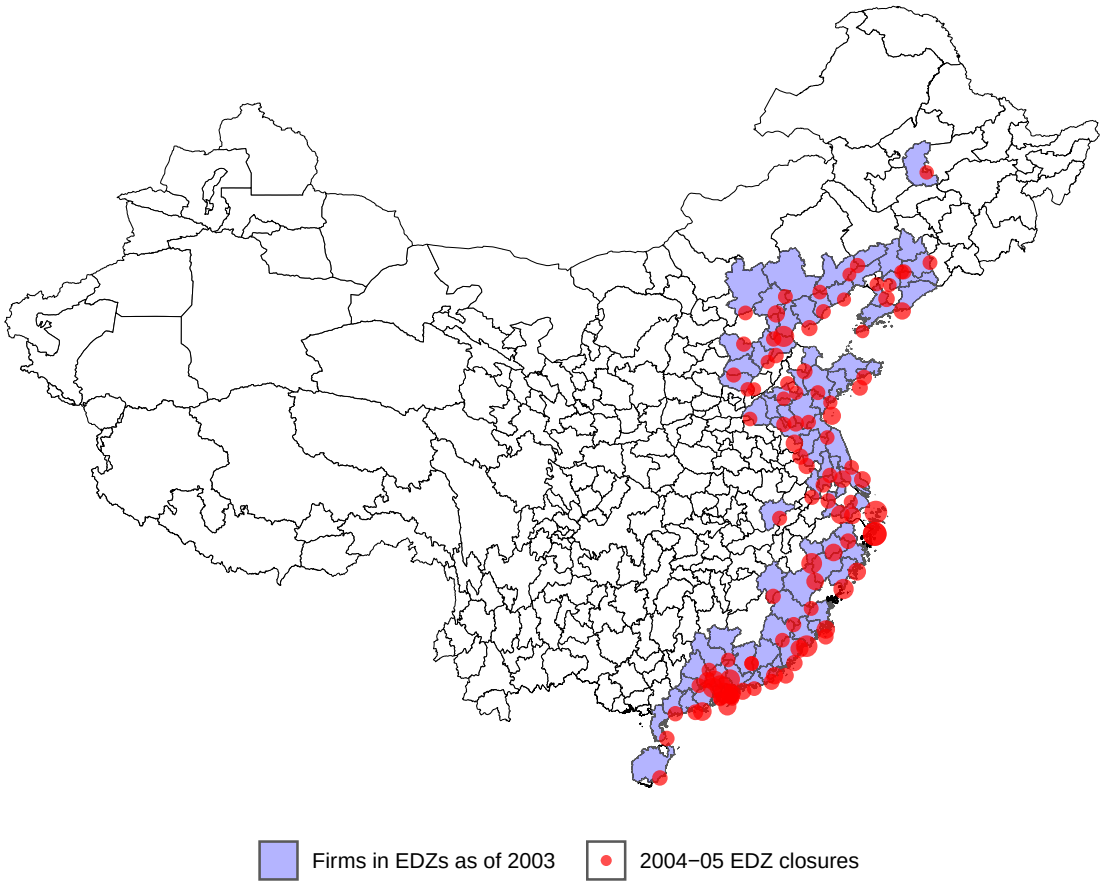


Figure S1: Coastal sample site locations and zone closures

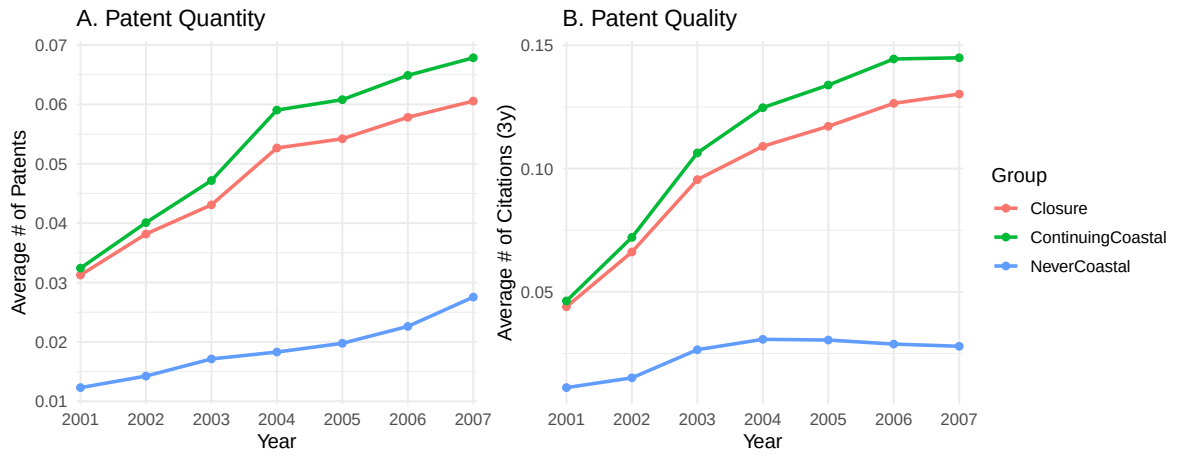


Figure S2: Average Levels of Patenting by Zone Status, 2001–2007

Notes: Figure reports mean patent quantity and patent quality by group (Continuing EDZ, Closed EDZ, Never EDZ) over 2001–2007. Outcomes are patent quantity $\ln(1 + \#$ patents) and patent quality ($\ln(1 + \#$3-year forward citations)).

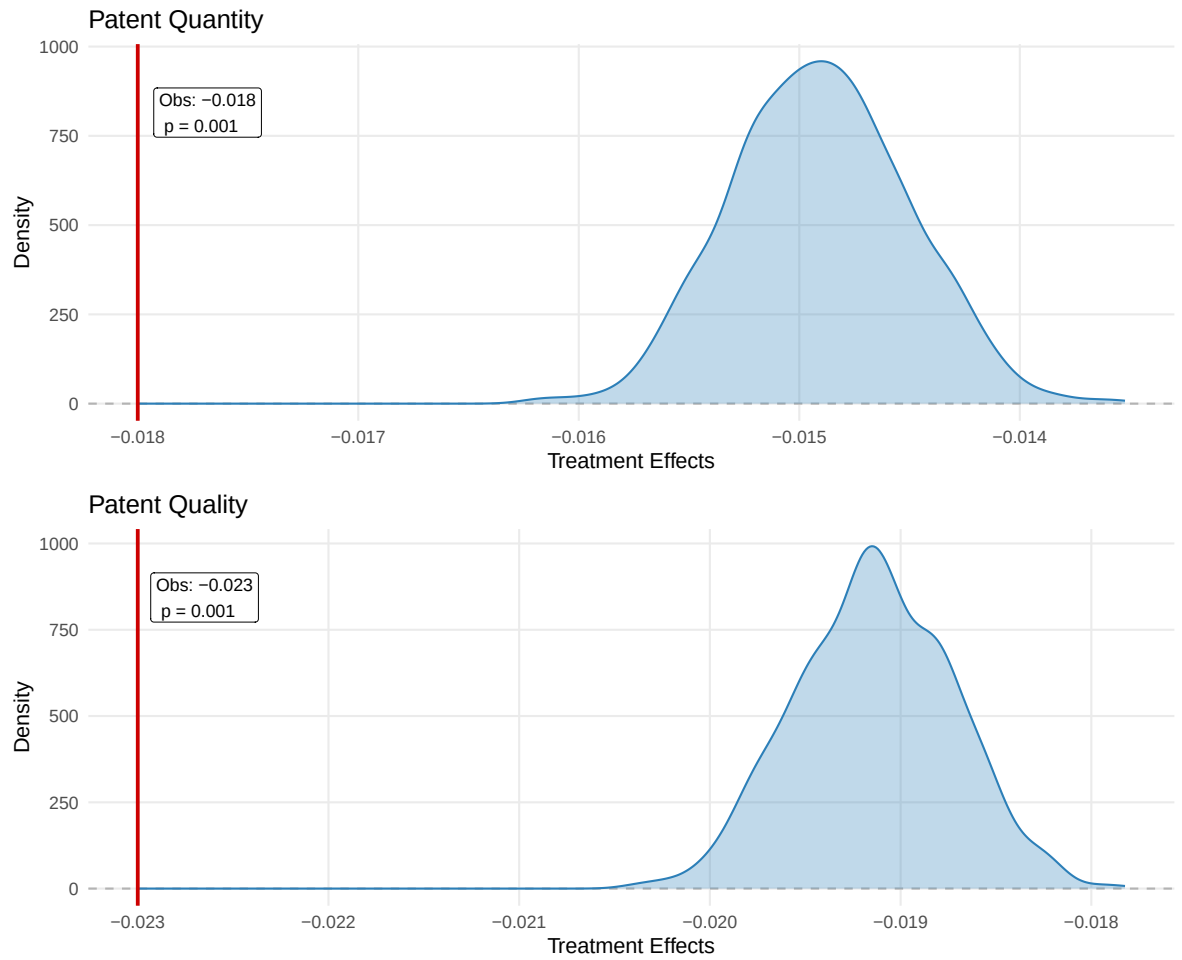


Figure S3: Falsification Test: Randomized Treatment Year (Timing Placebo)

Notes: Outcomes are patent quantity $\ln(1 + \#$ patents) and patent quality ($\ln(1 + \#$3-year forward citations)). Within prefecture×industry strata, the first-treatment year among treated firms is permuted (preserving the 2003 vs. 2004 cohort shares), the Column (4) IPW–TWFE from Table 1 is re-estimated each draw (B=1,000), and the resulting placebo coefficients are plotted as kernel densities. The red vertical line marks the observed estimate.

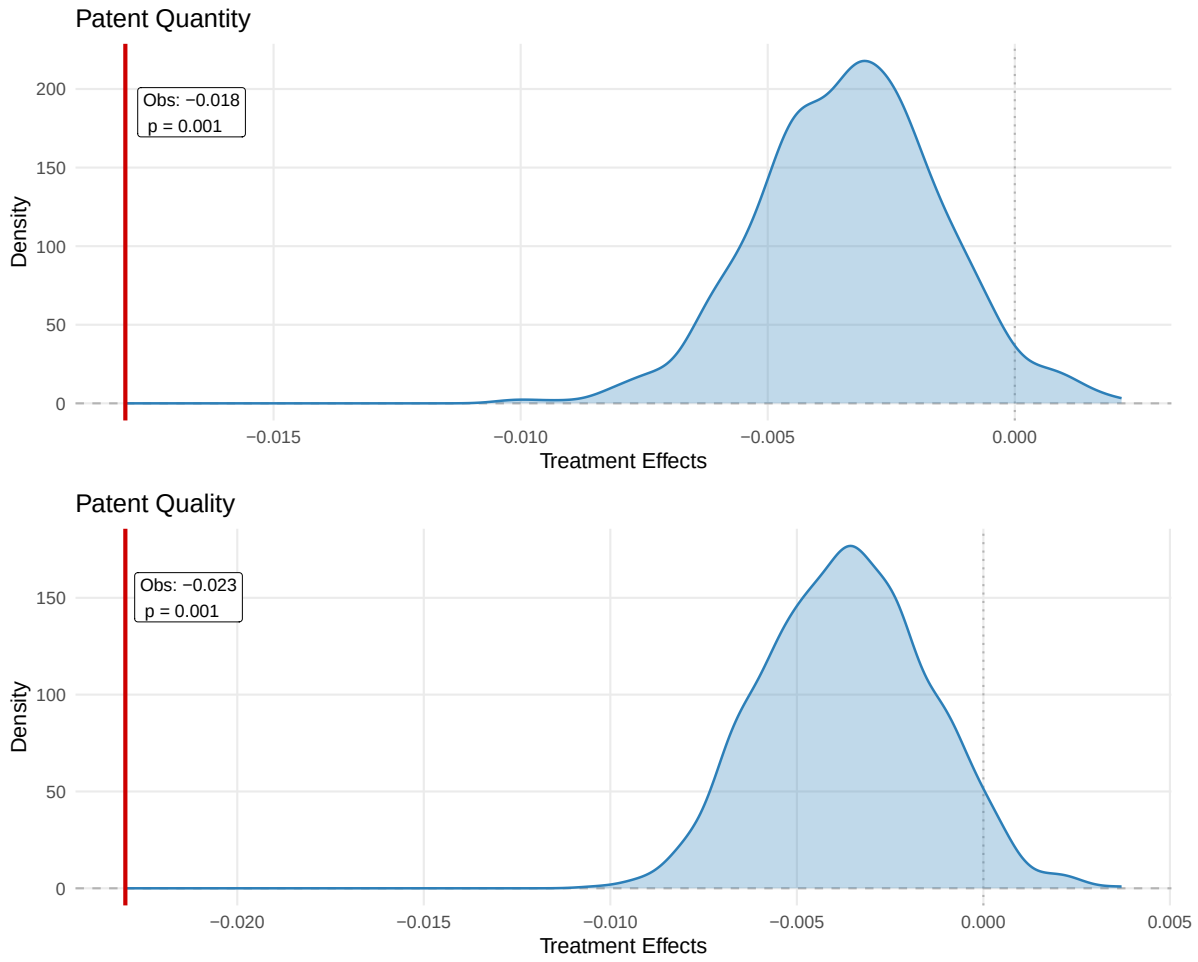


Figure S4: Placebo Test: Randomized Treated-Unit Assignment (Assignment Placebo)

Notes: Outcomes are patent quantity $\ln(1 + \#$ patents) and patent quality ($\ln(1 + \#$3-year forward citations)). Within prefecture×industry strata, treated firms are randomly reassigned while preserving the number of 2003 and 2004 treated in each stratum; the Column (4) IPW–TWFE from Table 1 is re-estimated each draw (B=1,000), and the resulting placebo coefficients are plotted as kernel densities. The red vertical line marks the observed estimate.

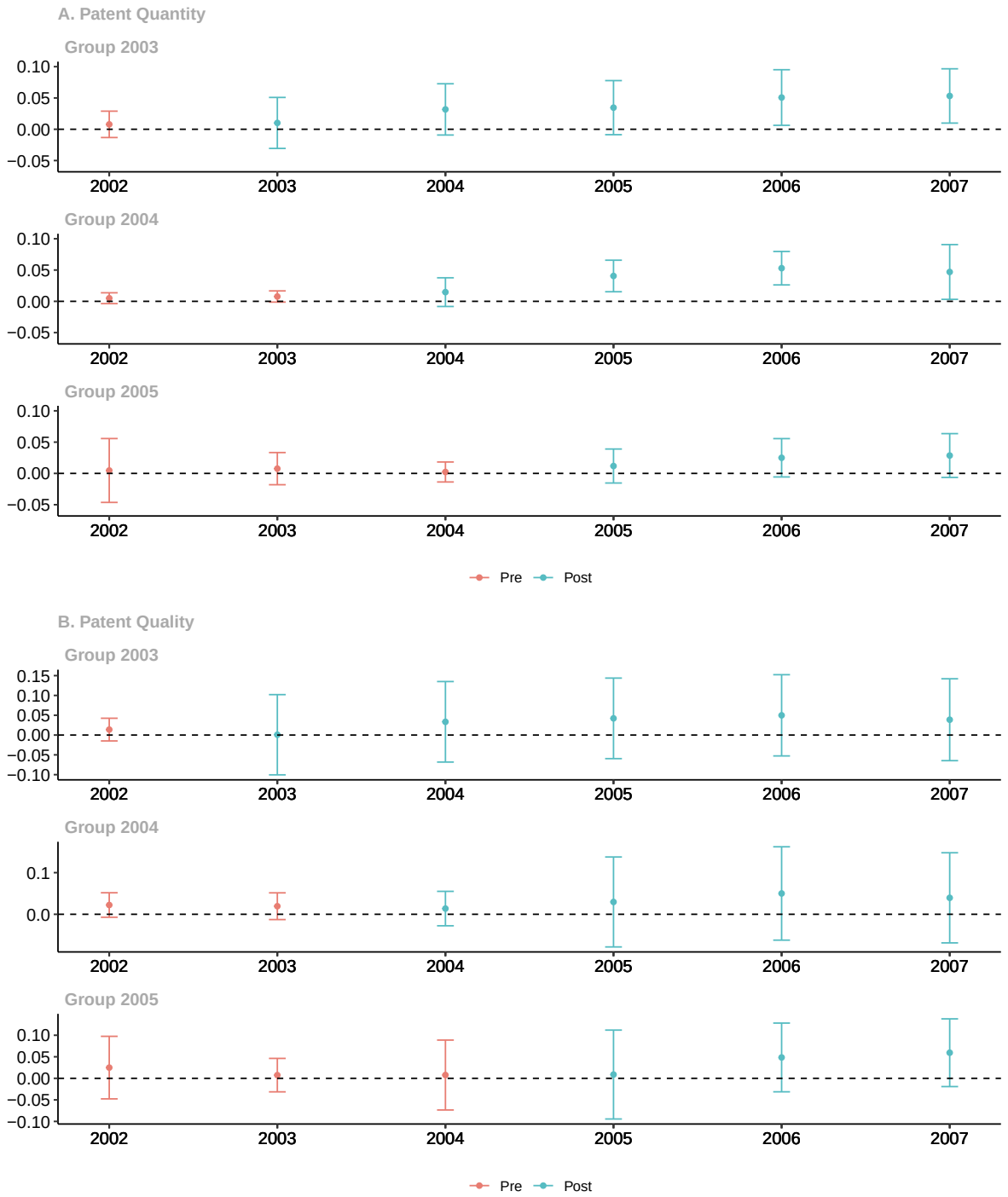


Figure S5: EDZ Opening Time-Varying Treatment Effects on Firm Patenting Outcomes

Notes: Inland sample only. Figure plots group–time average treatment effects, $\text{ATT}_{g,t}$ (Callaway and Sant'Anna, 2021). Outcomes are patent quantity $\ln(1 + \#\text{ patents})$ and patent quality ($\ln(1 + \#\text{3-year forward citations})$).

SI Tables

Table S1: Distribution of Firms and Districts

	Count	Share
Overall		
Total firms	46,840	
Firms		
Continuing EDZ	13,518	0.289
EDZ Closure	33,322	0.711
- 2003 Cohort	22,698	0.681
- 2004 Cohort	10,624	0.319
Districts		
Continuing EDZ	281	0.340
EDZ Closure	546	0.660

Notes: Balanced panel of coastal incumbent firms by treatment status.

Table S2: Pre-Treatment Means by Treatment Status

(1)	Continuing EDZ: Mean (SD) (2)	EDZ Closure: Mean (SD) (3)	Diff (4)
Main Outcomes			
Patent Quantity	0.051 (0.175)	0.047 (0.361)	−0.004*
Patent Quality	0.096 (0.349)	0.091 (0.301)	−0.005*
Other Outcomes			
Subsidy Intensity	0.195 (0.340)	0.204 (0.354)	0.009*
R&D Intensity	0.019 (0.033)	0.017 (0.025)	−0.002*
New Innovation (1=Yes)	0.091 (0.281)	0.086 (0.280)	−0.005*
Innovation Sales Intensity	0.034 (0.134)	0.030 (0.139)	−0.004
New Exporter (1=Yes)	0.138 (0.195)	0.121 (0.162)	−0.017*
Export Intensity	0.269 (0.397)	0.256 (0.398)	−0.013*
Zone Covariates			
High-Tech Zone	0.034 (0.181)	0.017 (0.128)	−0.017*
Upper-level GOV Zone	0.084 (0.278)	0.058 (0.233)	−0.027*
Distance to Nearest Port	203.5 (172.5)	215.0 (151.0)	11.5*
Firm Covariates			
TFP	1.928 (0.152)	1.919 (0.155)	−0.010*
Size	5.079 (1.072)	5.084 (1.082)	0.006
Age	12.2 (11.4)	12.4 (11.6)	0.200

Notes: * denotes two-tailed statistical significance of the mean at the 5% level. Means and standard deviations (in parentheses) for coastal firms in districts that experienced an EDZ closure compared to firms in districts with a continuing EDZ.

Table S3: Robustness Check: Alternative Estimator (PPML-TWFE)

	(1)	(2)	(3)	(4)
A. Patent Quantity				
Closure	-0.022^{*}	-0.021^{*}	-0.021^{*}	-0.020^{*}
	$[-0.029, -0.015]$	$[-0.027, -0.014]$	$[-0.028, -0.014]$	$[-0.026, -0.013]$
B. Patent Quality				
Closure	-0.028^{*}	-0.027^{*}	-0.026^{*}	-0.025^{*}
	$[-0.036, -0.019]$	$[-0.035, -0.018]$	$[-0.034, -0.017]$	$[-0.033, -0.016]$
Firms (#)	46,840	46,840	46,840	46,840
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	—	—	—
Industry-Year FE	No	Yes	Yes	Yes
City-Year FE	No	No	Yes	Yes
Covariate Trends	No	No	No	Yes

Notes: * indicates the null value lies outside the 95 percent confidence interval (reported in brackets). Robust standard errors are two-way clustered by firm and district. Estimates derived using Poisson Pseudo–MLE with high-dimensional fixed effects. Outcomes are patent quantity ln(1 + # patents) and patent quality (ln(1 + #3-year forward citations)). Column (1) includes year FE; Column (2) replaces year FE with industry-year FE; Column (3) additionally includes city-year FE; Column (4) further adds interactions between pre-treatment firm/zone characteristics and year dummies.

Table S4: Robustness Check: Semi-Balanced Panel (No Entry, Exits Allowed)

	(1)	(2)	(3)	(4)
A. Patent Quantity				
Closure	-0.025^{*}	-0.024^{*}	-0.023^{*}	-0.023^{*}
	$[-0.033, -0.017]$	$[-0.032, -0.016]$	$[-0.031, -0.015]$	$[-0.031, -0.015]$
B. Patent Quality				
Closure	-0.034^{*}	-0.033^{*}	-0.032^{*}	-0.031^{*}
	$[-0.044, -0.023]$	$[-0.043, -0.022]$	$[-0.042, -0.021]$	$[-0.041, -0.021]$
Firms (#)	95,125	95,125	95,125	95,125
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	—	—	—
Industry-Year FE	No	Yes	Yes	Yes
City-Year FE	No	No	Yes	Yes
Covariate Trends	No	No	No	Yes

Notes: * indicates the null value lies outside the 95 percent confidence interval (reported in brackets). Robust standard errors are two-way clustered by firm and district. Outcomes are patent quantity ln(1 + # patents) and patent quality (ln(1 + #3-year forward citations)). Semi-balanced panel fixes the pre-period firm set and allows post-treatment exit. Column (1) includes year FE; Columns (2)–(3) replace year FE with industry-year and city-year FE; Column (4) adds interactions between pre-treatment firm/zone characteristics and year dummies.

Table S5: Robustness Check: Direct Effects of EDZ Closures (Firm EDZ Participants Only)

	(1)	(2)	(3)	(4)
A. Patent Quantity				
Closure	-0.025^*	-0.024^*	-0.024^*	-0.024^*
	$[-0.035, -0.015]$	$[-0.033, -0.015]$	$[-0.033, -0.015]$	$[-0.033, -0.015]$
B. Patent Quality				
Closure	-0.047^*	-0.046^*	-0.046^*	-0.045^*
	$[-0.061, -0.033]$	$[-0.059, -0.032]$	$[-0.058, -0.034]$	$[-0.058, -0.032]$
Firms (#)	12,210	12,210	12,210	12,210
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	—	—	—
Industry×Year FE	No	Yes	Yes	Yes
City×Year FE	No	No	Yes	Yes
Covariate Trends	No	No	No	Yes

Notes: * indicates the null value lies outside the 95 percent confidence interval (reported in brackets). Robust standard errors are two-way clustered by firm and district.Outcomes are patent quantity ln(1 + # patents) and patent quality (ln(1 + #3-year forward citations)). This subsample restricts firms based on firm-level EDZ tag to capture direct effects of closure, excluding nearby district firms. Column (1) includes year FE; Columns (2)–(3) replace year FE with industry-year and city-year FE; Column (4) adds interactions between pre-treatment firm/zone characteristics and year dummies.

Table S6: Robustness Check: Extended District IPW Covariates and Inland Linkages

	(1)	(2)	(3)	(4)
A. Patent Quantity				
Closure	-0.020^*	-0.020^*	-0.021^*	-0.021^*
	$[-0.029, -0.011]$	$[-0.029, -0.011]$	$[-0.030, -0.012]$	$[-0.030, -0.012]$
B. Patent Quality				
Closure	-0.039^*	-0.038^*	-0.038^*	-0.035^*
	$[-0.056, -0.022]$	$[-0.055, -0.021]$	$[-0.054, -0.022]$	$[-0.052, -0.022]$
Firms (#)	46,840	46,840	46,840	46,840
IPW+				
District Covariates	Yes	Yes	Yes	Yes
IO Linkage	No	Yes	Yes	Yes
Trends+				
District Covariate Trends	No	No	Yes	Yes
IO Linkage Trend	No	No	No	Yes

Notes: * indicates the null value lies outside the 95% confidence interval (reported in brackets). Robust SEs are two-way clustered by firm and district. Outcomes are patent quantity ln(1 + # patents) and patent quality (ln(1 + #3-year forward citations)). Specifications include firm FE, industry-year FE, city-year FE, and interactions of pre-treatment firm/zone characteristics with year dummies. Column (1) extends IPW, adding pre-treatment district shares of SOEs, FIEs, and high-tech firms. Column (2) further extends IPW, adding the firm's pre-treatment inland IO linkage index, L^{IO}. Column (3) adds district covariate trends. Column (4) further adds an L^{IO} covariate trend.

Table S7: Spillover Checks in Continuing Zones

	Patent Quantity	Patent Quality	Employment
A. Prefecture			
Closure_{Share}	-0.004	-0.008^{*}	0.003
	$[-0.012, 0.004]$	$[-0.015, -0.001]$	$[-0.007, 0.013]$
B. Province			
Closure_{Share}	-0.003	-0.007	0.002
	$[-0.011, 0.005]$	$[-0.016, 0.002]$	$[-0.006, 0.010]$
Firms (#)	12,498	12,498	12,498
Firm FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes

Notes: * indicates the null value lies outside the 95 percent confidence interval (reported in brackets). Robust standard errors are two-way clustered by firm and district. Continuing–zone firms only; main window 2003–2005. Outcomes are patent quantity $\ln(1 + \#\text{ patents})$ and patent quality ($\ln(1 + \#\text{3-year forward citations})$). The main regressor is the cumulative share of EDZs in the firm's prefecture (Panel A) or province (Panel B) that have closed by year t, $\text{ClosureShare}_{\cdot,t} \in [0, 1]$.

Table S8: Effects of EDZ Closure on Patent Quality: Robustness to Citation Window

	(1)	(2)	(3)	(4)
A. Patent quality (1-year citations)				
Closure	-0.019^{*}	-0.020^{*}	-0.021^{*}	-0.020^{*}
	[-0.028, -0.010]	[-0.029, -0.012]	[-0.030, -0.013]	[-0.028, -0.012]
B. Patent quality (5-year citations)				
Closure	-0.026^{*}	-0.028^{*}	-0.029^{*}	-0.028^{*}
	[-0.037, -0.015]	[-0.039, -0.017]	[-0.040, -0.018]	[-0.039, -0.017]
Firms (#)	46,840	46,840	46,840	46,840
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	—	—	—
Industry-Year FE	No	Yes	Yes	Yes
City-Year FE	No	No	Yes	Yes
Covariate Trends	No	No	No	Yes

Notes: * indicates the null value lies outside the 95% confidence interval (reported in brackets). Robust SEs are two-way clustered by firm and district. Robustness of the closure effect on patent quality to alternative forward-citation windows. Outcomes are patent quantity $\ln(1 + \#\text{ patents})$ and patent quality ($\ln(1 + \#\text{3-year forward citations})$). Column (1) includes year FE; Columns (2)–(3) replace year FE with industry-year and city-year FE; Column (4) adds interactions between pre-treatment firm/zone characteristics and year dummies.

Table S9: Alternate Innovation Outcome: Effects of EDZ Closure on Firm Commercialization

	(1)	(2)	(3)	(4)
A. New innovator				
Closure	-0.009^{*}	-0.008^{*}	-0.006^{*}	-0.006^{*}
	$[-0.012, -0.006]$	$[-0.011, -0.005]$	$[-0.009, -0.003]$	$[-0.009, -0.003]$
B. Innovation Intensity				
Closure	-0.004^{*}	-0.004^{*}	-0.003^{*}	-0.003^{*}
	$[-0.005, -0.003]$	$[-0.005, -0.003]$	$[-0.004, -0.002]$	$[-0.005, -0.002]$
Firms (#)	46,840	46,840	46,840	46,840
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	—	—	—
Industry-Year FE	No	Yes	Yes	Yes
City-Year FE	No	No	Yes	Yes
Covariate Trends	No	No	No	Yes

Notes: * indicates the null value lies outside the 95 percent confidence interval (reported in brackets). Robust standard errors are two-way clustered by firm and district. New innovator equals 1 if the firm reports a new product/process, otherwise 0. Innovation sales intensity is new-product/process sales divided by total sales. Column (1) includes year FE; Columns (2)–(3) replace year FE with industry-year and city-year FE; Column (4) adds interactions between pre-treatment firm/zone characteristics and year dummies. with year dummies.

Table S10: Instrument relevance for closure-induced agglomeration disruption

	Outcome Variable: $D_{it}^{\text{close}} \times M_{im}^{\text{real}}$			
	Disruption Index:			
	Diversity	Specialization	Supplier	Buyer
	(1)	(2)	(3)	(4)
$D_{it}^{\text{close}} \times M_{im}^{\text{pred}}$	0.41^{*}	0.48^{*}	0.54^{*}	0.39^{*}
	[0.273, 0.547]	[0.343, 0.617]	[0.383, 0.697]	[0.253, 0.527]
Kleibergen–Paap rk F	33.8	45.2	46.9	31.4
Partial R^2	0.031	0.038	0.043	0.029
Firms (#)	46,840	46,840	46,840	46,840
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes
Covariate Trends	Yes	Yes	Yes	Yes

Notes: * indicates the null value lies outside the 95 percent confidence interval (reported in brackets). Robust standard errors are two-way clustered by firm and district. First-stage relevance for the endogenous interaction Closure × Disruption Index instrumented with Closure × Predicted Disruption. Predicted indices interact 2001-2002 local composition with national 1998-2002 industry shocks; Supplier and Buyer use 2002 input-output weights. The IV second-stage interaction coefficients appear in the main disruption table (Table 3).

Table S11: EDZ Closures, Agglomeration Disruptions, and Commercialization

	Disruption Index:			
	Diversity	Specialization	Supplier	Buyer
	(1)	(2)	(3)	(4)
A. New innovator				
Closure Intensity	−0.003*	−0.003*	−0.002*	−0.004*
	[−0.004, −0.001]	[−0.005, −0.002]	[−0.004, −0.001]	[−0.006, −0.002]
B. Innovation Intensity				
Closure Intensity	−0.002*	−0.002*	−0.003*	−0.006*
	[−0.002, −0.001]	[−0.003, −0.002]	[−0.004, −0.002]	[−0.007, −0.004]
Firms (#)	46,840	46,840	46,840	46,840
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes
Covariate Trends	Yes	Yes	Yes	Yes

Notes: * indicates the null lies outside the 95 percent confidence interval (reported in brackets). Robust standard errors are two-way clustered by firm and district. New innovator equals 1 if the firm reports a new product/process, otherwise 0. Innovation sales intensity is new-product/process sales divided by total sales. Entries report 2SLS estimates of Closure × Disruption Index for each channel (Diversity, Specialization, Supplier, Buyer). The endogenous interaction is instrumented with Closure × Predicted Disruption, where the predicted index interacts 2001-2002 local composition with national 1998-2002 industry employment shocks; Supplier/Buyer use 2002 input-output weights (Appendix A). First-stage results reported in Table S10. All lower-order terms implied by the interaction are included. Specifications include firm FE, industry-year FE, city-year FE, and interactions of pre-treatment covariates with year dummies.

Table S12: Effects of Zone Closure on Firm Export Performance

	(1)	(2)	(3)	(4)
A. New exporter				
Closure	−0.008*	−0.007*	−0.006*	−0.005*
	[−0.012, −0.005]	[−0.011, −0.004]	[−0.009, −0.003]	[−0.008, −0.002]
B. Export intensity				
Closure	−0.016*	−0.015*	−0.014*	−0.014*
	[−0.020, −0.013]	[−0.019, −0.012]	[−0.017, −0.011]	[−0.017, −0.011]
Firms (#)	46,840	46,840	46,840	46,840
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	—	—	—
Industry-Year FE	No	Yes	Yes	Yes
City-Year FE	No	No	Yes	Yes
Covariate trends	No	No	No	Yes

Notes: * indicates the null value lies outside the 95% confidence interval (reported in brackets). Robust standard errors are two-way clustered by firm and district. Outcomes are New exporter (indicator = 1 if the firm exports for the first time, 0 otherwise) and Export intensity (export sales divided by total sales). Column (1) includes year FE; Columns (2) and (3) replace year FE with industry-year and city×year FE to absorb sectoral and local shocks; Column (4) further adds interactions between pre-treatment firm/zone characteristics and year dummies.

Table S13: Effects of New Inland EDZ Opening on Patenting

	(1)	(2)	(3)	(4)
A. Patent quantity				
EDZ Opening	0.018*	0.015*	0.018*	0.017*
	[0.008, 0.029]	[0.006, 0.025]	[0.008, 0.028]	[0.007, 0.026]
B. Patent Quality				
EDZ Opening	0.009	0.006	0.015	0.013
	[-0.013, 0.031]	[-0.015, 0.027]	[-0.007, 0.037]	[-0.008, 0.034]
Firms (#)	9,106	9,106	9,106	9,106
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	—	—	—
Industry-Year FE	No	Yes	Yes	Yes
City-Year FE	No	No	Yes	Yes
Covariate Trends	No	No	No	Yes

Notes: Inland sample only. * indicates the null value lies outside the 95 percent confidence interval (reported in brackets). Robust standard errors are two-way clustered by firm and district. Outcomes are patent quantity ln(1+# patents) and patent quality (ln(1+#3-year forward citations)). Column (1) includes year FE; Columns (2)–(3) replace year FE with industry-year and city-year FE; Column (4) adds interactions between pre-treatment firm/zone characteristics and year dummies.

Table S14: Instrument relevance and IV estimates for zone opening-induced agglomeration formation (inland EDZs)

	Agglomeration Formation Index:			
	Diversity	Specialization	Supplier	Buyer
	(1)	(2)	(3)	(4)
A. First stage				
EDZ Opening × Formation (Pred)	0.34*	0.40*	0.46*	0.33*
	[0.164, 0.516]	[0.224, 0.576]	[0.264, 0.656]	[0.154, 0.506]
B. Patent quantity				
EDZ Opening × Formation (IV)	0.0015*	0.0021*	0.0032*	0.0013*
	[0.0005, 0.0025]	[0.0010, 0.0032]	[0.0019, 0.0045]	[0.0002, 0.0024]
C. Patent quality				
EDZ Opening × Formation (IV)	0.0018*	0.0026*	0.0037*	0.0021*
	[0.0002, 0.0034]	[0.0010, 0.0041]	[0.0020, 0.0054]	[0.0006, 0.0036]
Firms (#)	9,106	9,106	9,106	9,106
Kleibergen–Paap rk F	14.5	19.8	21.7	13.9
Partial R^2	0.017	0.022	0.026	0.016
Firm FE	Yes	Yes	Yes	Yes
Industry–Year FE	Yes	Yes	Yes	Yes
City–Year FE	Yes	Yes	Yes	Yes
Covariate Trends	Yes	Yes	Yes	Yes

Notes: Inland sample only. * indicates the null value lies outside the 95 percent confidence interval (reported in brackets). Robust standard errors are two-way clustered by firm and district. Panel A reports the first stage of 2SLS where the endogenous interaction $D_{it}^{\text{open}} \times M_{im}^{\text{real,formation}}$ is instrumented with $D_{it}^{\text{open}} \times M_{im}^{\text{pred,formation}}$. Predicted agglomeration formation indices interacts 2001–2002 district–industry composition with national 1998–2002 industry shocks; Supplier/Buyer use 2002 input–output weights (Appendix E). Panels B and C report the corresponding second-stage coefficients for patent quantity and citation-weighted quality. All lower-order terms implied by the interaction are included; specifications include firm, industry–year, and city–year fixed effects, and interactions of pre-treatment covariates with year dummies.

Table S15: Disruption Indices Averages by Treatment Status (Coastal EDZs)

Index	Continuing EDZs Mean (SD)	Closed EDZs Mean (SD)	Difference
A. Horizontal			
Diversity (M^{Jacobs})	0.034 (0.082)	0.057 (0.109)	0.023*
Specialization (M^{MAR})	0.028 (0.077)	0.065 (0.102)	0.037*
B. Vertical			
Supplier (upstream) (M^{Supplier})	0.041 (0.091)	0.083 (0.121)	0.042*
Buyer (downstream) (M^{Buyer})	0.037 (0.088)	0.070 (0.116)	0.033*

Notes: * denotes two-tailed statistical significance of the mean at the 5% level. Means and standard deviations (in parentheses) of disruption indices, computed using baseline composition (2001–2002) and closure-window thinning as described in Section A.

Table S16: Distribution of Firms and Districts (Inland Sample)

	Count	Share
Overall		
Total firms	9,106	
Firms		
Continuing EDZ	4,447	0.487
EDZ Opening	4,659	0.513
- 2003 Cohort	2,445	0.525
- 2004 Cohort	2,000	0.429
- 2005 Cohort	214	0.046
Districts		
Continuing EDZ	370	0.497
EDZ Opening	375	0.503

Notes: Balanced panel of inland incumbent firms by treatment status.

Table S17: Pre-Treatment Means by Treatment Status (Inland EDZs)

(1)	Continuing EDZ: Mean (SD) (2)	New EDZ Opening: Mean (SD) (3)	Diff (4)
Main Outcomes			
Patent Quantity	0.038 (0.250)	0.042 (0.274)	0.004
Patent Quality	0.072 (0.533)	0.077 (0.511)	0.005
Other Outcomes			
Subsidy Intensity	0.213 (0.320)	0.204 (0.324)	0.009*
R&D Intensity	0.012 (0.023)	0.010 (0.021)	−0.002*
New Innovation (1=Yes)	0.120 (0.325)	0.137 (0.344)	0.017*
Innovation Sales Intensity	0.024 (0.132)	0.029 (0.151)	0.005
Exporter (1=Yes)	0.145 (0.352)	0.144 (0.351)	−0.001
Export Intensity	0.057 (0.199)	0.058 (0.204)	0.001
Zone Covariates			
High-Tech Zone	0.021 (0.143)	0.025 (0.155)	0.004
Upper-level GOV Zone	0.030 (0.170)	0.038 (0.190)	−0.008*
Distance to Nearest Port	782.2 (421.2)	723.9 (359.7)	−58.3*
Firm Covariates			
TFP	1.888 (0.177)	1.890 (0.175)	0.003
Size	5.348 (1.164)	5.389 (1.182)	0.041*
Age	17.034 (14.731)	17.982 (15.458)	0.948*

Notes: * denotes two-tailed statistical significance of the mean at the 5% level. Means and standard deviations (in parentheses) for inland firms in districts with a new EDZ opening compared to firms in districts with a continuing EDZ that pre-existed the zone reform.

Table S18: Agglomeration Formation Indices by Treatment Status (Inland EDZs)

Index (standardized)	Continuing EDZs Mean (SD)	EDZ Opening Mean (SD)	Difference
A. Horizontal			
Diversity (M^{Jacobs})	0.022 (0.081)	0.048 (0.105)	0.026*
Specialization (M^{MAR})	0.019 (0.076)	0.041 (0.098)	0.022*
B. Vertical			
Supplier (upstream)	0.026 (0.088)	0.055 (0.118)	0.029*
Buyer (downstream)	0.023 (0.086)	0.051 (0.114)	0.028*

Notes: * denotes two-tailed statistical significance of the mean at the 5% level. Means and standard deviations (in parentheses) of agglomeration formation indices, computed using baseline composition (2001–2002) and new zone opening-window as described in Section E.